

Supplemental Appendix

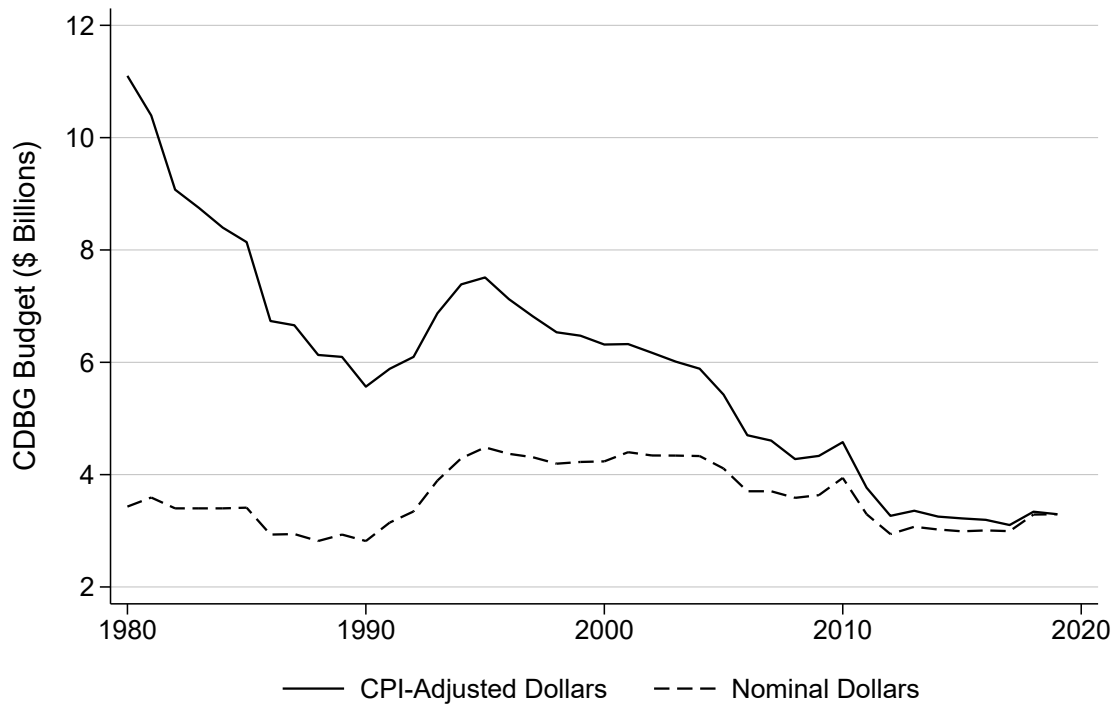
Building Blocks of Prosperity: The Job Impacts of Federal Block Grants for Developing
Low-Income Communities

George Zuo

For Online Publication

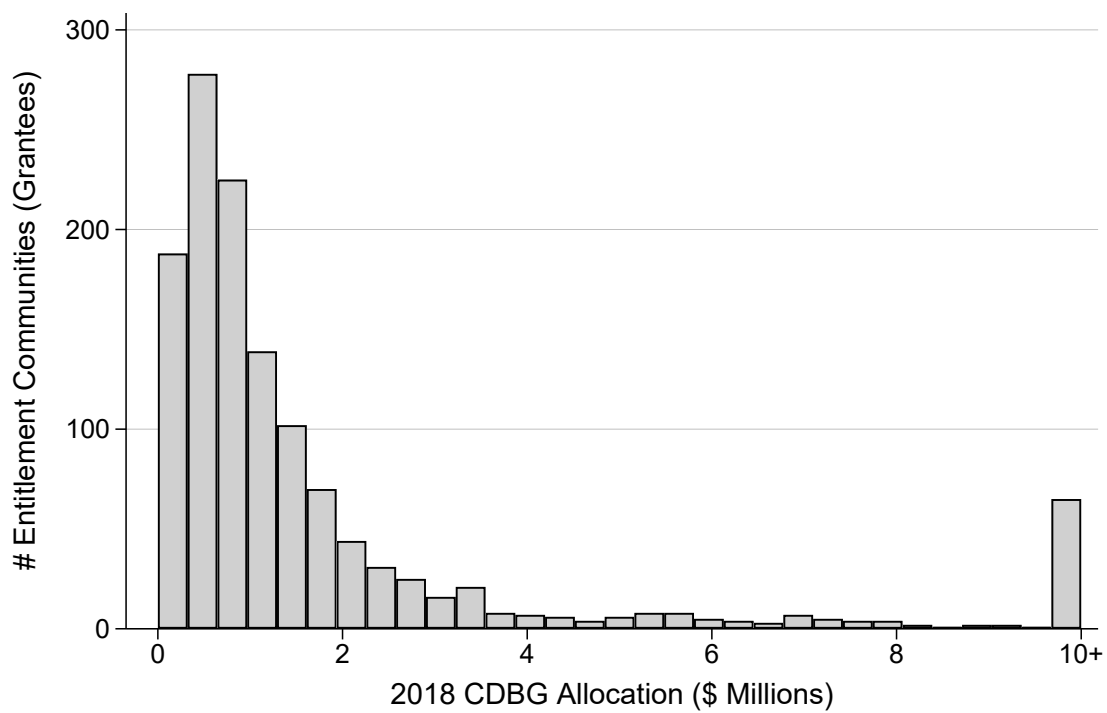
Appendix A: Appendix Tables and Figures

Figure A1: Historical CDBG appropriations



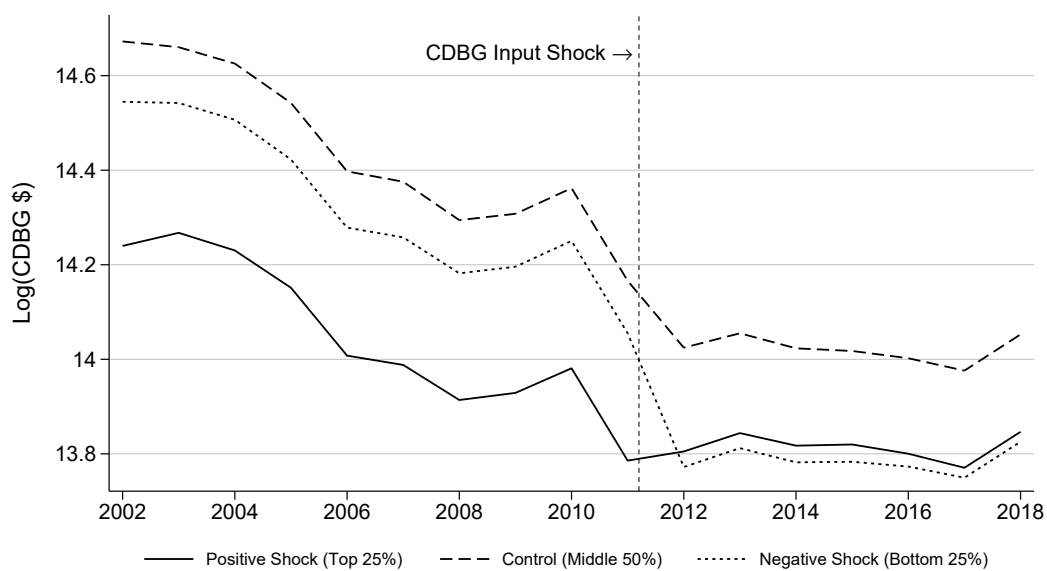
Note: This figure presents the evolution of the CDBG budget appropriated by Congress over time. CDBG budget in real dollars was adjusted relative to the 2019 CPI. Data were obtained from the U.S. Department of Housing and Urban Development.

Figure A2: Distribution of grantee-level allocations



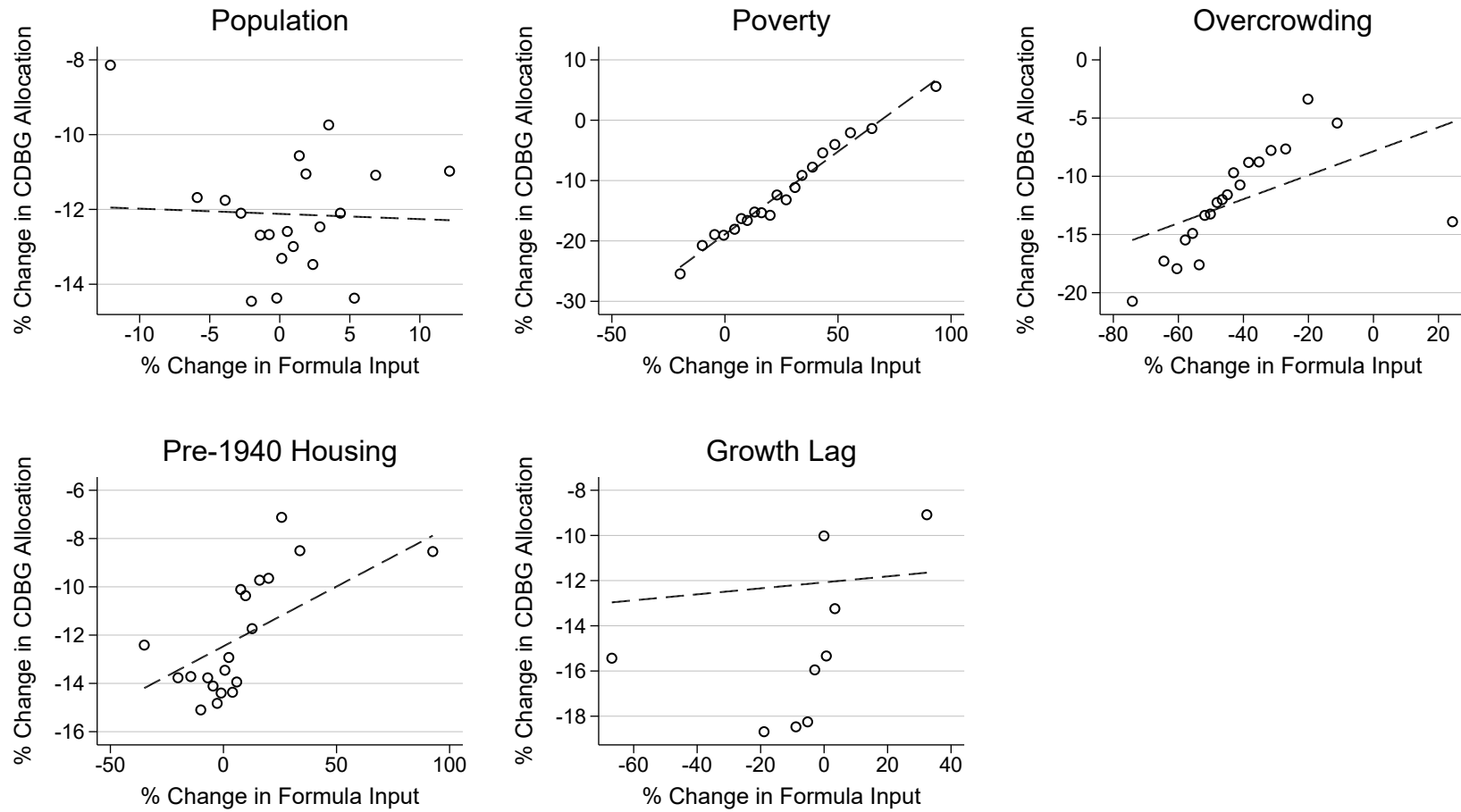
Note: This figure presents the distribution of grantee-level CDBG allocations in 2018. Data come from CDBG allocation spreadsheets provided by the U.S. Department of Housing and Urban Development.

Figure A3: Changes in CDBG funding, uncentered



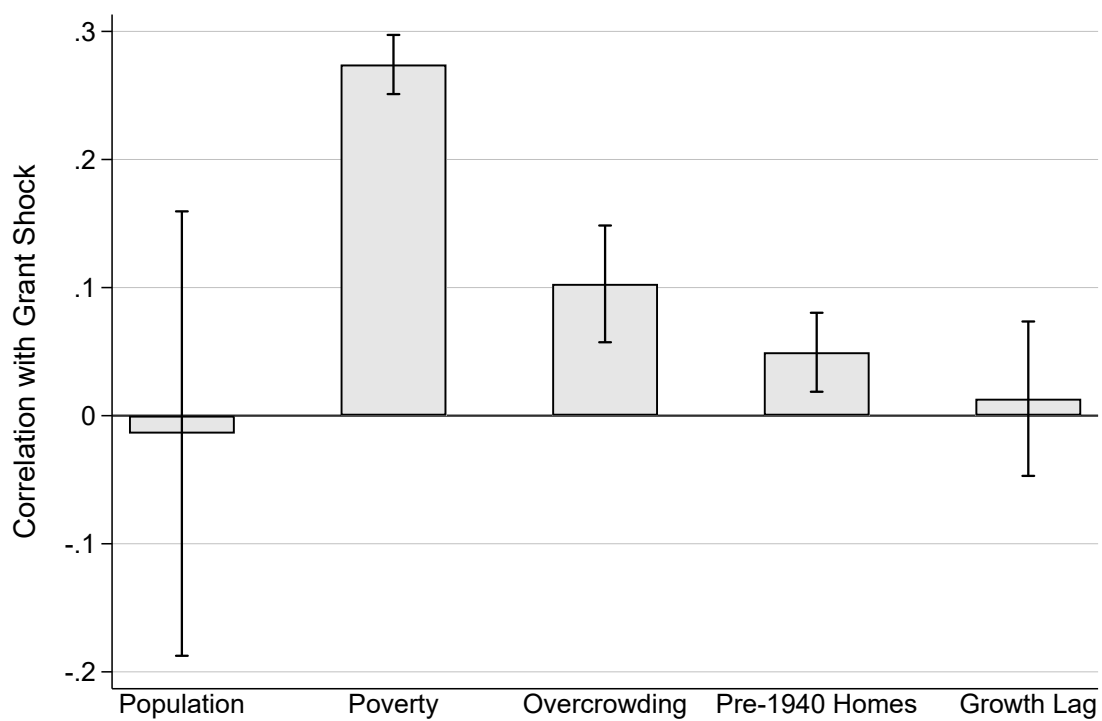
Note: This figure provides the uncentered version of Figure 2, minus the centering to show differences relative to 2011 levels.

Figure A4: Relationship between Input Shocks and CDBG Funding Shocks



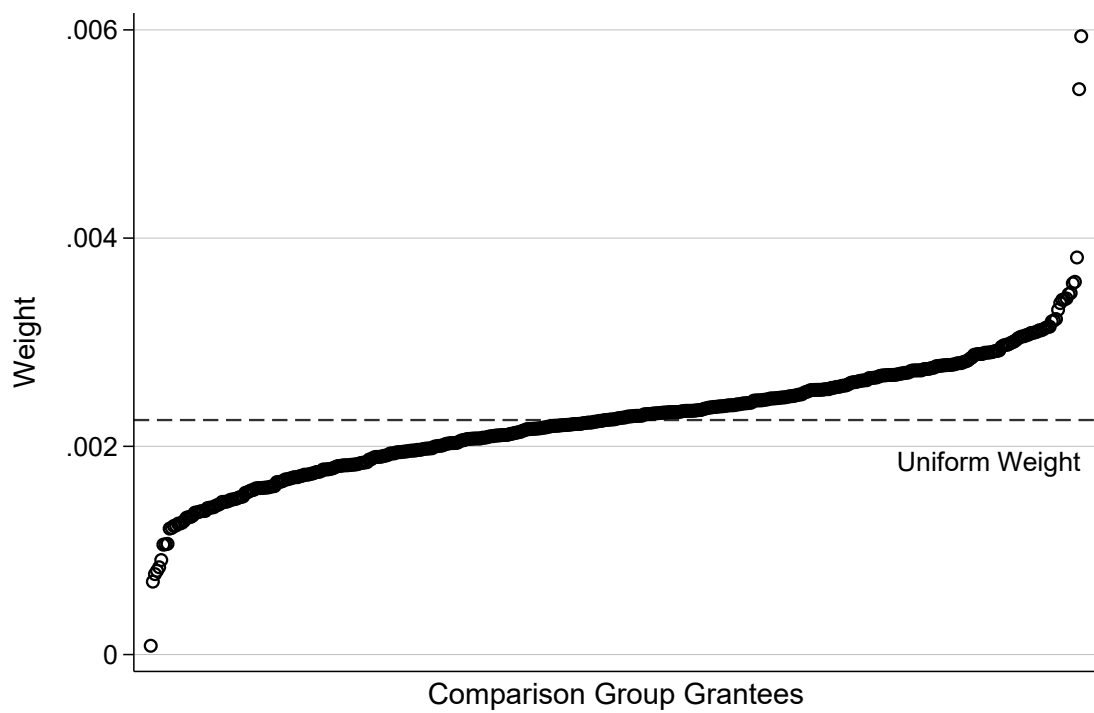
Note: This figure provides binned scatterplots illustrating the relationship between the 2011 and 2012 changes in formula inputs versus the 2011 and 2012 changes in CDBG allocations. Each point represents an equally-sized bin—with the exception of growth lag where there is a much larger mass of observations at zero.

Figure A5: Correlation between Input Shocks and CDBG Funding Shocks



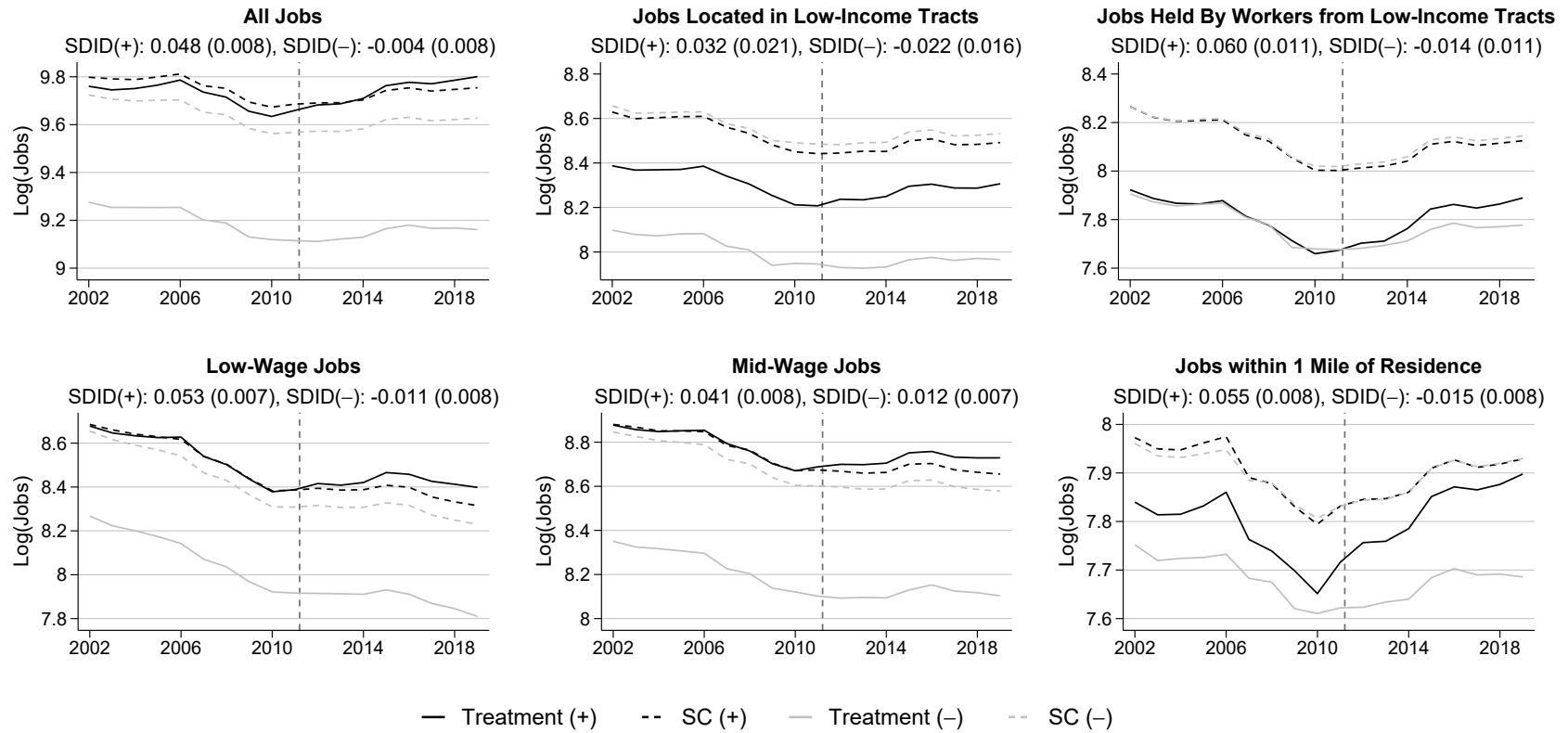
Note: This figure provides regression estimates showing the association between changes in individual formula inputs and changes in CDBG allocations between 2011 and 2012 (when the data shock occurred). 95 percent confidence intervals are included.

Figure A6: SDID Comparison Group Weights



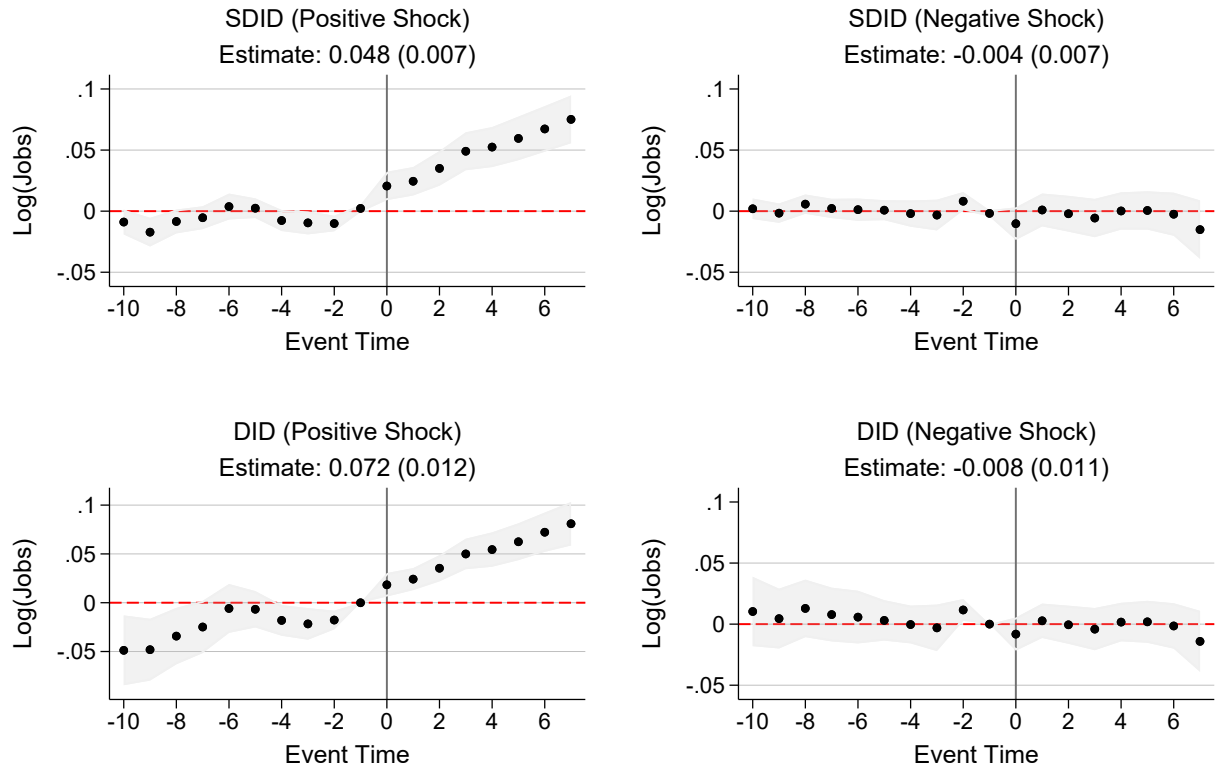
Note: This figure plots the weights underlying the synthetic control, relative to what uniform weights would imply.

Figure A7: Uncentered job impacts



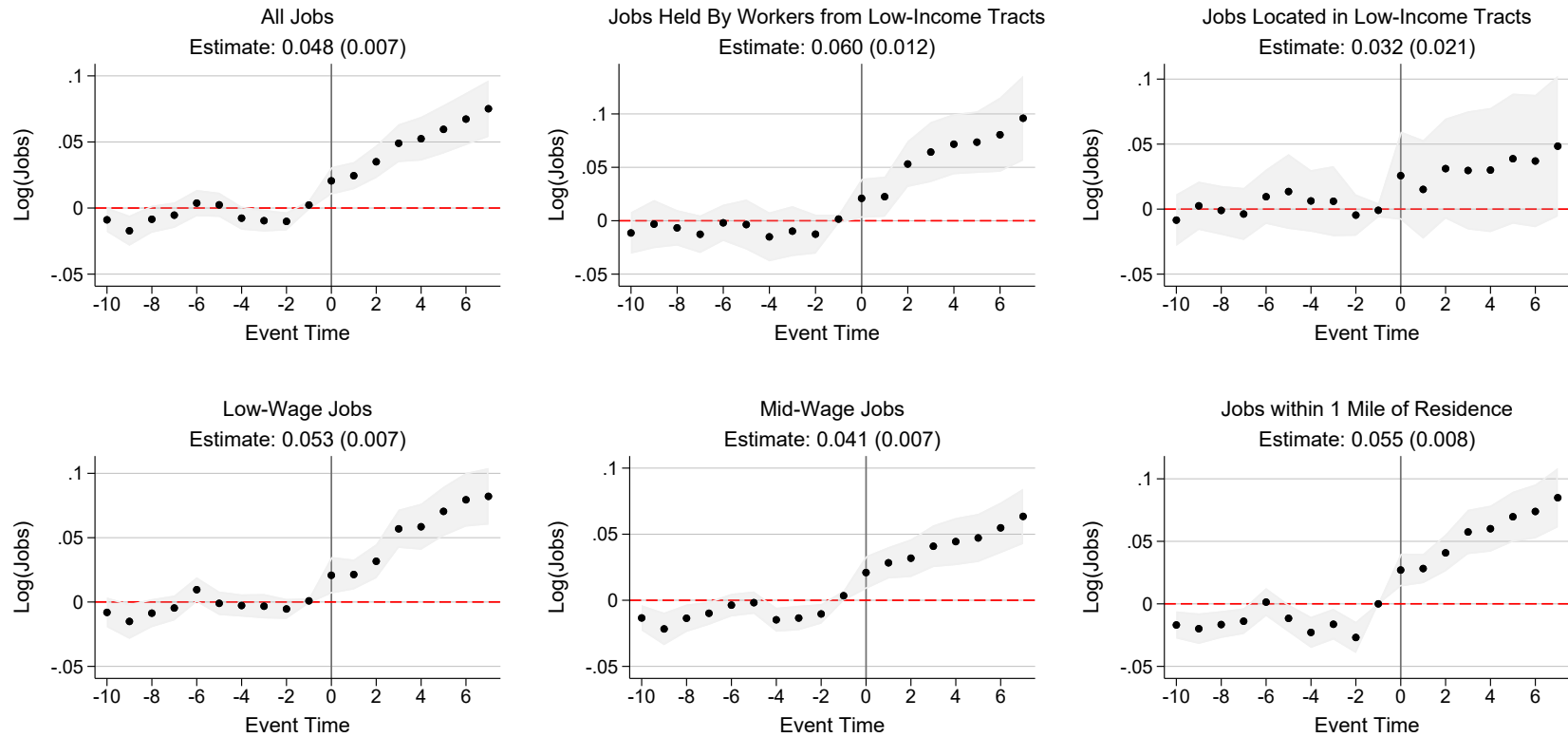
Note: This figure presents the impact of CDBG investments on six different job count outcomes. It departs from Figure 4 in that the y-axis has been uncentered from showing job counts relative to 2011 levels.

Figure A8: Event Study: Jobs



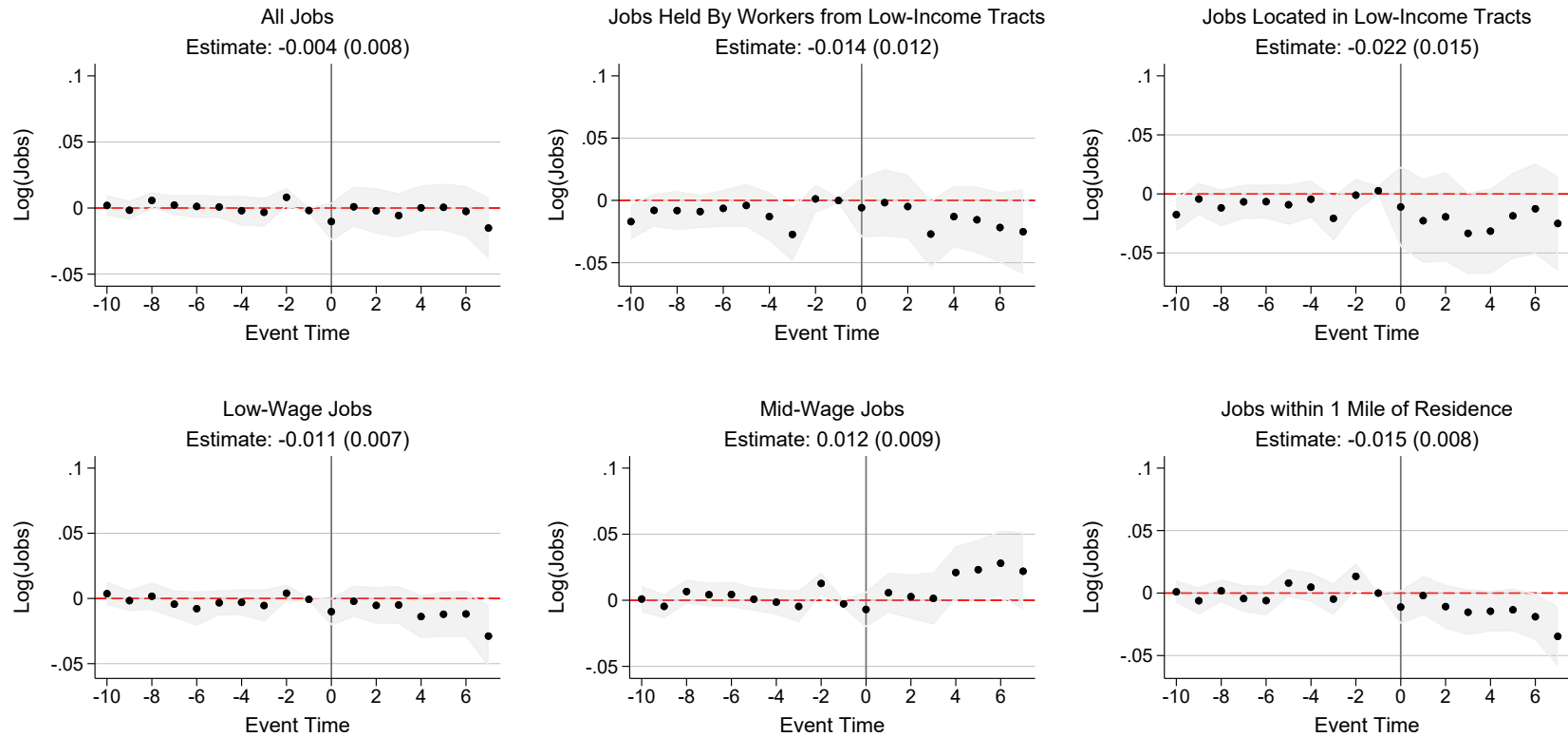
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on job counts, accompanying Figure 3. SDID event studies were generated following Ciccina (2024) using bootstrap inference with 100 iterations to construct standard errors. Shown SDID standard errors differ marginally from the standard errors shown in Figure 3 due to seed differences.

Figure A9: Event Studies by Job Type (Positive Shock)



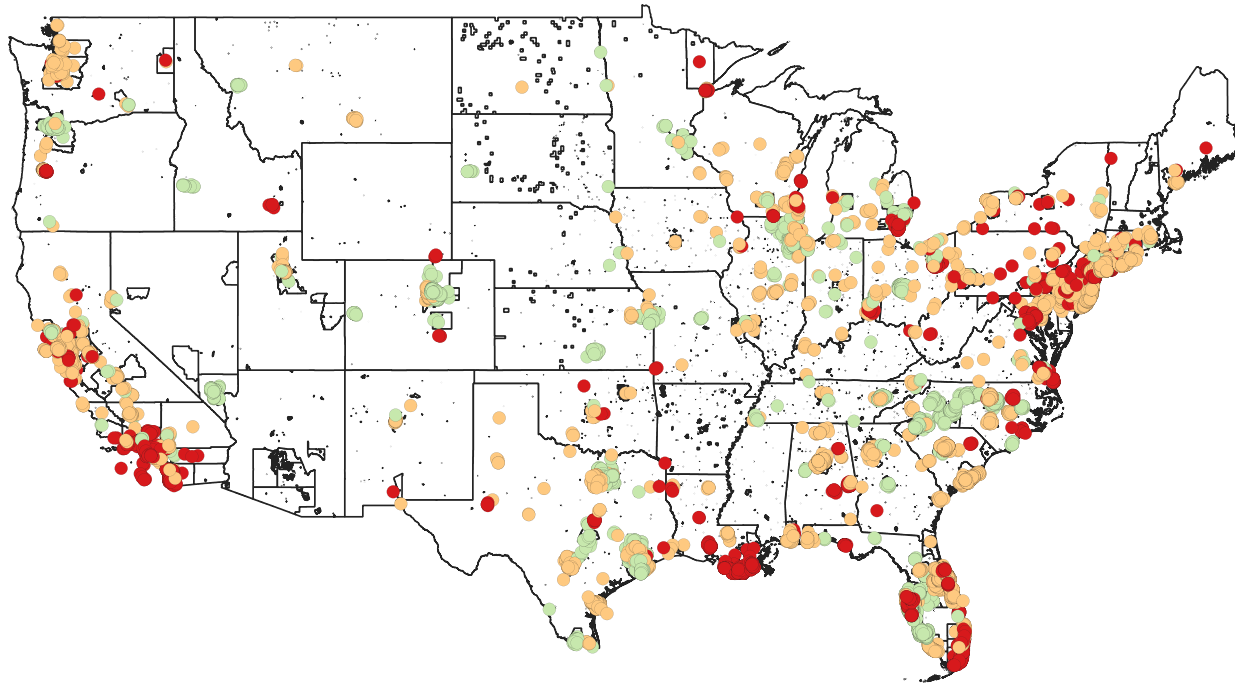
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on job counts for different job types when comparing positively shocked vs. control grantees, accompanying the darker series plotted in Figure 4. SDID event studies were generated following Ciccio (2024) using bootstrap inference with 100 iterations to construct standard errors. Shown SDID standard errors differ marginally from the standard errors shown in Figure 4 due to seed differences.

Figure A10: Event Studies by Job Type (Negative Shock)



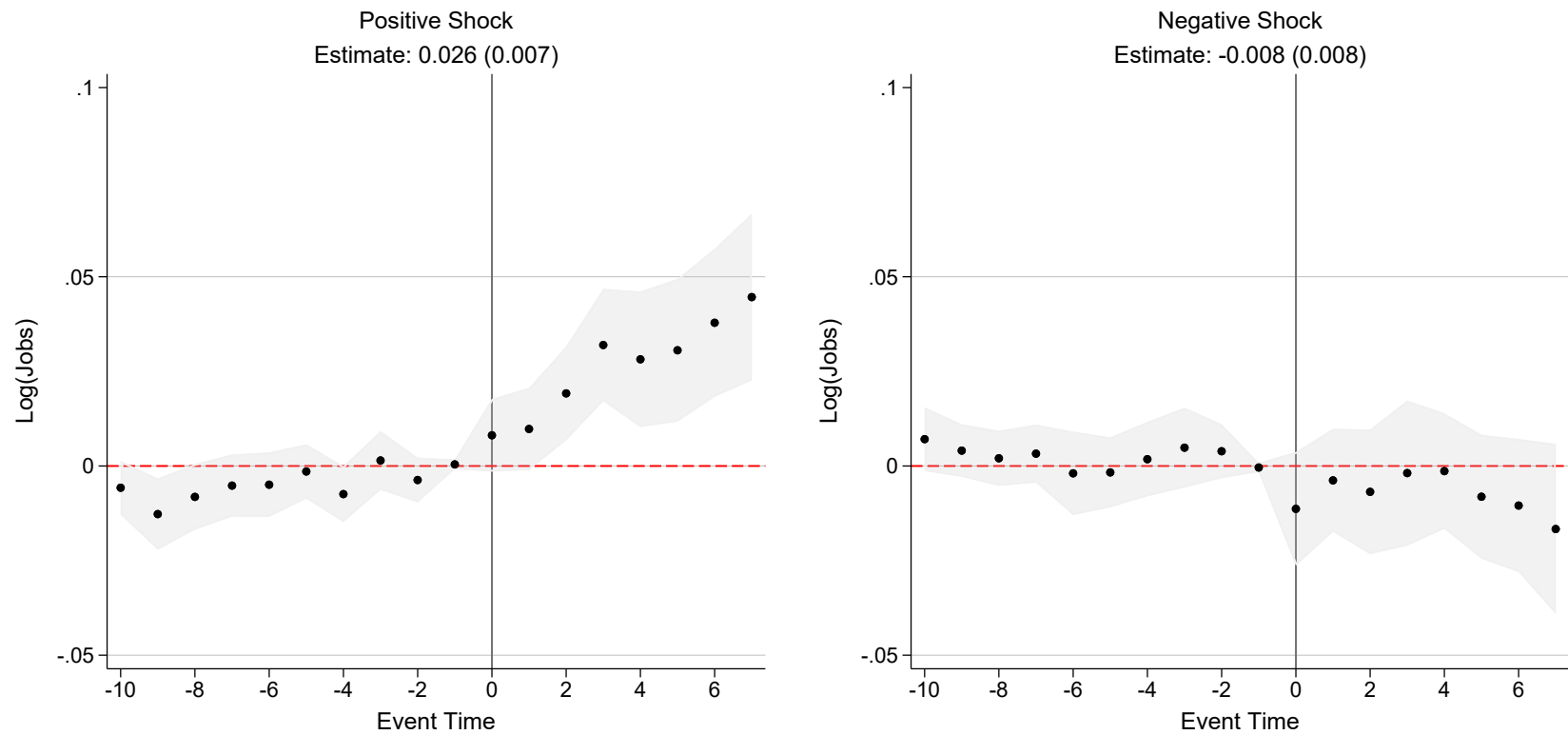
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on job counts for different job types when comparing negatively shocked vs. control grantees, accompanying the lighter series plotted in Figure 4. SDID event studies were generated following Ciccio (2024) using bootstrap inference with 100 iterations to construct standard errors. Shown SDID standard errors differ marginally from the standard errors shown in Figure 4 due to seed differences.

Figure A11: Geographic distribution of the CDBG shock



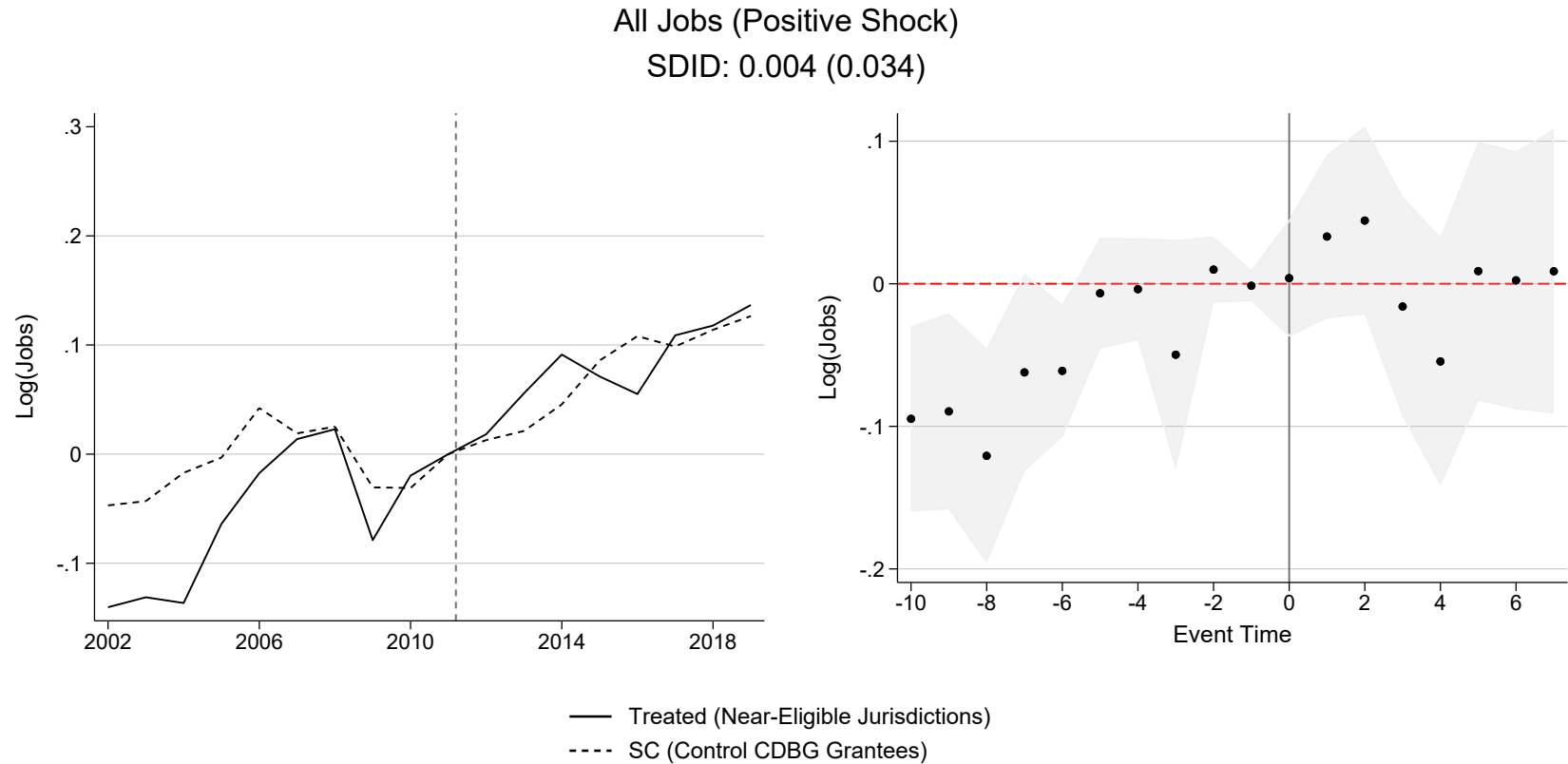
Note: This figure presents the spatial distribution of positively shocked (green), control (yellow), and negatively shocked (red) grantees across the U.S. This map excludes grantees in states for which LODS-LEHD data were not available for certain years (i.e., MA, MS, AZ, NH, AR).

Figure A12: Robustness: Within-State Assignment of Treatment



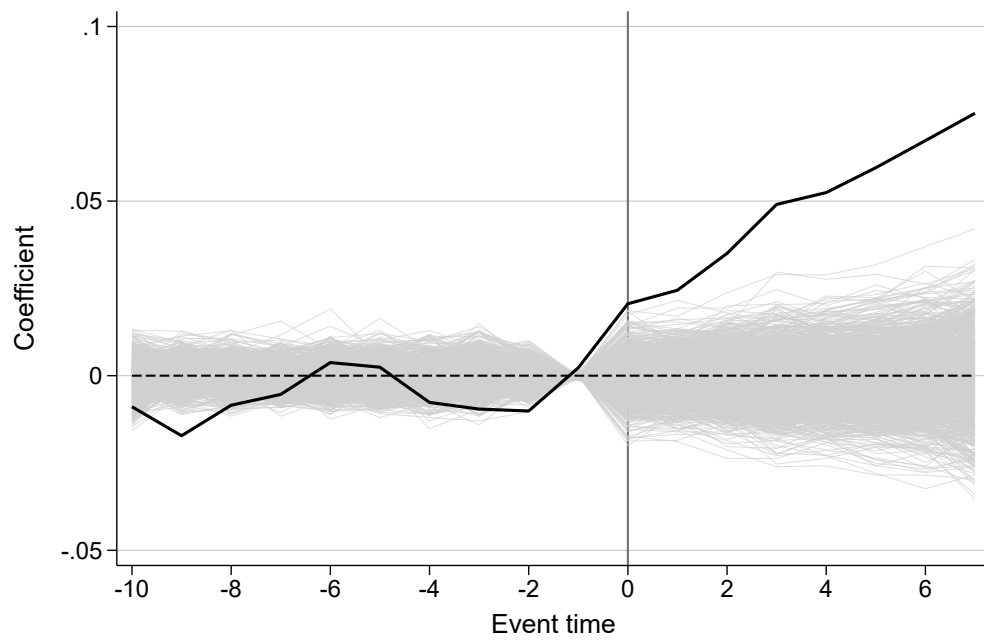
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on job counts, now restricting assignment of treatment status (i.e., positive shock vs. negative shock vs. control) to grantees within the same state.

Figure A13: Falsification Test: Near-Eligible Positive Shocks



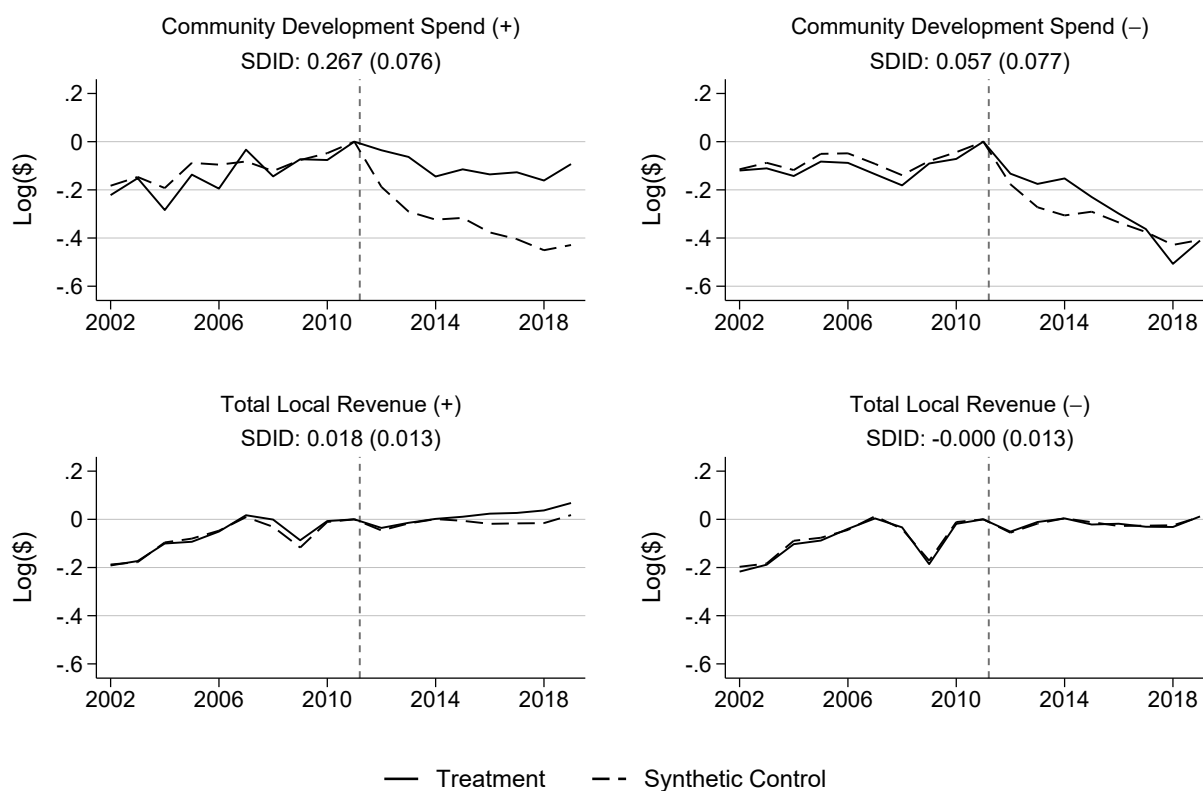
Note: This figure presents a falsification test using a set of near-eligible non-CDBG jurisdictions within 25% below the CDBG population threshold that would have received a positive shock from the CDBG had they been a part of the program (11 jurisdictions). Grant amounts for these jurisdictions were simulated using CDBG formula inputs from Decennial Censuses and the ACS. These jurisdictions are compared against CDBG grantees with populations within 25% above the population threshold which fell into the control set of jurisdictions for the main analysis (95 jurisdictions). The plots show SDID effects when comparing job counts for positively shocked, near-eligible non-CDBG jurisdictions versus control, near-eligible CDBG grantees.

Figure A14: Permutation Test



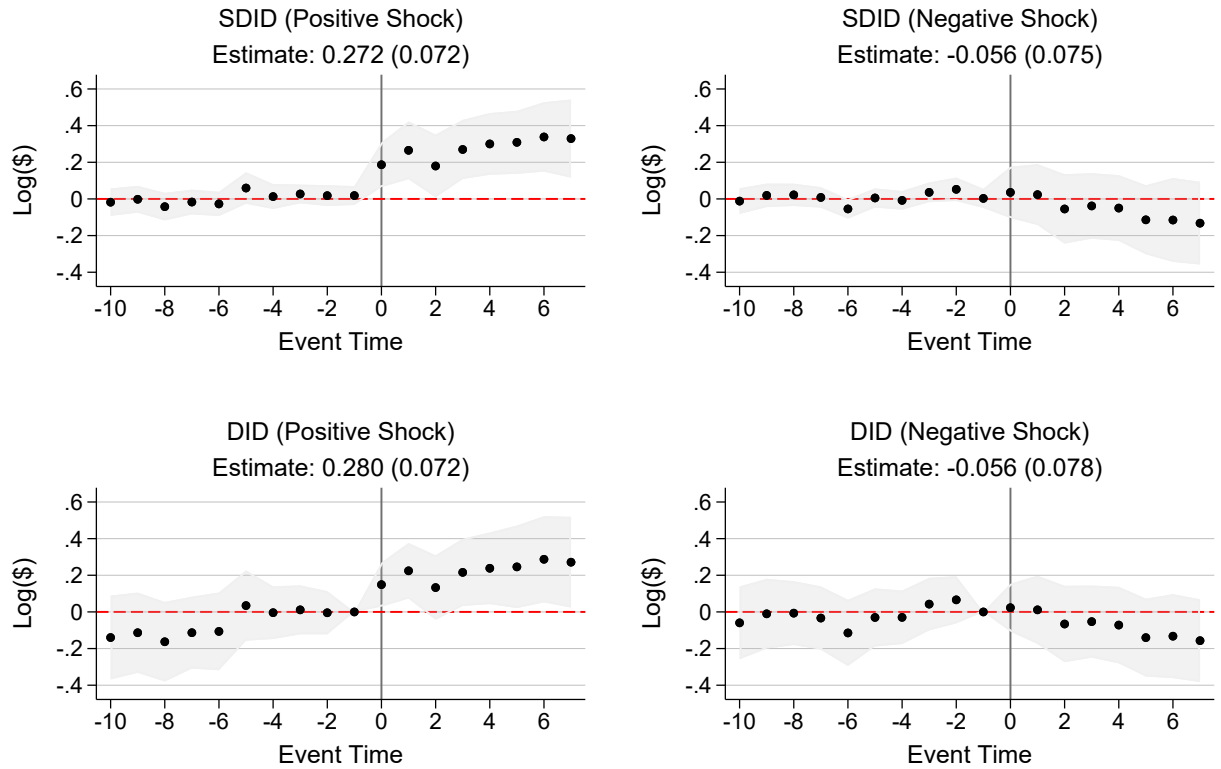
Note: This figure presents the distribution of 1,000 permutation-based SDID event study estimates, generated by randomly reassigning positive-shock, control, and negative-shock treatment labels across grantees while preserving group sizes. Light gray lines represent placebo event-study paths from permuted assignments; the solid black line shows the actual SDID estimate.

Figure A15: Impacts on local public spending (dropping grantees with any missing data)



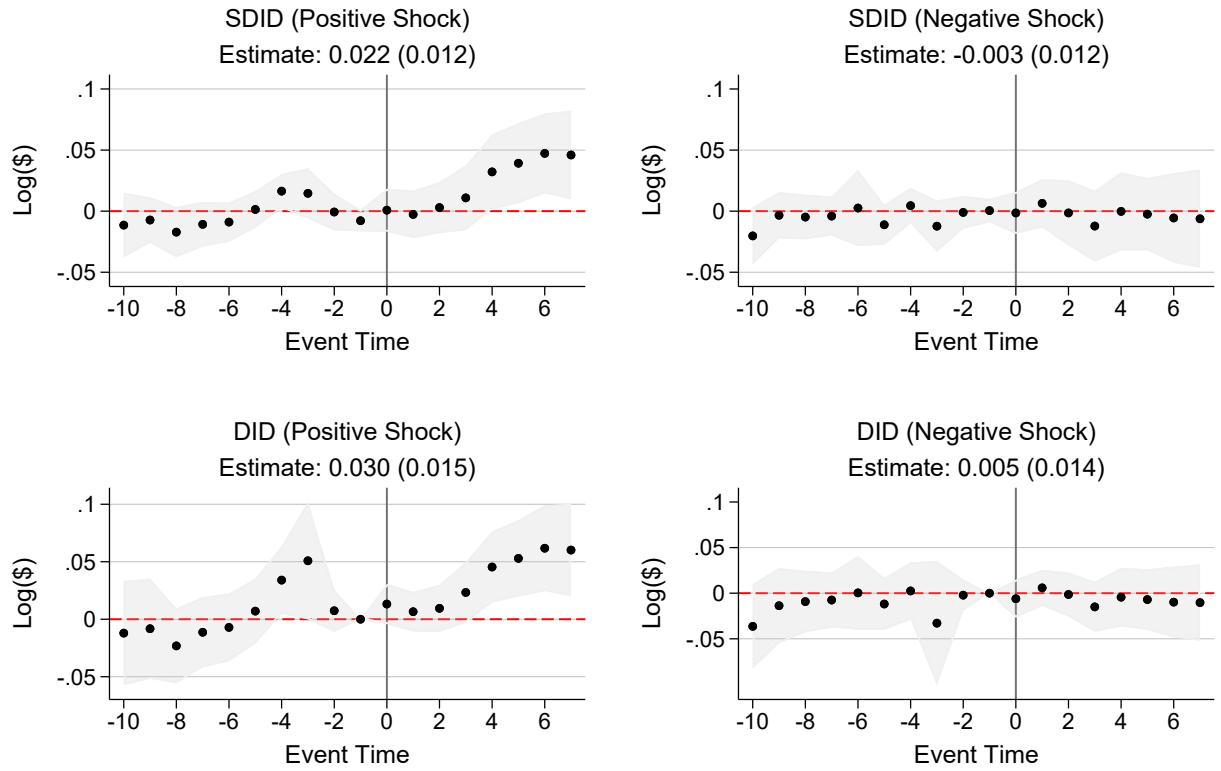
Note: This figure presents the impact of the CDBG shock for positively and negatively shocked grantees on 1) local public spending for community development, and 2) total local revenue. In contrast to Figure 6, this figure provides estimates when grantees missing any data are dropped from the sample. This decreases the number of grantees from 664 to 476.

Figure A16: Event Study: Community Development Spending



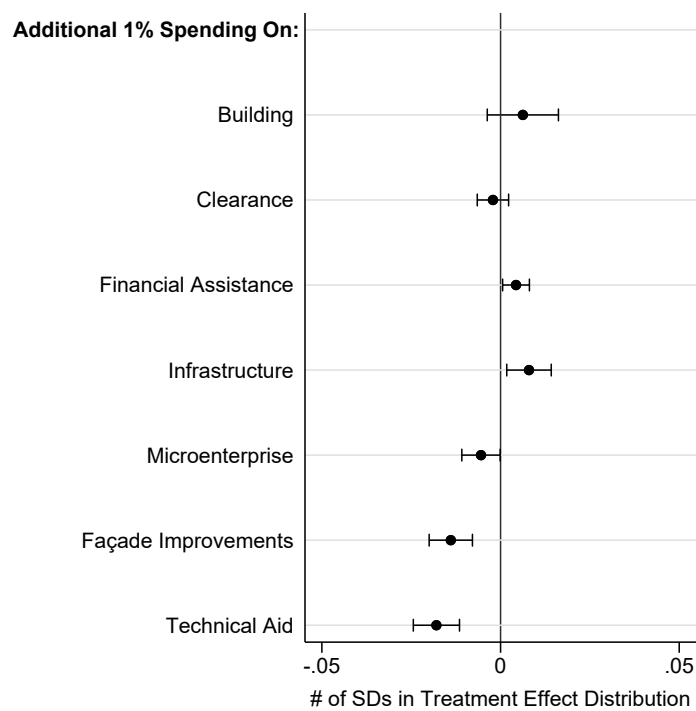
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on public spending on community development, accompanying the top two graphs in Figure 6. SDID event studies were generated following Ciccia (2024) using bootstrap inference with 100 iterations to construct standard errors. Shown SDID standard errors differ marginally from the standard errors shown in Figure 6 due to seed differences.

Figure A17: Event Study: Total Local Revenue



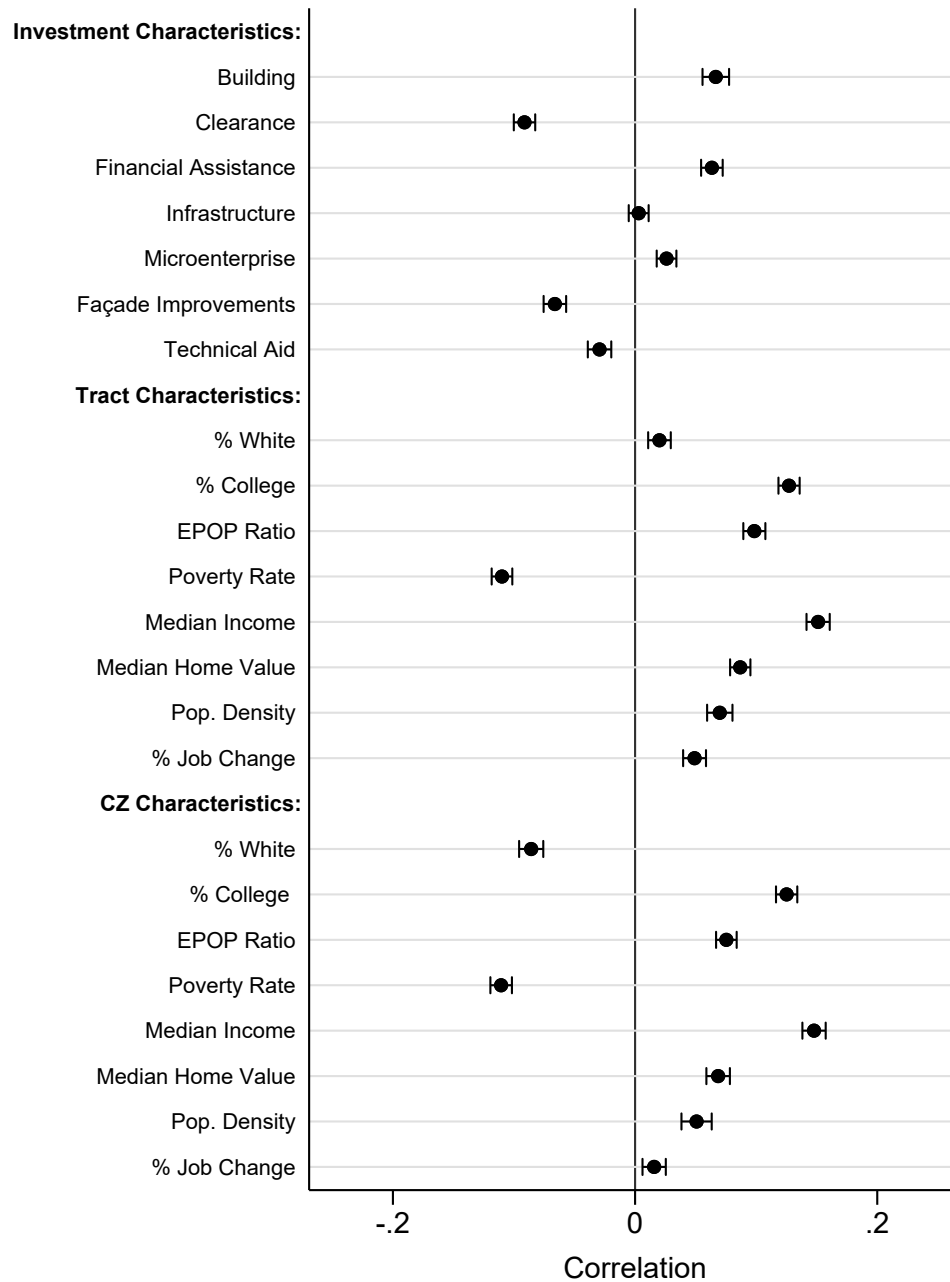
Note: This figure presents event study graphs depicting the impact of the CDBG funding shock on public spending on total local revenue, accompanying the bottom two graphs in Figure 6. SDID event studies were generated following [Ciccio \(2024\)](#) using bootstrap inference with 100 iterations to construct standard errors. Shown SDID standard errors differ marginally from the standard errors shown in Figure 6 due to seed differences.

Figure A18: Correlates of place-based investments in economic development



Note: This figure provides a version of Figure 7 focusing on investment characteristics, scaled to show the effect of a 1% change in investment in any given investment category.

Figure A19: Correlates of place-based investments in economic development, with tract spillovers



Note: This figure provides a version of Figure 7 using an alternate outcome: the average number of jobs in the treated tract as well as all bordering tracts.

Table A1: Summary of eligible CDBG activities

Activity Type	Description	# Investments	Total Invested (\$M)	Avg. Investment (\$)
Acquisition and Clearance	Acquiring or disposing of land, air rights, easements, water rights, rights-of-way, and buildings	38,438	3,980	103,542
Administrative/Planning	Administration costs related to planning/execution of community development activities. Capped at 20% of annual allocation.	106,136	10,747	101,255
Economic Development	Activities aimed at job creation/retention, establishing/stabilizing/expanding small businesses; see Section 6	45,848	5,754	125,492
Housing	Construction or rehabilitation of housing, homeownership assistance, inspections/code enforcement	250,629	17,921	71,505
Public Improvements	Acquiring, constructing, or rehabilitating public improvements or facilities (e.g., streets, parks, sewer lines, parking lots, beautification)	162,788	24,693	151,688
Public Services	Covers labor, supplies, materials, and other costs of various public services (e.g., public safety, homelessness programs, job training, health care, recreation, education, etc.). Spend is capped at 15% of annual CDBG allocation.	223,282	7,888	35,326

Note: This table summarizes the different activities that are eligible for CDBG funding. Activity-level data were obtained from the U.S. Department of Housing and Urban Development.

Table A2: CDBG activities, by subcategory

Activity	Activity Sub-Category	# Activities	Total \$ (\$M)	\$/Activity	Category %
Acquisition	Acquisition of Real Property	10,587	1,861	175,739	46.7
	Clearance and Demolition	21,163	1,430	67,589	35.9
	Relocation	4,069	465	114,281	11.7
	Disposition	1,921	130	67,587	3.3
	Cleanup of Contaminated Sites	698	94	134,905	2.4
Admin & Planning	General Program Administration	78,103	9,164	117,332	85.3
	Planning	15,863	768	48,387	7.1
	State Administration	751	285	379,037	2.6
	Fair Housing Activities (subject to 20% Admin Cap)	5,151	186	36,149	1.7
	Indirect Costs	1,459	180	123,051	1.7
	State Planning ONLY	3,309	108	32,577	1.0
Economic Development	ED Direct Financial Assistance to For-Profits	16,964	2,647	156,029	46.0
	CI Infrastructure Development	2,072	765	369,437	13.3
	Rehab; Publicly or Privately-Owned Commercial/Industrial	7,934	623	78,542	10.8
	ED Technical Assistance	7,247	613	84,619	10.7
	Micro-Enterprise Assistance	9,027	502	55,625	8.7
	CI Building Acquisition, Construction, Rehabilitation	1,425	310	217,210	5.4
	Other Commercial/Industrial Improvements	887	177	199,826	3.1
	CI Land Acquisition/Disposition	292	116	397,030	2.0
Housing	Rehab; Single-Unit Residential	173,962	9,406	54,072	52.5
	Rehabilitation Administration	18,011	2,487	138,092	13.9
	Code Enforcement	9,588	1,602	167,075	8.9
	Rehab; Multi-Unit Residential	15,052	1,579	104,891	8.8
	Direct Homeownership Assistance	16,050	711	44,312	4.0
	Construction of Housing	3,511	689	196,196	3.8
	Public Housing Modernization	1,127	376	333,226	2.1
	Acquisition for Rehabilitation	2,075	374	180,372	2.1
	CDBG Operation and Repair of Foreclosed Property	222	210	947,274	1.2
	Lead-Based/Lead Hazard Test/Abate	5,832	157	26,877	0.9
Public Improvements	Water/Sewer Improvements	32,007	8,091	252,790	32.8
	Street Improvements	28,721	4,823	167,921	19.5
	Other Public Improvements Not Listed in 03A-03S	31,645	3,517	111,138	14.2
	Parks, Recreational Facilities	17,890	1,988	111,115	8.1
	Sidewalks	11,793	1,267	107,469	5.1
	Neighborhood Facilities	8,532	1,212	142,086	4.9
	Senior Centers	4,958	687	138,628	2.8
	Fire Station/Equipment	4,155	591	142,224	2.4
	Flood Drainage Improvements	3,215	517	160,964	2.1
	Homeless Facilities (not operating costs)	4,062	417	102,569	1.7
	Health Facilities	1,881	347	184,544	1.4
	Child Care Centers	1,844	260	141,102	1.1
	Facility for Persons with Disabilities	2,374	199	83,800	0.8
	Youth Centers	2,049	196	95,735	0.8
	Interim Assistance	2,631	141	53,548	0.6
	Non-Residential Historic Preservation	1,650	140	84,591	0.6
Public Services	Other Public Services Not Listed in 05A-05Y, 03T	68,899	2,548	36,986	32.3
	Youth Services	42,584	1,135	26,662	14.4
	Senior Services	25,721	751	29,197	9.5
	Operating Costs of Homeless/AIDS Patients Programs	10,964	632	57,646	8.0
	Employment Training	9,719	529	54,454	6.7
	Health Services	8,307	323	38,889	4.1
	Child Care Services	8,629	286	33,134	3.6
	Crime Awareness	3,990	236	59,143	3.0
	Services for victims of domestic violence, sexual assault, stalking	8,072	225	27,869	2.9
	Housing Counseling only, under 24 CFR 5.100	2,819	179	63,503	2.3
	Services for Persons with Disabilities	6,886	164	23,821	2.1
	Fair Housing Activities (if CDBG, then subject to 15% cap)	3,228	104	32,104	1.3
	Transportation Services	3,161	97	30,699	1.2
	Mental Health Services	2,578	96	37,122	1.2
	Legal Services	2,607	90	34,632	1.1
	Substance Abuse Services	2,502	80	31,816	1.0
	Subsistence Payment	2,775	78	28,266	1.0
	Tenant/Landlord Counseling	1,679	69	41,191	0.9
	Homebuyer Downpayment Assistance	1,403	66	46,806	0.8
	Abused and Neglected Children	3,450	65	18,961	0.8
	Food Banks	2,176	63	28,990	0.8
	Screening for Lead-Based Paint/Lead Hazards Poisoning	160	41	255,204	0.5

Note: This table presents CDBG activity sub-categories. Sub-categories comprising less than 0.5 percent of the overall category were excluded.

Table A3: Cost-per-job estimates of place-based jobs policies

Name of Program	Category	Implied Cost per Job	References
General Firm Subsidies	Business Incentives	\$30k–\$300k+	Slattery and Zidar (2020)
Federal Empowerment Zones	Business Incentives	\$18,000	Busso, Gregory and Kline (2013)
State Enterprise Zones	Business Incentives	Mixed Effectiveness	Neumark and Kolko (2010) , Ham et al. (2011)
New Markets Tax Credit	Business Incentives	\$50,000	Freedman (2012)
Opportunity Zones	Business Incentives	Small/no effect	Freedman, Khanna and Neumark (2023)
Tennessee Valley Authority (TVA)	Infrastructure	\$77,000	Kline and Moretti (2013)
ARRA Highway Stimulus	Infrastructure	\$125,000–\$150,000	Wilson (2012) , Garin (2019)
Small Business Loans	Financial Assistance	\$14,000	Brown and Earle (2013)
EPA Brownfield Cleanup	Clearance	\$18,000	Paull (2008)
Microenterprise Assistance	Microenterprise	Small/mixed impacts	Grimm and Paffhausen (2015)
Customized Job Training	Social Services	\$15,000–\$34,000	Bartik (2018)
Small Business Development Centers	Technical Assistance	\$6,000	Chrisman (2017)

Note: This table summarizes cost-per-job estimates from a variety of programs with features related/relevant to activities funded by the CDBG.

Table A4: Using Census-ACS Measurement Error to Instrument for Treatment

	Positive Shock		Negative Shock	
	(1)	(2)	(3)	(4)
IV Estimate	0.046*** (0.006)	0.052*** (0.007)	0.001 (0.011)	-0.018 (0.018)
N	666	666	667	667
First Stage F-Stat	6.07	17.72	2.01	5.05
Predictor Selection	All	Lasso	All	Lasso

Note: This table presents results regressing treatment status on average job growth (in percent terms) in the post-period, instrumenting for treatment status using measurement error calculated using common variables shared between the 2010 Decennial Census and corresponding 5-year estimates from the American Community Survey (2006-2010). The first two columns compare positively shocked versus control grantees. The last two columns compare negatively shocked versus control grantees. I present results using both 1) the full set of predictor variables, and 2) a refined set of predictor variables selected via LASSO. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: The CDBG Allocation Formula

Prior to the beginning of each fiscal year t , Congress determines the amount of funding A_t available for CDBG use, which typically ranges from \$3-4 billion nominally. The funds are then allocated to grantees via a funding formula which attempts to measure the relative need of each grantee i . The allocation formula is as follows:

$$CDBG_{it} = s_t \times A_t \times \max\left(\underbrace{0.25 \times \frac{Population_{it}}{\sum_i Population_{it}} + 0.5 \times \frac{Poverty_{it}}{\sum_i Poverty_{it}} + 0.25 \times \frac{Overcrowd_{it}}{\sum_i Overcrowd_{it}}}_{\text{Formula A}}, \underbrace{0.2 \times \frac{GrowthLag_{it}}{\sum_i GrowthLag_{it}} + 0.3 \times \frac{Poverty_{it}}{\sum_i Poverty_{it}} + 0.5 \times \frac{Pre1940Housing_{it}}{\sum_i Pre1940Housing_{it}}}_{\text{Formula B}} \right) \quad (5)$$

$Population_{it}$ represents total population. $Poverty_{it}$ represents the number of people below the federal poverty limit. $Overcrowd_{it}$ represents the number of housing units where the ratio of occupants to rooms exceeds 1.01. $GrowthLag_{it}$ represents the difference between the current population and what the population would have been if population growth had followed the national trajectory since 1960. $Pre1940Housing$ represents the number of housing units built prior to 1940. Prior to 2012, formula inputs were calculated using estimates from decennial censuses. Poverty, overcrowded housing, and pre-1940 housing were updated every ten years. Population and growth lag were updated annually via census estimates.³⁹ Starting in 2012, all formula inputs began updating annually using 5-Year ACS estimates. The 2012 inputs were determined using the 2005-09 ACS, the 2013 inputs were determined using the 2006-10 ACS, etc.

The contribution of each input k (e.g. population, poverty, etc.) to a grantee's allocation is based on that grantee's share of the national total for k . Each share is then multiplied by a constant c^k . These constants sum to one across the three inputs on either side of the formula. Grantees are then assigned an allocation based on the maximum of Formula A and Formula B. This amount is then multiplied by the federal appropriation A_t and then re-adjusted *pro-rata* by s_t such that the sum of allocations across all grantees matches the appropriated budget A_t .⁴⁰

One way to interpret the formula is to collapse together inputs that do not vary at the grantee

³⁹These annual updates are not surveys, but rather modeled estimates based on decennial censuses.

⁴⁰Without s_t , the formula typically allocates more money than what is actually available. As such, $s_t < 1$.

level as follows:

$$CDBG_{it} = \max \left(\sum_{k=1}^3 v_t^k X_{it}^k, \sum_{k=4}^6 v_t^k X_{it}^k \right) \quad (6)$$

where X_{it}^k is the value of the k th input for grantee i in year t (e.g. $Population_{it}$, $Poverty_{it}$, etc.), and the v_t^k include the following terms:

$$v_t^k = \frac{c^k s_t A_t}{\sum_i X_{it}^k} = \frac{c^k s_t A_t}{\bar{X}_t^k} \quad (7)$$

v_t^k has the straightforward representation of the *dollar value* or “price” associated with an additional unit of input k . These prices vary over time based on their corresponding inputs.

The defining feature of the allocation formula is its two-pronged categorization of grantees. “Formula A” favors grantees that are typically fast-growing cities with limited housing supply. “Formula B” typically favors grantees in older, deteriorating cities. While the two formulas should theoretically provide more funding to localities with greater needs, [Collinson \(2014\)](#) points out several of the formula’s redistributive shortcomings. In particular, Formula A communities tend to be underfunded relative to actual need, whereas many high-income Formula B communities with older housing stock and slow growth tend to be overfunded.⁴¹

⁴¹In addition to redistributive shortcomings of the CDBG formula, [Brooks and Sinitsyn \(2014\)](#) also find that within localities, CDBG funding does not consistently reach communities with high levels of need.

Appendix C: SDID mechanics

In this appendix, I discuss the setup for SDID, how it differs from and improves upon DID and traditional synthetic controls, and conditions for unbiased estimates of treatment effects. I observe a panel for $i = 1, \dots, N$ grantees, N_{tr} of which comprise the treatment group and N_{co} of which comprise the comparison group. The panel extends over the years $t = 1, \dots, T$ and there are $T_{pre} = 10$ pre-treatment periods from 2002 to 2011. Treatment status W_{it} is zero for all grantees prior to 2012 and is one for treated grantees after T_{pre} . In standard differences-in-differences (DID), the estimated treatment effect τ solves the following optimization problem:

$$\left(\hat{\tau}^{did}, \hat{\mu}, \hat{\alpha}, \hat{\beta} \right) = \underset{\tau, \mu, \alpha, \beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \right\} \quad (8)$$

where each unit i and time period t is given equal weight. Synthetic differences-in-differences (SDID) allows these weights $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ to vary, leading to the modified optimization problem:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta} \right) = \underset{\tau, \mu, \alpha, \beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^N \sum_{t=1}^T (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \quad (9)$$

The weights $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ are determined algorithmically prior to solving Equation 9. Like in the traditional synthetic control method (SCM) (Abadie, Diamond and Hainmueller, 2010), the unit weights $\hat{\omega}_i^{sdid}$ are chosen to minimize pre-treatment differences in outcomes between the treatment group and the weighted comparison group. The overarching intuition is that a weighted combination of untreated tracts may represent a more appropriate comparison group than any single tract or unweighted combination of untreated tracts.

Formal results from Eli Ben-Michael and Rothstein (2021) show that strong pre-treatment fit is critical for reducing bias when the data-generating process reflects a linear factor model (from which DID and synthetic controls are derived), justifying the use of flexible unit weights to improve pre-treatment fit. Crucially, Eli Ben-Michael and Rothstein (2021) also show that the validity of synthetic control methods is not just tied to the strength of pre-treatment fit, but also to the number of pre-treatment periods available. Bias reduction improves as the number of pre-treatment periods increases. Intuitively, a design with strong pre-treatment matching over a small number pre-treatment periods is highly exposed to bias from overfitting to noise. The greater the number of pre-treatment periods, the greater the likelihood that strong pre-treatment fit reflects a true match on underlying factors in the

data generating process as opposed to noise.

Unlike traditional synthetic control methods (SCM), SDID permits estimation with multiple treated units—much like DID. The SDID calculation of these weights also differs from standard SCM in two key ways. First, SDID incorporates a regularization parameter ξ which increases dispersion of the weights and ensures a unique solution.⁴² Second—and more importantly, SDID includes an intercept term ω_0 which relaxes the SCM requirement that pre-treatment outcomes match in levels. Instead, parallel trends are sufficient in SDID—a weaker assumption which is made possible by the inclusion of unit fixed effects α_i in Equation (9). The weights $(\hat{\omega}_0, \hat{\omega}^{sdid})$ representing the intercept and unit weights are chosen to solve the following optimization problem:

$$(\hat{\omega}_0, \hat{\omega}^{sdid}) = \underset{\omega_0, \omega}{\operatorname{argmin}} \sum_{t=1}^{T_{pre}} \left(\omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^N Y_{it} \right)^2 + \xi^2 T_{pre} \|\omega\|_2^2 \quad (10)$$

In short, SDID boasts the strengths of SCM by allowing comparison units to have flexible weights—reducing bias by improving pre-treatment fit—while also retaining the flexibility of the DID parallel trends assumption and allowing estimation with multiple treated units.

Unlike both SCM and DID, the SDID estimator also applies weights to pre-treatment time periods. The weights are calculated using control units and attempt to equalize the weighted average of pre-period outcomes with the simple average of post-period outcomes. Weights are intuitively greater for pre-periods that are more similar to post-periods (again, after eliminating a constant difference λ_0 between pre- and post-periods). The weights $(\hat{\lambda}_0, \hat{\lambda}^{sdid})$ solve the following optimization problem:

$$(\hat{\lambda}_0, \hat{\lambda}^{sdid}) = \underset{\lambda_0, \lambda}{\operatorname{argmin}} \sum_{n=1}^{N_{co}} \left(\lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_i Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^T Y_{it} \right)^2 \quad (11)$$

With respect to inference, [Arkhangelsky et al. \(2021\)](#) present a variety of approaches. With multiple treated units, the authors provide variations of the clustered bootstrap ([Efron, 1979](#)) and jackknife applied to SDID which both produce conservative confidence intervals. I report standard errors from the bootstrap approach which generally produces more conservative confidence intervals. Each SDID estimate I present utilizes 100 iterations in the bootstrapping process.⁴³

⁴²I use the default regularization parameter proposed by [Arkhangelsky et al. \(2021\)](#) based on the size of a typical one-period change for comparison units prior to the event.

⁴³I use the `synthdid` package in Stata, detailed in [Clarke et al. \(2023\)](#).