Funding, Facilities, and the Face of Homelessness: Heterogeneous Impacts of Federal Grants on Sheltered and Unsheltered Counts

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Abstract

This paper examines the causal impact of federal homeless-assistance grants on both reported homelessness and shelter capacity across 370 Continuums of Care (CoCs) in 2019. We exploit cross-sectional variation in the share of pre-1940 housing units, used as a component for Community Development Block Grant (CDBG) formula funding allocations, as an instrument for combined CoC and Emergency Solutions Grant (ESG) funding, implementing a cross-sectional two-stage least-squares (2SLS) design. Our first-stage results confirm that cross-CoC differences in the pre-1940 housing share generate substantial power for instrumenting funding. In the second stage, we find that federal funding allocations produce significant increases in sheltered homelessness—driven primarily by increases to emergency and transitional bed spaces—while having no detectable effect on aggregate unsheltered counts. Heterogeneous effects reveal that working-age adults, men, and black individuals account for most of the shelter response, while racial disparities emerge in unsheltered outcomes, with white individuals experiencing decreases and black individuals experiencing increases in unsheltered homelessness when funding rises. These findings suggest that federal grants primarily attract certain groups into formal shelters without directly reducing street homelessness, highlighting the need for targeted interventions to address barriers to shelter access and the persistent challenge of unsheltered homelessness. We discuss policy implications for balancing immediate shelter capacity expansion with long-term permanent supportive housing investments and highlight the importance of addressing systemic barriers that prevent equitable shelter access across demographic groups.

Keywords: Homelessness, Emergency Shelter, Permanent Supportive Housing, Continuums of Care, Emergency Solutions Grant

JEL Codes: H75, I31, I38, R23, R28

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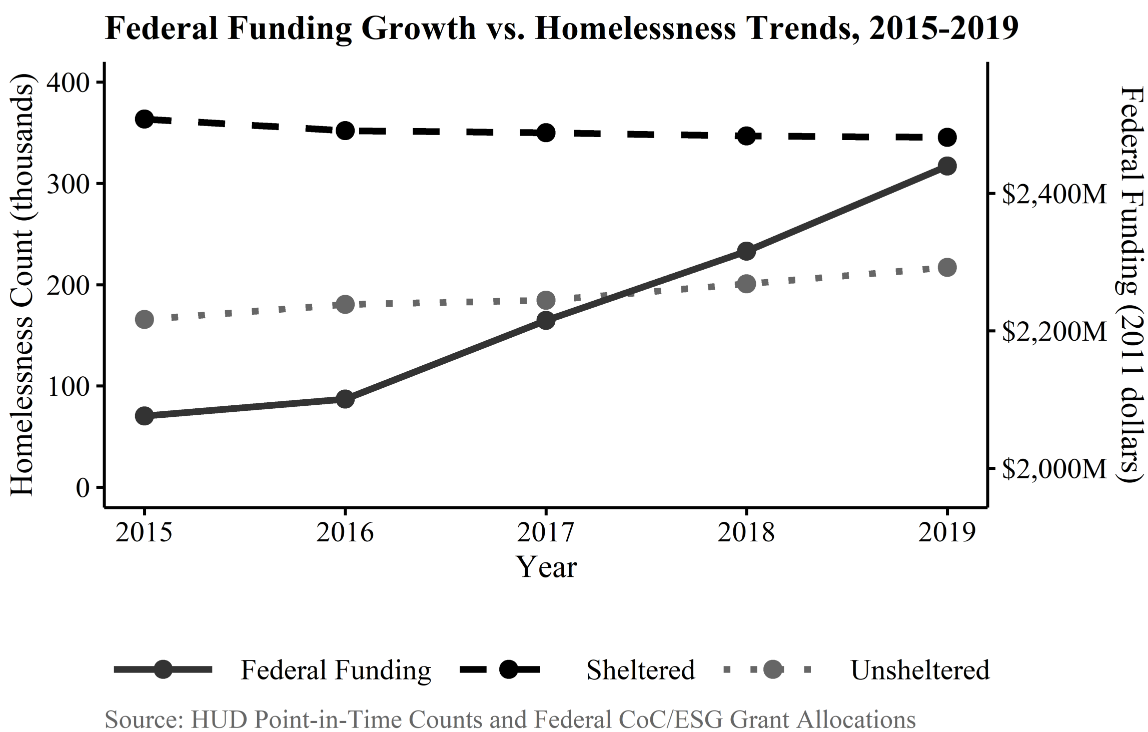
1 Introduction

Despite a 16 percent real-term increase in U.S. Department of Housing and Urban Development (HUD) homeless-assistance appropriations, from $2.1 billion in fiscal year (FY) 2015 to $2.5 billion in FY 2019, annual Point-in-Time (PIT) counts have remained stubbornly high (above 550,000 people) and unsheltered homelessness has persisted near 200,000 persons. (Figure 1; U.S. Department of Housing and Urban Development (2019a)). This disconnect suggests that simply scaling up federal grants does not necessarily translate into fewer people sleeping rough or a commensurate expansion of shelter capacity.

Figure 1: Growth in Federally Allocated Funding for Homelessness Assistance vs. Counts of Sheltered and Unsheltered Homelessness in the U.S., 2015-2019, Authors' Calculations



Empirical evidence on the effectiveness of federal homeless-assistance grants—for both the Continuum of Care (CoC) grant and the Emergency Solutions Grant (ESG)—remains mixed. On one hand, more generous funding is theorized to relax local capacity constraints by underwriting new emergency shelter beds, improving service quality, and financing transitional as well as permanent supportive housing, thereby drawing individuals off the streets into stable accommodations (Moulton, 2013; Popov, 2016; Lucas, 2017). On the other hand, several studies argue that additional dollars disproportionately benefit those already marginally housed—households doubling up or in precarious rental situations—without materially reducing unsheltered counts captured in street-based PIT surveys (Culhane et al., 2011; Tsai and Alarcón, 2022). Compounding these divergent findings, HUD's formulaic targeting of resources to jurisdictions with higher measured homelessness creates a mechanical endogeneity: areas with rising PIT counts receive larger grants, so naïve correlations between funding and outcomes risk conflating cause and effect (Popov, 2016).

This paper provides new causal estimates of how combined CoC and ESG funding shapes both reported homelessness and Housing Inventory Count (HIC) shelter-bed capacity across 370 CoCs in 2019. Building on Popov (2016) and Lucas (2017), we instrument each CoC's per-capita funding with its share of housing units built before 1940 in the Community Development Block Grant (CDBG) formula (Congressional

Research Service, 2014). Because the pre-1940 housing share reflects long-run stock vintage rather than contemporaneous homelessness shocks, it shifts allocations exogenously, satisfying the exclusion restriction and isolating the impact of marginal federal dollars. Focusing on a single, cross-sectional snapshot sidesteps concerns that year-to-year changes in the instrument may themselves correlate with local demolition or gentrification. We show that a $10,000 increase in annual funding per 10,000 residents leads to roughly 1 more sheltered person per 10,000, driven primarily by expansions in emergency and transitional beds, and yet produces no detectable short-run decline in unsheltered counts despite significant increases to permanent supportive housing (PSH) bed space capacity. We further document that impacts vary sharply by geography (urban vs. rural/suburban), household type (individuals vs. families), and demographic subgroup (age, gender, race, and chronicity).

Our contributions are threefold. First, we deliver the most recent national, causal estimate of federal homeless-assistance grants on both PIT homelessness—total, sheltered, unsheltered, and demographic subgroups—and on HIC bed categories (emergency, seasonal, overflow, and permanent supportive housing). Second, we document rich heterogeneity: funding differences disproportionately expand shelter use among people of different ages, gender, and race, while producing little-to-no meaningful short-run reduction in unsheltered counts. Third, we introduce a transparent, population-weighted tract-to-CoC crosswalk and share our geoprocessing code, enabling replication and extension.

The remainder of the paper is organized as follows. Section 2 reviews related economic and policy studies on homelessness and funding efficacy. Section 3 outlines the institutional mechanics of the federal grant allocations and the conceptual pathways through which grants may affect homelessness. Section 4 describes our 2019 outcome measures, funding data, the instrument, and the tract-to-CoC crosswalk for covariate construction. Section 5 presents the cross-sectional IV specification and discusses key identification assumptions. Section 6 reports our main and subgroup results, along with associational "between-CoC" contrasts. Finally, Section 7 interprets the findings, discusses policy implications, and outlines directions for future research.

2 Literature Review

Research on homelessness has evolved from early enumeration and descriptive studies to rigorous evaluations of policy interventions. Initial efforts focused on counting and profiling the homeless population. Elias (1952) developed one of the first systematic nighttime counts, foundational for the PIT, while Bahr and Caplow (1968) compared life trajectories of homeless men versus housed peers. Later on, sociologists such as Lamb (1984), Tsemberis and Eisenberg (2000), Yates et al. (1988), and Jencks (1994) documented nationwide increases in homelessness, exploring mental illness, substance use, and family breakdown among the unhoused. Appelbaum et al. (1991) examined how rent-control policies were blamed for homelessness despite broader structural factors.

Economists entered the field in the early 1990s, linking homelessness to housing and labor markets. Elliott and Krivo (1991) and Honig and Filer (1993) showed how local housing supply constraints, welfare generosity, and labor conditions influenced homelessness incidence. O'Flaherty (1995)'s bid-rent framework modeled housing choice under budget constraints, tying rent, wages, and welfare benefits to homelessness risk. However, these studies often assumed accurate PIT and HIC data—an assumption challenged by O'Flaherty (2004) and Early (2004), who highlighted undercounts and misclassifications in administrative counts. The Homeless Emergency Assistance and Rapid Transition to Housing Act of 2009 (HEARTH) subsequently standardized reporting protocols to improve data quality (U.S. Department of Housing and Urban Development, 2012).

With better data, attention turned to funding efficacy. Culhane et al. (2011) advocated a prevention-centered approach, emphasizing rapid re-housing over emergency shelter. Byrne et al. (2013, 2014) showed that local investment in PSH correlated with lower chronic homelessness, even controlling for economic factors. Moulton (2013) found that PSH and rent subsidies reduced chronic homelessness more effectively than general CoC awards. In a landmark effort, Popov (2016) addressed endogeneity in funding allocations by instrumenting with annual fluctuations in the pre-1940 housing share, isolating causal impacts on shelter use and homelessness counts. Lucas (2017) extended this by disaggregating outcomes by demographic group, revealing that family groups responded more to funding increases than individuals.

Geographic and behavioral factors also matter. Cragg and O'Flaherty (1999) found that improved shelter conditions could attract individuals from neighboring jurisdictions. Corinth and Lucas (2018) documented how winter climate biases PIT counts, echoed by Tsai and Alarcón (2022); Meyer et al. (2023), who proposed enumeration improvements for unsheltered populations.

Additionally, experimental and quasi-experimental studies evaluated intervention models. Stefancic and Tsemberis (2007) showed high housing retention under Housing First programs for psychiatric-disabled homeless adults. Rog et al. (2014) reviewed PSH evidence, noting improved stability with scattered-site rental subsidies plus services. Stergiopoulos et al. (2015) found that scattered-site rent supplements and case management improved housing stability among mentally ill homeless adults. Tsemberis and Eisenberg (2000) demonstrated long-term retention through Pathways to Housing for street-dwelling individuals with psychiatric disabilities.

Our study builds on these contributions by exploiting across-CoC variation in the pre-1940 housing share and employing a cross-sectional 2SLS design that examines both PIT and HIC outcomes with detailed subpopulation breakdowns. By creating a granular boundary crosswalk (Ferrara et al., 2024), we address time-heterogeneity and endogeneity concerns, providing robust causal estimates of how federal grants affect service utilization, capacity expansion, and the composition of homelessness across U.S. CoCs.

3 Conceptual Framework

3.1 Funding Determination

Under the CDBG program, HUD annually apportions block-grant funds to eligible entitlement jurisdictions (cities and counties) based on a two-part index that captures relative levels of community development need. Each entitlement jurisdiction is evaluated on five core indicators expressed as shares of national totals: population growth lag (since 1960), overcrowded housing units, individuals in poverty, a composite "growth-poverty" index, and the stock of pre–1940 housing (Congressional Research Service, 2014; Collinson, 2014; Miller and Richardson, 2024). These five shares feed into two weighted formulas:

$$FundingShare = k \max \Bigg\{ \underbrace{0.25 PopulationShare + 0.5 PovertyShare + 0.25 OvercrowdedShare,}_{\text{Formula A}} \tag{1}$$

$$\underbrace{0.2 GrowthLagShare + 0.3 PovertyShare + 0.5 Pre1940HousingShare}_{\text{Formula B}} \Bigg\} \tag{2}$$

Each variable is expressed as that jurisdiction's share of the national total. The entitlement share is then

$$EntitlementShare_j = k \times max[FormulaA_j, FormulaB_j] \tag{3}$$

where k normalizes the maximum index so that shares sum to one across all entitlements. Prior to FY2013, all inputs were drawn from the decennial Census; since FY2013, HUD has relied on rolling American Community Survey (ACS) 5-year survey table estimates for these shares (Congressional Research Service, 2014; Miller and Richardson, 2024; Popov, 2016).

Each formula produces an index value for a jurisdiction by multiplying its local share of each indicator by the specified weight and summing the results. HUD then takes the maximum of Formula A and Formula B for each jurisdiction, yielding the preliminary entitlement index. A normalization constant ensures that the sum of all entitlement jurisdictions' indices equals one, so that each jurisdiction's entitlement share is the higher value of the output from Formula A or Formula B, where k rescales national indices to budget shares (Congressional Research Service, 2014; Miller and Richardson, 2024). Once Congress enacts the annual CDBG appropriation, HUD applies these entitlement shares to allocate block-grant dollars to each jurisdiction.

Once CDBG shares are determined for each entitlement jurisdiction, HUD channels those allocations into the two principal homeless-assistance programs: the CoC grant and the ESG. To convert entitlement shares into CoC grant and ESG amounts, HUD applies each jurisdiction's CDBG-derived share to the total CoC appropriation, awarding funds directly to each CoC as its prorated allocation (U.S. Department of Housing and Urban Development, 2024). In this way, CDBG entitlement shares serve as the underlying distribution key for both ESG and CoC grants, ensuring that areas with higher composite need scores receive proportionally larger homeless-assistance awards each year.

Within each CoC, grant administrators allocate the awarded CoC and ESG funds across diverse program types to expand and manage local homeless-assistance capacity. The ESG is oriented toward the immediate crisis end of the continuum: current regulations permit spending on street outreach, emergency shelter construction and operations, shelter resident services, rapid re-housing assistance, homelessness prevention, and the maintenance of the local Homeless Management Information System, with administrative expenses capped at seven and one-half per cent of the award (U.S. Department of Housing and Urban Development, 2019c). CoC grants, by contrast, finance longer-term or system-level solutions such as permanent supportive housing, rapid re-housing projects, transitional housing, joint transitional–rapid re-housing initiatives, safe-haven beds, supportive-services-only projects, CoC planning activities, enhancements to local Homeless Management Information System (HMIS) capabilities, and unified funding agency costs (U.S. Department of Housing and Urban Development, 2020).

Some funding allocations convert swiftly into additional bed inventory, such as leasing new shelter units, expanding emergency or seasonal beds, and opening overflow facilities, thereby increasing year-round and emergency-supply capacity in the immediate term (Moulton, 2013; Stergiopoulos et al., 2015). Other allocations underwrite capital projects for PSH or TH, which involve land acquisition, construction or rehabilitation, and service coordination; these activities unfold over longer horizons, yielding gradual increases in housing stock and supportive-services infrastructure (Popov, 2016). Furthermore, planning and HMIS investments strengthen a CoC's operational capacity—improving bed utilization tracking, placement protocols, and data quality—but do not directly add new beds. By combining rapid-deployment resources (e.g., ESG-funded rental assistance and emergency-shelter contracts) with capital and service investments (e.g., CoC-funded PSH development and planning), CoC administrators dynamically adjust both short-run shelter availability and long-run housing infrastructure in response to annual funding variations.

3.2 Heterogeneity in Utilization

As CoCs expand bed capacity, people experiencing homelessness respond to the availability of new resources in heterogeneous ways. Overnight shelters frequently target certain population groups: individual adult men, women and families with children, or people suffering from severe mental illness or substance use. Emergency and transitional beds often attempt to accommodate families with children, people fleeing domestic violence, and other vulnerable subpopulations who prefer shelter over doubling up or couch-surfing when space opens (Cragg and O'Flaherty, 1999; Wong et al., 1997; Culhane et al., 2011; O'Flaherty, 2019). Conversely, individuals with chronic patterns of unsheltered homelessness may face substantial barriers to entering new shelters, such as eligibility restrictions, perceived stigma, or behavioral health challenges, and therefore may remain unsheltered even as beds increase (Stefancic and Tsemberis, 2007; Byrne et al., 2014). Rapid re-housing subsidies and overflow/seasonal options can draw in marginally housed persons who were not previously counted in street-based PIT surveys, causing a rise in reported shelter-use without a corresponding decline in unsheltered PIT counts (Schneider et al., 2016; Tsai and Alarcón, 2022). By contrast, PSH units take longer to develop but eventually provide stable housing for those with long-term needs, potentially reducing chronic unsheltered homelessness only over extended horizons (Stergiopoulos et al., 2015).

Behavioral and spillover pathways further complicate local utilization patterns. First, as some CoCs gain new beds, individuals may migrate from neighboring jurisdictions to access more resources (Tsemberis and Eisenberg, 2000; Popov, 2016). Such movements may depress unsheltered counts in lower-funded CoCs while boosting sheltered utilization in higher-funded ones, confounding direct comparisons of funding and outcomes. Second, because HUD's formula indices embed prior homelessness indicators—such as overcrowding and poverty—there exists endogenous targeting: areas with historically high PIT counts receive larger entitlement shares in subsequent years, creating reverse-causality concerns (Popov, 2016; Bunce, 1979; Collinson, 2014). By instrumenting contemporaneous funding changes with the exogenous annual fluctuations in the pre–1940 housing share, our design isolates the causal effect of new bed capacity on utilization and prevents bias from these spillover and targeting channels.

To connect the conceptual framework to the empirical implementation, we now describe the data sources and measurement procedures used to capture both the variation in CoC-level funding allocations and the resulting changes in homeless counts and bed capacity. Specifically, we begin by detailing how annual PIT counts of sheltered and unsheltered persons are collected at the Continuum of Care level, which form our primary outcome measures.

4 Data

4.1 Point–in–Time Homelessness Counts

Every January, during the final ten days of the month, each CoC must conduct a PIT enumeration under the McKinney–Vento Homeless Assistance Act, as amended by the HEARTH Act of 2009. HUD is authorized by the McKinney–Vento Act and implements this authority through the CoC Program Interim Rule, which obligates CoCs to conduct a one-night count of sheltered and unsheltered persons at least biennially (U.S. Department of Housing and Urban Development, 2012). Although the statutory minimum for unsheltered counts remains once every two years, HUD has required—and CoCs now effectively conduct—annual PIT counts to satisfy both CoC Program Competition and Emergency Solutions Grants reporting requirements (U.S. Department of Housing and Urban Development, 2024).

Sheltered counts, which cover people in emergency shelters, transitional housing, and safe havens, are compiled primarily from Homeless Management Information System (HMIS) bed-night records, supplemented by facility surveys for programs not participating in HMIS (U.S. Department of Housing and Urban Development, 2014). Unsheltered counts enumerate persons residing in places not meant for human habitation—such as streets, parks, vehicles, and encampments—using route-based canvassing, short intercept interviews, and partnerships with outreach workers, law enforcement, and other service providers to identify and survey individuals (U.S. Department of Housing and Urban Development, 2014). Data collection protocols—including sampling frames, volunteer deployment, use of mobile survey tools, and quality-assurance checks—are prescribed in HUD's annual guidance but implemented locally, resulting in variation in precision and coverage across CoCs (Government Accountability Office, 2020, 2021).

PIT count data and accompanying methodology documentation are submitted each spring via the Homelessness Data Exchange as a non-waivable condition for HUD CoC and ESG funding eligibility. HUD uses these submissions both to produce the Annual Homelessness Assessment Report to Congress and as scoring factors in the CoC Program Competition, meaning that failure to submit compliant PIT data can directly affect a CoC's funding allocation (U.S. Department of Housing and Urban Development, 2012).

This study draws raw CoC-level tabulations from HUD's Homelessness Data Exchange and the publicly released Annual Homeless Assessment Report (AHAR). For each CoC reported within the AHAR in 2019, the dataset captures total homelessness, the sheltered and unsheltered subtotals, mutually exclusive demographic splits by age, race, gender, and chronicity, and four non-exclusive subpopulations—severe mental illness, chronic substance abuse, domestic-violence survivorship, and veterans. [1]

All PIT counts are converted to rates per ten thousand total residents within a CoC to achieve comparability across CoCs and to align with the funding denominators. Year-specific total population comes from the tract-level American Community Survey five-year files aggregated to the CoC level, which is described later in this section.

4.2 Shelter and Housing Capacity

To observe how federal dollars translate into physical capacity, the analysis incorporates the annual HIC that HUD collects in tandem with the PIT enumeration. Each CoC submits a census of beds and housing units that are dedicated to people experiencing homelessness as of the same night as the PIT count. The HIC distinguishes year-round beds in emergency shelters (ES), transitional housing (TH) and safe-haven projects

[1] Because many subpopulation cells appear only in image-based tables, they are digitised with optical-character-recognition using the `tesseract` package in R (U.S. Department of Housing and Urban Development, 2019b).

(SH); seasonal and overflow ES beds; and PSH beds, among other components (U.S. Department of Housing and Urban Development, 2023).

Each program describes a different form of sheltered experience for a person utilizing its space. First, *total year-round ES–TH–SH beds* measure the stock of beds that operate every night in emergency shelters, transitional housing, and safe-haven programs. Emergency shelters provide short-term crisis accommodation, transitional-housing projects offer time-limited stays (usually up to twenty-four months) coupled with supportive services, and safe havens are low-barrier facilities intended for persons with severe mental-health conditions who may not initially engage with standard shelter settings (U.S. Department of Housing and Urban Development, 2023). Second, *year-round PSH beds* represent permanent supportive-housing capacity; these beds come with indefinite tenure and wrap-around services and are therefore the principal vehicle for the "Housing First" model emphasised in Continuum of Care funding. Third, *seasonal ES beds* are activated only during defined periods—typically winter months or extreme-weather declarations—and thus expand crisis capacity when exposure risk is highest. Fourth, *overflow ES beds* are temporary placements, often in congregate spaces such as cots in cafeteria areas, that CoCs open whenever demand exceeds regular and seasonal supply; they provide the most flexible but least stable form of shelter. We measure the response of the bed-capacity of the four programs to better understand how CoC coordinators allocate funding resources across varying forms of shelter programs.

The raw data are published through HUD's Homelessness Data Exchange in a series of yearly spreadsheets, where each row represents a Continuum of Care and columns record bed counts by project type. We retain four aggregate measures: total year-round ES, TH and SH beds; total year-round PSH beds; total seasonal ES beds; and total overflow ES beds. We transform the bed counts similarly to allow each capacity measure to be expressed per ten thousand residents of the corresponding CoC.

4.3 Federal Homelessness–Assistance Funding

Funding award information is obtained from the HUD Exchange *Awards and Allocations* workbooks for 2019 (U.S. Department of Housing and Urban Development, 2020). CoC grant totals are reported at the CoC level and therefore require no further geographic manipulation. ESG allocations, issued to states, counties, and entitlement cities, are matched to CoCs using the tract-based spatial crosswalk described in Section 4.5. When a state possesses a designated Balance-of-State CoC, the statewide ESG portion is assigned in full to that CoC; otherwise the statewide amount is prorated across constituent CoCs according to the same population weights employed elsewhere in the study. All dollar figures are expressed in 2011 values using the Consumer Price Index.

For each CoC, we measure the total amount of funding through the summation of the ESG and CoC grant award as our primary funding variable of interest. The amount is expressed in thousands of dollars and divided by the corresponding CoC population and multiplied by ten thousand residents, yielding per-10,000 funding rates that are directly comparable with the population-scaled homelessness outcomes introduced in Section 4.1.

Despite their differences, both ESG and CoC allocations ultimately derive from an underlying Community Development Block Grant (CDBG) allocation mechanism, which assigns entitlement shares to cities and counties based on a weighted combination of need-based and demographic variables. The CDBG formula computes two indices for each entitlement jurisdiction in a given fiscal year, as seen in equations (1) and (2) above.

Popov (2016) and Lucas (2017) observe that the pre-1940 housing share generates idiosyncratic variation in entitlement shares that is plausibly orthogonal to differences in homelessness across the recipient communities. In our study, we exploit exactly this feature to instrument CoC and ESG funding with the ACS-derived pre-1940 share, thereby isolating exogenous differences in grant allocations. We discuss the plausibility of the instrumental variable strategy further in Section 5.

4.4 Panel Construction

Our primary causal analysis focuses on a cross-section of Continuums of Care (CoCs) in 2019. To provide auxiliary "between-CoC" estimates leveraging longer-run variation in funding and homelessness, we also construct a panel spanning 2015–2019. We apply the data assembly steps described in Sections 4.1, 4.2, and 4.3 for each year from 2015 through 2019, yielding an unbalanced panel of 373 unique CoCs (total observations $N = 1{,}840$), with annual coverage from 365 CoCs in 2015 to 370 in 2019. Missingness reflects intermittent non-submission of PIT or HIC data and the creation/merging of new CoCs. Chi-square tests confirm that neither geographic nor temporal patterns of missing observations correlate with funding or outcomes ($\chi^2_{\text{state, completeness}} = 34.89$, $p = 0.92$; $\chi^2_{\text{year, completeness}} = 4.4$, $p = 0.35$), indicating randomness in attrition. While our main specification exploits only 2019 data for a purely cross-sectional IV analysis, this multi-year panel supports robustness checks and descriptive between-CoC regressions based on five-year averages, illustrating how long-run funding differences relate to homelessness and capacity outcomes.

4.5 Geographically Harmonised Covariates

The empirical strategy requires that every explanatory variable share a common CoC geography. Because socioeconomic data most relevant to this problem are published only at more orthodox scales, a Census tract–to–CoC spatial crosswalk is constructed and applied uniformly to all tract–based inputs. The procedure follows best practice in Ferrara et al. (2024) and improves on the county merges used by Popov (2016) and Lucas (2017).

The crosswalk is rebuilt for each study year because HUD occasionally redraws CoC boundaries. Annual CoC shapefiles are projected into the USA Contiguous Albers equal–area coordinate system (EPSG 5070) and intersected with the same-year Census tracts, obtained from TIGRIS-line files. The intersection yields a complete partition: each tract is split into one or more polygons whose union exactly reconstructs the parent tract. We overlay the Global Human Settlement Population raster (100m, R2015-R2019) and compute, for each polygon, its share of tract population; where raster data are unavailable the polygon's equal–area share is used. These weights sum to one by construction and ensure that allocations reflect where people actually live rather than where land area is largest. Diagnostic statistics show that the median tract retains 96% of its population in a single CoC, but 17% (about 15,000 total) of tracts straddle two or more CoCs, warranting the population-weighting scheme (Ferrara et al., 2024).

For our main (cross-sectional) IV analysis, we focus on 2019 covariates, but we construct the same rich panel for 2015–2019 to support our between-CoC robustness checks for each CoC via the population-weighted crosswalk. These include total population, vacant housing units, units built before 1940, persons below poverty, unemployed individuals, overcrowded households, rent-burdened households, households receiving SNAP and SSI benefits, uninsured households, non-Hispanic Black and Hispanic population counts, persons aged sixty-five or older, veterans, and persons with disabilities. After summing each count across tracts within a CoC, we compute shares or rates as appropriate: for example, the pre-1940 housing share is the ratio of pre-1940 units to total housing units, while demographic and program-receipt shares divide subgroup counts by total population. This aggregation-then-ratio approach preserves internal consistency and avoids the ratio-of-ratios bias detailed in Ferrara et al. (2024). This effort results in a cross-section for the year 2019 of 370 CoCs and a panel that comprises 1,840 CoC–year observations across 2015-2019, each endowed with a rich set of harmonized housing, demographic, and socioeconomic covariates[2].

Weather controls are derived from the National Oceanic and Atmospheric Administration's (NOAA) daily county–level data (Durre et al., 2022). For every county and year we compute the mean January temperature and the total January precipitation. Counties are then intersected with the same CoC polygons used in the tract procedure, except that simple polygon area shares replace population weights because climate variables are physical rather than demographic quantities. Area-weighted means and totals are aggregated to the CoC level. Tying the climate window to January matches the conditions encountered by PIT enumerators and the visibility of unsheltered homelessness (Elliott and Krivo, 1991; Corinth and Lucas, 2018).

Spatial spillovers pose a significant threat to identification if individuals experiencing homelessness relocate across CoC boundaries in response to differences in service availability. To account for the relative strength of nearby funding, we compute for each CoC–year a "nearby funding ratio," defined as the total contemporaneous per-capita funding summed over all proximate CoCs within a fifty-mile radius, divided by the focal CoC's own per-capita funding. Formally, letting F_{jt} denote the per-10,000-resident funding level in CoC j and $N(c)$ the set of nearby CoCs c, we first calculate:

[2] For more technical information about the construction of the crosswalk, see Appendix A.1

$$NearbySum_{ct} = \sum_{j \in \mathcal{N}(c)} F_{jt}, \tag{4}$$

and then construct

$$\text{Nearby\_ratio}_{ct} = \frac{NearbySum_{ct}}{F_{ct}}. \tag{5}$$

By expressing proximate resources in units of the focal CoC's own funding intensity, this ratio absorbs both demand-side migration incentives and supply-side strategic complementarity in program provision across adjacent jurisdictions. Omitting this control would risk conflating the effect of a CoC's own awards with the influence of better- or worse-resourced neighbours—an issue Popov (2016) demonstrates is empirically important, as people experiencing homelessness are able to move toward higher-resource areas.

Table 1 displays summary statistics of our outcome variables of interest, which includes homelessness rates per 10,000 CoC residents by sheltered status and demographic group as well as HIC bed space counts per 10,000 CoC residents. Table 2 displays the funding values of the ESG and CoC grants in thousands of dollars per 10,000 CoC residents, as well as the full set of harmonised covariates at the CoC level.

5 Methods

5.1 Primary Specification

Our core identification strategy exploits the cross-section of 370 CoCs in 2019, using each CoC's share of pre-1940 housing stock—measured in the 2015–2019 ACS five-year estimates—as an instrument for its per-10,000 resident federal grants (CoC + ESG). By anchoring the analysis in a single year, we avoid concerns that year-to-year changes in old-housing shares might reflect contemporaneous demolition or renovation activity correlated with local homelessness trends. Instead, we draw on long-run, historically determined variation in housing-stock vintage while leveraging modern ACS data.

Concretely, let i index the 370 CoCs observed in 2019. Our funding variable of interest, $Fund_i$, is the sum of CoC and ESG grant dollars (in 2011-adjusted thousands of dollars) per 10,000 residents in CoC i. The instrument, $OldHousing_i$, is the fraction of all housing units in CoC i constructed prior to 1940, drawn from the 2015–2019 ACS five-year estimates; as shown in Section 4.5, this share varies meaningfully across CoCs but is predetermined with respect to 2019 homelessness. A rich set of control variables, X_i, captures contemporaneous CoC characteristics: demographic shares (non-Hispanic Black, Hispanic, age groups, SNAP and SSI receipt, veteran status, disability status), housing-market indicators (vacancy rate, overcrowding rate, rent-burdened households), the ratio of nearby CoC funding to own CoC funding (nearby ratio), and climatic factors (January mean temperature and total precipitation).

Our two-stage least squares (2SLS) procedure proceeds as follows, with the first stage as:

$$Fund_i = \pi OldHousing_i + X_i'\gamma + \epsilon_i \tag{6}$$

Here, π captures how long-run housing-age differences predict cross-CoC funding levels, after adjusting for contemporaneous covariates X_i.

The second stage is:

$$Outcome_i = \beta Fund_i + X_i'\delta + u_i \tag{7}$$

where $Outcome_i$ is one of our per-10,000 CoC measures in 2019 (total, sheltered or unsheltered PIT counts; subgroup counts; or HIC bed-capacity metrics). The coefficient β captures the local average treatment effect of an exogenous increase in federal funding.

All standard errors are heteroskedasticity-robust and clustered by CoC. First-stage F-statistics on $OldHousing_i$ exceed 40 in our preferred specifications, comfortably above the conventional threshold, confirming strong instrument relevance.

Although HUD's CDBG mechanism classifies individual entitlement jurisdictions as Formula A or Formula B, our unit of analysis—the CoC—typically aggregates multiple entitlement areas. Even CoCs whose largest entitlement share is driven by the "Formula A" index often contain at least one county or city whose allocation is determined by the pre-1940 housing share (the Formula B inputs) (Popov, 2016). As

Table 1: Summary Statistics: Homelessness and Housing Inventory, 2015-2019 Averages

Variable	N	Mean	Std. Dev.	Min	Max
Overall Homelessness Counts (per 10,000 residents)					
Total Homeless	1,840	17.61	18.61	1.23	205.71
Sheltered	1,840	11.37	12.54	0.13	160.89
Unsheltered	1,840	6.24	11.72	0.00	123.69
Sheltered Population by Demographics (per 10,000 residents)					
Under 18	1,840	2.97	4.44	0.00	65.11
Age 18–24	1,840	0.90	1.10	0.00	13.69
Over 24	1,840	7.49	7.99	0.02	135.52
Women	1,840	4.89	5.76	0.00	65.65
Men	1,840	6.44	7.10	0.07	99.15
White	1,840	6.06	7.18	0.05	144.61
Black	1,840	4.23	7.55	0.00	115.83
Chronically Homeless	1,840	1.31	1.93	0.00	22.00
Individuals	1,840	6.64	6.86	0.00	115.64
People in Families	1,840	4.73	7.70	0.00	108.66
Mental Illness[a]	1,792	2.06	2.55	0.00	28.08
Substance Abuse	1,792	1.83	2.75	0.00	28.47
Domestic Violence	1,790	1.29	1.42	0.00	14.46
Unsheltered Population by Demographics (per 10,000 residents)					
Under 18	1,840	0.38	1.11	0.00	11.52
Age 18–24	1,840	0.60	1.83	0.00	25.20
Over 24	1,840	5.26	9.81	0.00	120.25
Women	1,840	1.86	3.49	0.00	39.82
Men	1,840	4.34	8.37	0.00	95.45
White	1,840	4.17	8.79	0.00	102.92
Black	1,840	1.21	2.44	0.00	34.47
Chronically Homeless	1,840	1.97	3.72	0.00	40.42
Individuals	1,840	5.65	10.84	0.00	122.43
People in Families	1,840	0.60	1.96	0.00	34.81
Mental Illness	1,792	1.58	3.44	0.00	37.83
Substance Abuse	1,792	1.33	2.79	0.00	33.26
Domestic Violence	1,790	0.73	2.30	0.00	38.22
Housing Inventory (beds per 10,000 residents)					
Emergency Shelter, Transitional & Safe Haven	1,840	12.33	12.96	0.00	181.90
Permanent Supportive Housing	1,840	11.17	12.63	0.00	125.28
Seasonal Beds	1,840	0.92	1.58	0.00	13.74
Overflow Beds	1,840	0.86	1.91	0.00	22.37

[a] Counts for Mental Illness, Substance Abuse, and Domestic Violence were extracted via OCR from image-based tables in HUD's CoC reports. Some CoCs did not report these categories in all years, resulting in a small percentage of missing observations.

Table 2: Summary Statistics: Federal Funding and Community Covariates, 2015-2019 Averages

Variable	N	Mean	Std. Dev.	Min	Max
Federal Funding (thousands of dollars per 10,000 residents)					
CoC Grant ($1000s)	1,840	64.72	69.99	0.15	555.20
Emergency Solutions Grant ($1000s)	1,840	5.49	7.51	0.00	62.30
Total Federal Funding ($1000s)	1,840	71.17	75.28	0.15	573.06
Housing and Demographic Characteristics					
CoC Total Population (divided by 10,000)	1,840	84.09	119.69	3.33	1,090.29
CoC Total Population in Poverty (divided by 10,000)	1,840	11.98	19.28	0.34	188.32
Pre-1940's Housing Unit Share (% of total housing units)	1,840	13.64	11.60	0.20	64.75
Black Population Share (%)	1,840	12.31	12.66	0.42	80.17
Housing Vacancy Rate (%)	1,840	12.49	6.83	3.33	48.66
Overcrowding Rate (%)	1,840	0.82	0.74	0.06	5.48
Rent Burden Rate (%)	1,840	13.57	4.49	4.61	33.91
Socioeconomic Characteristics					
Poverty Rate (%)	1,840	14.07	4.49	3.38	39.77
SNAP Recipients Share (%)	1,840	12.48	4.86	2.52	42.79
SSI Recipients Share (%)	1,840	5.44	1.93	1.41	15.79
College Education Rate (%)	1,840	66.11	22.62	8.15	88.11
Unemployment Rate (%)	1,840	3.35	0.97	1.41	10.30
Health and Special Populations					
Veteran Population Rate (%)	1,840	79.73	37.00	1.58	99.74
Disabled Population Share (%)	1,840	20.47	4.70	5.76	34.18
Uninsured Population Share (%)	1,840	25.31	11.26	5.02	80.86
Population Over 65 Share (%)	1,840	25.45	12.05	7.59	45.65
Geographic and Climate Controls					
Nearby Funding Ratio (Nearby CoC Funding / Own, $1000s)	1,840	21.36	102.74	0.00	2,116.89
January Average Temperature (°C)	1,840	2.09	6.91	−16.73	21.01
January Precipitation (inches)	1,840	2.76	2.19	0.00	21.02

shown in Popov (2016), the choice between A and B formulas at the entitlement level is a "max" operation that does not fully mute the B-formula's influence once grants are pooled, so even "Formula A" CoCs receive an identifiable dose of pre-1940 driven variation, warranting the full sample inclusion of all CoCs across the time period. Within the 2019 sample, 85% of CoCs were "Formula B" communities[3].

5.2 Between-CoC IV Specification

While our primary 2SLS estimates report a causal interpretation, it is also informative to examine how sustained differences in average funding levels relate to average homelessness and capacity outcomes across CoCs. To that end, we complement the cross-sectional 2SLS analysis with a panel "between" IV specification that operates on five-year averages of each CoC's outcomes, funding, and covariates. Although this approach does not eliminate time-invariant CoC heterogeneity and thus cannot be interpreted as strictly causal, it descriptively links long-run, average funding intensity to long-run, average outcome levels, offering a perspective on the cumulative scale of federal grants and their association with homelessness and bed capacity.

Formally, let $\overline{Fund_i}$ be equal to the average of total CoC grant and ESG funding in CoC i over the years 2015 to 2019. Additionally, let $\overline{OldHousing_i}$ represent the average level of pre-1940's housing share and $\overline{X_i}$ to represent average levels of the covariate vector across the same time span. The between-CoC first stage is then:

$$\overline{Fund_i} = \pi \overline{OldHousing_i} + \overline{X_i}' \gamma + \epsilon_i \tag{8}$$

The corresponding second stage is then:

$$\overline{Outcome_i} = \beta \overline{Fund_i} + \overline{X_i}' \delta + u_i \tag{9}$$

Where $\overline{Outcome_i}$ is the average of the sheltered and unsheltered PIT counts and the HIC counts across 2015 to 2019 for each CoC.

These between-CoC regressions offer a useful complement to our primary cross-sectional IV results, highlighting the scale of longer-run associations between federal grant levels and both homelessness and shelter capacity.

5.3 Robustness Checks

The primary sheltered and unsheltered specifications are repeated for the rates of people experiencing homelessness per 10,000 total CoC population living below the federal poverty line (Lucas, 2017). This alternative scale helps control for secular shifts in local poverty levels, and tests the concern that a CoC with rising poverty rates could mechanically exhibit more "homeless per 10,000" just because its denominator decreased.

Additionally, the sheltered and unsheltered specifications are conducted after dropping observations for the New York City CoC (NY-600) and the Los Angeles City/County CoC (CA-600), as those areas experienced growth in homelessness at incomparable rates to all other parts of the U.S. over this panel period[4] (Lucas, 2017; O'Flaherty, 2019).

6 Results

6.1 First-Stage Estimates

Table 3 presents our four first-stage specifications, in which the dependent variable is total federal funding (CoC + ESG) per 10,000 residents. Columns (1) and (2) use the 2019 cross-section; Columns (3) and (4) use CoC-level five-year averages (2015–2019).

[3] Author's calculations using ACS 5-year survey values of CDBG formula variables.

[4] In 2015, New York City and Los Angeles together held nearly 15% of the nation's sheltered beds and 20% of unsheltered counts, even though they represent just 2 of 370 nationwide CoCs.

Table 3: First Stage: Effect of Pre-1940 Housing Share on Federal Funding

	Dependent Variable: Total Federal Funding (per 10,000 residents)			
	Cross-Section, 2019		Between CoC, 2015-2019	
	(1)	(2)	(3)	(4)
Instrument				
Old Housing Share (pre-1940, %)	4.332***	4.340***	3.852***	3.961***
	(0.291)	(0.364)	(0.264)	(0.366)
Black Population Share (%)		0.672**		0.981***
		(0.273)		(0.256)
Population Over 65 Share (%)		−2.273**		−2.960*
		(1.098)		(1.559)
SNAP Recipients Share (%)		−0.111		0.325
		(1.227)		(1.166)
SSI Recipients Share (%)		4.852*		−0.427
		(2.839)		(2.416)
Poverty Rate (%)		0.429		−0.355
		(1.432)		(1.231)
College Education Rate (%)		5.346***		10.685***
		(0.572)		(2.448)
Unemployment Rate (%)		15.436***		7.426
		(5.796)		(4.865)
Vacancy Rate (%)		0.225		−0.359
		(0.496)		(0.456)
Overcrowding Rate (%)		12.894***		2.220
		(4.945)		(5.053)
Rent Burden Rate (%)		0.576		2.924**
		(1.163)		(1.151)
Veteran Population Rate (%)		−0.725		−6.775***
		(1.990)		(1.839)
Disabled Population Share (%)		5.352**		9.145**
		(2.330)		(3.893)
Nearby Funding Ratio		−0.067**		−0.031
		(0.026)		(0.025)
January Average Temperature (°C)		2.205***		1.916***
		(0.589)		(0.621)
January Precipitation (inches)		−4.752***		0.995
		(1.744)		(1.841)
Constant	16.415***	−217.486***	16.666***	−338.998***
	(5.112)	(30.186)	(4.727)	(113.872)
Model Specifications				
Observations	370	370	373	373
R^2	0.375	0.688	0.366	0.639
F-Statistic	220.898***	48.630***	213.743***	39.318***

Notes: Robust standard errors clustered at CoC level in parentheses. Cross-section specifications use 2019 data. Between specifications use 2015–2019 averages. *p<0.1; **p<0.05; ***p<0.01

In Column (1), we regress 2019 per-capita funding on the pre-1940 housing share without any additional covariates. A one-percentage-point higher share of pre-1940 housing is associated with an extra \$4,332 of funding per 10,000 residents (SE = 0.291, $p < 0.01$), and the first-stage F-statistic on the instrument is 220.9, confirming very strong relevance. Column (2) adds the full set of time-varying controls—demographic shares (e.g. Black population share, share over age 65), housing-market indicators (vacancy, overcrowding, rent burden), special-population shares (SNAP, SSI, veteran, disability), the nearby-funding ratio, and January temperature and precipitation. Even after adjusting for these covariates, the coefficient on the pre-1940 share remains virtually unchanged at 4.340 (SE = 0.364, $p < 0.01$), and the instrument's F-statistic remains high at 48.6.

Panels (3) and (4) repeat the exercise using five-year CoC averages. In the unadjusted between-CoC regression (Column 3), a one-point increase in average pre-1940 housing share is associated with \$3,852 more funding per 10,000 residents (SE = 0.264, $p < 0.01$, F = 213.7). Adding the same covariate averages in Column (4) leaves the point estimate at \$3,961 (SE = 0.366, $p < 0.01$, F = 39.3). Although these between-CoC estimates do not purge fixed, unobserved CoC characteristics, they confirm that long-run variation in pre-1940 housing share captures the bulk of cross-sectional funding differences driven by HUD's CDBG formula.

Together, these results demonstrate that the ACS-derived pre-1940 housing share is a highly relevant instrument: it generates substantial within-CoC variation in annual funding (Columns 1–2) and is associated with large cross-CoC differences in average funding levels (Columns 3–4), even after controlling for a rich set of contemporaneous community characteristics.

6.2 Sheltered and Unsheltered Homelessness

Table 4 reports our 2SLS estimates of how per-capita federal funding affects sheltered and unsheltered homelessness, using both the 2019 cross-section (Columns 1–2 and 4–5) and the 2015–2019 between-CoC averages (Columns 3 and 6). All specifications instrument total funding per 10,000 residents with the pre-1940 housing share and cluster standard errors at the CoC level.

In the simple cross-section without additional controls (Column 1), a \$1,000 increase in annual funding per 10,000 residents raises the sheltered count by 0.123 persons (SE = 0.011, $p < 0.01$). When we add the full suite of demographic, housing-market, special-population, nearby-funding, and January climate controls (Column 2), the point estimate falls slightly to 0.100 (SE = 0.017, $p < 0.01$), but remains highly significant.

Turning to the between-CoC specification (Column 3), which regresses five-year average sheltered rates on five-year average funding and covariates, the coefficient is 0.092 (SE = 0.019, $p < 0.01$). Although smaller than the within-CoC estimates, this long-run association confirms that CoCs with persistently higher funding support modestly higher average sheltered counts.

In contrast, higher funding does not translate into fewer unsheltered individuals in the same year. In the unadjusted cross-section (Column 4), the point estimate is −0.034 (SE = 0.014, $p < 0.05$), suggesting a small negative effect; however, once we add the full control set (Column 5), the coefficient attenuates to −0.001 (SE = 0.015, $p > 0.10$) and loses statistical significance. The between-CoC estimate (Column 6) is −0.004 (SE = 0.016, $p > 0.10$), again indistinguishable from zero.

These results indicate that exogenous increases in federal homeless-assistance funding robustly expand sheltered placements within the same year—on the order of about 1 additional sheltered persons per \$10,000 per 10,000 residents—while having no meaningful short-run impact on street-sleeping counts. The between-CoC findings reinforce this pattern over longer horizons: sustained funding differentials are correlated with modestly higher average shelter use but do not alter unsheltered rates. This divergence suggests that additional beds primarily draw in people who were not previously counted as unsheltered, rather than directly converting street homelessness into shelter stays.

6.3 Shelter Capacity: Total Beds and Permanent Supportive Housing

Table 5 presents 2SLS estimates of how per-capita federal funding affects two measures of bed capacity: total year-round shelter beds (emergency, transitional, and safe-haven) and permanent supportive housing (PSH). Columns (1) and (3) use the 2019 cross-sectional specification; Columns (2) and (4) report the 2015–2019 between-CoC averages.

Table 4: Main Results: Effect of Federal Funding on Sheltered and Unsheltered Homelessness

	Dependent Variables (per 10,000 residents)					
	Sheltered			Unsheltered		
	2019 (No Covs) (1)	2019 (Full) (2)	Between CoC (3)	2019 (No Covs) (4)	2019 (Full) (5)	Between CoC (6)
Total Federal Funding	0.123^{***}	0.099^{***}	0.092^{***}	-0.034^{**}	-0.001	-0.004
($1000s)	(0.011)	(0.017)	(0.019)	(0.014)	(0.015)	(0.016)
Black Pop. Share (%)		-0.103^{*}	-0.097^{*}		-0.342^{***}	-0.266^{***}
		(0.056)	(0.056)		(0.051)	(0.047)
Pop. Over 65 (%)		0.003	-0.098		-0.233	-0.464^{*}
		(0.218)	(0.325)		(0.199)	(0.272)
SNAP Recipients (%)		0.585^{**}	0.719^{***}		-0.814^{***}	-0.606^{***}
		(0.247)	(0.242)		(0.225)	(0.203)
SSI Recipients (%)		-0.239	0.063		0.452	0.315
		(0.591)	(0.495)		(0.540)	(0.414)
Poverty Rate (%)		-0.484^{*}	-0.601^{**}		0.473^{*}	0.432^{**}
		(0.287)	(0.256)		(0.262)	(0.214)
College Educ. (%)		-0.189	-0.149		0.081	-0.258
		(0.158)	(0.555)		(0.144)	(0.464)
Unemployment (%)		-2.905^{**}	-2.663^{***}		6.164^{***}	3.128^{***}
		(1.173)	(1.002)		(1.070)	(0.839)
Vacancy Rate (%)		0.103	0.228^{**}		0.238^{***}	0.246^{***}
		(0.101)	(0.094)		(0.092)	(0.079)
Overcrowding (%)		0.145	-0.404		5.580^{***}	3.287^{***}
		(1.026)	(1.047)		(0.936)	(0.876)
Rent Burden (%)		0.919^{***}	1.031^{***}		0.144	0.075
		(0.238)	(0.256)		(0.217)	(0.215)
Veteran Pop. (%)		0.375	0.134		0.982^{***}	0.190
		(0.404)	(0.406)		(0.369)	(0.340)
Disabled Pop. (%)		-0.101	-0.482		0.063	-0.799
		(0.487)	(0.801)		(0.445)	(0.671)
Nearby Ratio		0.009^{*}	0.008		0.001	-0.002
		(0.005)	(0.005)		(0.005)	(0.004)
Jan. Temp. (°C)		-0.138	-0.045		0.207^{**}	0.260^{***}
		(0.100)	(0.110)		(0.091)	(0.092)
Jan. Precip. (in.)		0.377	-0.043		1.929^{***}	2.425^{***}
		(0.359)	(0.378)		(0.327)	(0.316)
Constant	1.680^{*}	1.753	9.191	9.499^{***}	-25.437^{***}	15.108
	(0.952)	(7.713)	(24.048)	(1.218)	(7.038)	(20.135)
Observations	370	370	373	370	370	373
R^2	0.256	0.400	0.433	-0.105	0.547	0.545
F-Statistic			270.6^{***}			430.5^{***}

Notes: 2SLS with pre-1940 housing share as instrument. Robust SEs clustered at CoC level. 2019 = Cross-section 2019 data. Between = 2015–2019 averages. *p<0.1; **p<0.05; ***p<0.01

Table 5: Housing Inventory Results: Effect of Federal Funding on Bed Capacity

	Dependent Variables (beds per 10,000 residents)			
	Total Shelter Beds		**Permanent Supportive Housing**	
	2019	Between CoC	2019	Between CoC
	(1)	(2)	(3)	(4)
Total Federal Funding	0.087^{***}	0.085^{***}	0.131^{***}	0.111^{***}
(\$1000s)	(0.018)	(0.020)	(0.013)	(0.013)
Black Population Share (%)	−0.083	−0.053	−0.016	0.020
	(0.061)	(0.060)	(0.043)	(0.039)
Population Over 65 Share (%)	−0.036	−0.028	−0.079	−0.175
	(0.238)	(0.325)	(0.165)	(0.210)
SNAP Recipients Share (%)	0.583^{**}	0.715^{***}	−0.104	0.066
	(0.269)	(0.260)	(0.187)	(0.168)
SSI Recipients Share (%)	−0.137	−0.096	−0.515	−0.460
	(0.644)	(0.530)	(0.448)	(0.341)
Poverty Rate (%)	−0.366	−0.351	0.292	0.288
	(0.313)	(0.274)	(0.217)	(0.177)
College Education Rate (%)	−0.043	−0.052	0.268^{**}	0.336
	(0.172)	(0.595)	(0.119)	(0.383)
Unemployment Rate (%)	-2.683^{**}	-3.247^{***}	1.275	0.354
	(1.277)	(1.078)	(0.888)	(0.695)
Vacancy Rate (%)	0.110	0.210^{**}	0.017	0.019
	(0.110)	(0.101)	(0.076)	(0.065)
Overcrowding Rate (%)	1.056	−0.157	1.155	0.849
	(1.117)	(1.126)	(0.777)	(0.726)
Rent Burden Rate (%)	0.868^{***}	0.973^{***}	0.210	0.177
	(0.259)	(0.276)	(0.180)	(0.178)
Veteran Population Rate (%)	0.564	0.071	0.542^{*}	−0.161
	(0.440)	(0.434)	(0.306)	(0.280)
Disabled Population Share (%)	0.174	−0.357	0.600	−0.504
	(0.530)	(0.844)	(0.369)	(0.544)
Nearby Funding Ratio	0.008	0.009	0.0005	0.0001
	(0.006)	(0.005)	(0.004)	(0.004)
January Average Temperature	−0.064	0.030	−0.084	−0.121
	(0.109)	(0.118)	(0.075)	(0.076)
January Precipitation	0.012	−0.231	−0.403	−0.101
	(0.390)	(0.406)	(0.271)	(0.262)
Instrumental Variable	Pre-1940 Housing Share (%)			
Summary Statistics				
Observations	370	373	370	373
R^2	0.353	0.381	0.740	0.737
F-Statistic		211.936^{***}		670.931^{***}

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument.
Total Shelter Beds include Emergency Shelter, Transitional Housing, and Safe Haven beds.
Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data.
Between = 2015–2019 averages. *p<0.1; **p<0.05; ***p<0.01

In the cross-section (Column 1), a $1,000 increase in annual funding per 10,000 residents is associated with 0.087 additional shelter beds per 10,000 (SE = 0.018, $p < 0.01$). This result confirms that same-year grants rapidly translate into expanded emergency and transitional capacity—consistent with the notion that ESG-funded shelter contracts and CoC-funded rapid re-housing can be deployed quickly when funds arrive (Moulton, 2013). In the between-CoC specification (Column 2), CoCs with $1,000 higher average funding per 10,000 residents have, on average, 0.085 more beds per 10,000 (SE = 0.020, $p < 0.01$). Although correlational, this long-run association illustrates how sustained resource differences map into baseline shelter infrastructure.

By contrast, PSH capacity follows a slower time path. In the 2019 within-CoC model (Column 3), the point estimate is 0.131 PSH beds per 10,000 per $1,000 funding (SE = 0.013, $p < 0.01$), suggesting that a portion of funding does flow into PSH in the short run. However, this estimate conflates immediate re-allocations with longer-run stock adjustments. In the between-CoC regression (Column 4), CoCs with $1,000 higher mean funding per 10,000 residents are associated with 0.111 more PSH beds per 10,000 (SE = 0.013, $p < 0.01$). This demonstrates that areas with persistently higher funding ultimately accumulate greater PSH capacity, consistent with capital-intensive, multi-year development timelines for permanent supportive units (Rog et al., 2014; Stergiopoulos et al., 2015).

Table 6: Effects on Seasonal and Overflow Bed Capacity

	Dependent Variables (beds per 10,000 residents)			
	Overflow Beds		**Seasonal Beds**	
	2019 (1)	Between CoC (2)	2019 (3)	Between CoC (4)
Total Federal Funding ($1000s)	0.009*** (0.003)	0.005 (0.003)	0.004 (0.004)	−0.0005 (0.003)
Model Specifications				
Full Control Set	Yes	Yes	Yes	Yes
Instrumental Variable	Pre-1940 Housing Share			
Summary Statistics				
Observations	370	373	370	373
R^2	0.139	0.151	0.192	0.206
F-Statistic		76.023***		94.112***

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument. Full control set includes all demographic, socioeconomic, housing market, special population, and geographic/climate controls as shown in previous tables.
Between = 2015–2019 averages. *p<0.1; **p<0.05; ***p<0.01

Table 6 examines two additional bed types that may surge during the January PIT count. In the 2019 within-CoC model (Column 1), a $1,000 per 10,000 funding increase yields 0.009 overflow beds per 10,000 (SE = 0.003, $p < 0.01$), indicating that some new funding goes to surge-capacity arrangements (e.g. overflow cots) when demand spikes (Byrne et al., 2013). The effect on seasonal beds (Column 3) is small (0.004) and not statistically significant. Between-CoC associations for both bed types (Columns 2 and 4) are modest and imprecise, underscoring that these temporary categories fluctuate year-to-year with policy and weather conditions rather than long-run funding levels.

In sum, these results reveal that federal homeless-assistance grants expand immediate shelter options in the short run—consistent with our finding that funding allocations raise sheltered homelessness counts—while only sustained, multi-year funding differentials accumulate into the permanent housing infrastructure, which in turn helps explain why unsheltered counts remain largely unchanged in the short run despite larger average bed stocks.

These combined patterns raise a critical question: if federal grants are swiftly constructing new temporary beds and sheltered counts rise accordingly, why do we not observe a corresponding decline in unsheltered homelessness? One explanation is that the additional shelter capacity is drawing in individuals who were never counted as unsheltered in the first place. For example, families and individuals doubling up in overcrowded or precarious housing (e.g. those coping with domestic violence, severe mental-health conditions, or substance-use challenges) may opt into stable shelter programs without ever appearing in the street-based Point-in-Time enumeration (Byrne et al., 2013; O'Flaherty, 2019; Tsai and Alarcón, 2022; Wong et al., 1997). A second, complementary mechanism is geographic re-sorting: as Popov (2016) argues, people experiencing homelessness will migrate toward jurisdictions with more robust service networks. Our finding that neighboring CoC funding is negatively associated with local unsheltered counts supports this view, suggesting that some portion of the sheltered increase reflects in-migration of individuals seeking shelter rather than direct transitions out of street homelessness.

6.4 Heterogeneity by CoC Category

Disaggregating our analysis by HUD's four CoC geographic categories—"Major City CoC," "Other Largely Urban CoC," "Largely Suburban CoC," and "Largely Rural CoC" (U.S. Department of Housing and Urban Development, 2012)—allows us to probe whether funding effects vary with population density and service-delivery infrastructure. HUD assigns each CoC to one of these categories based on census definitions of urbanized areas, metropolitan adjacency, and rural composition, under the logic that densely populated centers operate very different shelter and outreach systems than more dispersed jurisdictions.

Table 7 reports our 2SLS estimates separately for (i) Urban CoCs (Major City + Other Largely Urban) and (ii) Rural/Suburban CoCs (Largely Suburban + Largely Rural). In both settings, exogenous increases in per-capita federal funding predict nearly identical boosts in sheltered homelessness: roughly 0.09 additional sheltered persons per 10,000 residents for each extra \$1,000 of funding, significant at the 1 percent level in both strata. This uniformity suggests that, regardless of density, communities are able to deploy new grants rapidly into emergency, transitional, or safe-haven beds.

However, the impact on unsheltered homelessness diverges sharply. In Urban CoCs, higher funding yields no statistically detectable change in street-sleeping counts (coefficient = 0.023, $p > 0.10$), whereas in Rural/Suburban CoCs a \$1,000 funding increase is associated with a significant decline of 0.096 unsheltered individuals per 10,000 residents ($p < 0.05$). This pattern implies that in less densely settled areas, where baseline shelter capacity and outreach networks are thinner, marginal resources can directly draw more people off the streets. In contrast, in urbanized CoCs—often already operating near capacity or facing logistical constraints—additional dollars primarily expand formal shelter placements without immediately reducing the unsheltered population. Understanding this geographic heterogeneity is critical for tailoring federal grant strategies: urban centers may need complementary investments in outreach, transportation, or data-driven targeting to convert shelter-capacity gains into declines in street homelessness, whereas rural and suburban areas appear to benefit from more straightforward capacity additions.

6.5 Heterogeneity by Individuals and Families

Disaggregating our analysis by household type—single individuals versus families—sheds light on which groups capture new shelter capacity and who remains on the street when funding rises. Under HUD's PIT framework, "individuals" are single adults or unrelated persons counted separately, while "families" include at least one adult and one or more children sharing living quarters, often housed in dedicated family units with wrap-around services (U.S. Department of Housing and Urban Development, 2014; O'Flaherty, 2019).

Table 8 presents our 2SLS estimates, instrumenting per-capita federal grants with the pre-1940 housing share. In the cross-sectional 2019 model, a \$1,000 increase in funding per 10,000 residents leads to an additional 0.047 sheltered individuals per 10,000 (SE = 0.009, $p < 0.01$) and an additional 0.052 sheltered family members per 10,000 (SE = 0.012, $p < 0.01$). Both effects are highly significant, but the slightly larger coefficient for families suggests that when new beds become available—often larger or more specialized units—households with children marginally outcompete single adults for these slots.

In contrast, the unsheltered margins barely budge. We estimate 0.006 additional unsheltered individuals per 10,000 (SE = 0.014, *n.s.*) and a 0.007 change for unsheltered family members (SE = 0.002, $p < 0.01$). Although the decline in unsheltered families is statistically significant, its magnitude is small: roughly one fewer person in a family moves out of unsheltered homelessness for an additional \$143,000 in funding per

Table 7: Heterogeneous Effects by CoC Geography: Urban vs. Rural/Suburban Areas

	Dependent Variables (per 10,000 residents)			
	Urban CoCs		**Rural/Suburban CoCs**	
	Sheltered (1)	Unsheltered (2)	Sheltered (3)	Unsheltered (4)
Total Federal Funding ($1000s)	0.087***	0.023	0.091***	−0.096**
	(0.026)	(0.014)	(0.034)	(0.045)
Black Population Share (%)	0.108	−0.087	−0.143**	−0.390***
	(0.138)	(0.077)	(0.057)	(0.076)
Population Over 65 Share (%)	0.440	0.126	0.187	0.024
	(0.773)	(0.428)	(0.198)	(0.264)
SNAP Recipients Share (%)	0.661	−0.508*	0.296	−1.121***
	(0.533)	(0.295)	(0.255)	(0.340)
SSI Recipients Share (%)	−2.927**	−0.254	2.919***	2.227**
	(1.233)	(0.682)	(0.721)	(0.963)
Poverty Rate (%)	−0.689	−0.114	−0.875***	0.318
	(0.732)	(0.405)	(0.308)	(0.411)
College Education Rate (%)	−0.068	0.073	−0.200	0.207
	(0.334)	(0.185)	(0.165)	(0.221)
Unemployment Rate (%)	−2.164	2.786*	−4.276***	7.130***
	(2.870)	(1.588)	(1.089)	(1.454)
Vacancy Rate (%)	−0.563	−0.449	0.160*	0.204*
	(0.562)	(0.311)	(0.083)	(0.110)
Overcrowding Rate (%)	1.158	6.276***	−0.123	3.838**
	(2.007)	(1.110)	(1.120)	(1.495)
Rent Burden Rate (%)	1.165**	−0.273	1.015***	1.220***
	(0.522)	(0.289)	(0.336)	(0.449)
Veteran Population Rate (%)	−0.453	−0.113	0.288	1.373***
	(1.001)	(0.554)	(0.393)	(0.524)
Disabled Population Share (%)	1.755	1.426*	−0.867**	−0.318
	(1.433)	(0.793)	(0.420)	(0.561)
Nearby Funding Ratio	−0.105	−0.176***	0.009*	−0.006
	(0.112)	(0.062)	(0.005)	(0.006)
January Average Temperature (°C)	−0.586**	0.341**	0.101	−0.047
	(0.251)	(0.139)	(0.118)	(0.157)
January Precipitation (inches)	1.081	1.911***	−0.376	1.889***
	(0.947)	(0.524)	(0.338)	(0.451)
Constant	−10.873	−15.852	5.612	−40.978***
	(18.138)	(10.034)	(8.423)	(11.240)
Instrumental Variable	Pre-1940 Housing Share (%)			
Summary Statistics				
Observations	106	106	264	264
R^2	0.463	0.705	0.486	0.483

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument.
Urban CoCs include "Major City CoC" and "Other Largely Urban CoC" categories.
Rural/Suburban CoCs include "Largely Rural CoC" and "Largely Suburban CoC" categories.
Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data.
*p<0.1; **p<0.05; ***p<0.01

Table 8: Federal Funding Effects by Household Type and Shelter Status

	Dependent Variables (per 10,000 residents)			
	Sheltered		Unsheltered	
	Individuals (1)	Families (2)	Individuals (3)	Families (4)
Total Federal Funding ($1000s)	0.047***	0.052***	0.006	−0.007***
	(0.009)	(0.012)	(0.014)	(0.002)
Black Population Share (%)	−0.053*	−0.049	−0.325***	−0.017**
	(0.029)	(0.041)	(0.047)	(0.008)
Population Over 65 Share (%)	−0.022	0.025	−0.230	−0.003
	(0.114)	(0.159)	(0.184)	(0.031)
SNAP Recipients Share (%)	−0.068	0.654***	−0.892***	0.078**
	(0.129)	(0.180)	(0.208)	(0.035)
SSI Recipients Share (%)	−0.852***	0.613	0.433	0.019
	(0.308)	(0.431)	(0.499)	(0.084)
Poverty Rate (%)	0.247	−0.731***	0.526**	−0.053
	(0.150)	(0.209)	(0.242)	(0.041)
College Education Rate (%)	0.051	−0.240**	0.046	0.034
	(0.082)	(0.115)	(0.133)	(0.022)
Unemployment Rate (%)	−0.091	−2.813***	5.898***	0.266
	(0.611)	(0.855)	(0.989)	(0.166)
Vacancy Rate (%)	0.099*	0.004	0.213**	0.025*
	(0.052)	(0.073)	(0.085)	(0.014)
Overcrowding Rate (%)	0.259	−0.113	4.988***	0.592***
	(0.534)	(0.747)	(0.865)	(0.146)
Rent Burden Rate (%)	0.408***	0.511***	0.142	0.002
	(0.124)	(0.174)	(0.201)	(0.034)
Veteran Population Rate (%)	0.318	0.057	0.937***	0.045
	(0.211)	(0.295)	(0.341)	(0.057)
Disabled Population Share (%)	0.251	−0.353	0.002	0.061
	(0.254)	(0.355)	(0.411)	(0.069)
Nearby Funding Ratio	0.004	0.006	0.001	−0.0002
	(0.003)	(0.004)	(0.005)	(0.001)
January Average Temperature	−0.070	−0.068	0.199**	0.008
	(0.052)	(0.073)	(0.084)	(0.014)
January Precipitation	0.075	0.303	1.820***	0.108**
	(0.187)	(0.261)	(0.302)	(0.051)
Constant	−6.976*	8.729	−22.672***	−2.765**
	(4.018)	(5.620)	(6.506)	(1.094)
Instrumental Variable	Pre-1940 Housing Share (%)			
Summary Statistics				
Observations	370	370	370	370
R^2	0.391	0.305	0.561	0.136

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument. Dependent variables disaggregate homelessness by household type (individuals vs. families) and shelter status. Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data. *p<0.1; **p<0.05; ***p<0.01

10,000 CoC residents. This negligible shift implies that most of the rise in sheltered counts reflects the intake of people who were previously doubled-up or in precarious housing—particularly families—rather than a direct conversion of street-sleepers into shelter clients.

These findings underscore two important points. First, federal grants rapidly expand formal shelter capacity in proportion to need and design: family units respond slightly more strongly when more funding arrives compared to individuals. Second, the minimal movement among unsheltered individuals suggests that simple bed-count increases are mostly ineffective in moving people experiencing unsheltered homelessness into immediate shelter. Policymakers seeking to reduce unsheltered homelessness may therefore need to pair capacity expansions with targeted outreach, transportation supports, or flexible shelter entry policies, especially for single adults who face unique barriers to accessing congregate or gender-segregated facilities.

6.6 Heterogeneity by Subpopulation

Table 9: Heterogeneous Effects on Sheltered Population Subgroups

	Panel A: Age and Gender Groups					
	Dependent Variables: Sheltered Homeless by Subgroup (per 10,000 residents)					
	Under 18	Age 18–24	Over 24	Women	Men	Chronically Homeless
	(1)	(2)	(3)	(4)	(5)	(6)
Total Federal Funding	0.031***	0.008***	0.061***	0.044***	0.054***	0.018***
($1000s)	(0.007)	(0.001)	(0.010)	(0.009)	(0.009)	(0.003)
Observations	370	370	370	370	370	370
Full Control Set Used?	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.311	0.367	0.419	0.357	0.417	0.460
	Panel B: Race and Special Conditions					
	Dependent Variables: Sheltered Homeless by Subgroup (per 10,000 residents)					
	White	Black	Mental Illness	Substance Abuse	Domestic Violence	
	(7)	(8)	(9)	(10)	(11)	
Total Federal Funding	0.038***	0.055***	0.021***	0.022***	0.006***	
($1000s)	(0.009)	(0.010)	(0.004)	(0.004)	(0.002)	
Observations	370	370	359	359	359	
Full Control Set Used?	Yes	Yes	Yes	Yes	Yes	
R^2	0.396	0.425	0.400	0.323	0.201	
	Model Specifications					
Instrumental Variable: Pre-1940 Housing Share						

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument.
Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data.
*p<0.1; **p<0.05; ***p<0.01

Table 9 presents the 2SLS estimates for demographic and subpopulation groups in the sheltered counts. In nearly every sheltered category, a $1,000 increase in per-10,000 funding yields a statistically significant rise in shelter use. Among age groups, adults over 24 show the largest response with 0.061 additional sheltered individuals per 10,000 (SE = 0.010, $p < 0.01$), followed by children under 18 at 0.031 per 10,000 (SE = 0.007, $p < 0.01$), and young adults aged 18–24 with a smaller but significant effect of 0.008 per 10,000 (SE = 0.001, $p < 0.01$). Both women (0.044, SE = 0.009, $p < 0.01$) and men (0.054, SE = 0.009, $p < 0.01$) experience significant increases in shelter access, with men showing a slightly larger response. Among racial groups, Black individuals demonstrate a stronger shelter response (0.055, SE = 0.010, $p < 0.01$) compared to white individuals (0.038, SE = 0.009, $p < 0.01$). Subpopulations facing chronic challenges also respond positively: those with mental illness (0.021, SE = 0.004, $p < 0.01$), substance abuse issues (0.022, SE = 0.004, $p < 0.01$), and domestic violence survivors (0.006, SE = 0.002, $p < 0.01$) all show significant increases. People experiencing chronic homelessness increase by 0.018 per 10,000 in response to additional funding (SE = 0.003, $p < 0.01$).

An advantage of our heterogeneity analysis is that the subgroup coefficients can be interpreted as shares of the overall sheltered response. Recall that the total within-CoC effect of funding on sheltered homelessness is 0.099 per 10,000. Because the age groups are mutually exclusive, we can decompose the total effect mechanically: adults over 24 account for approximately 61% of the overall sheltered increase (0.061/0.099), children under 18 contribute 31% (0.031/0.099), and young adults aged 18–24 represent 8% (0.008/0.099). Similar calculations for gender yield that men comprise 54% of the shelter response (0.054/0.099) and women 44% (0.044/0.099), while for race, Black individuals represent 55% of the total response (0.055/0.099) compared to 38% for white individuals (0.038/0.099). By contrast, the subpopulations defined by severe conditions overlap—an individual may belong to multiple categories—so their coefficients (0.021, 0.022, 0.006) imply a combined share ranging from 22% (0.022/0.099) to 49% ((0.021+0.022+0.006)/0.099) of the total sheltered effect, depending on overlap assumptions. People experiencing chronic homelessness represent 18% of the shelter response (0.018/0.099). This decomposition reveals that working-age adults and men drive the majority of the shelter response, while highlighting substantial representation across demographic groups and vulnerable subpopulations.

Table 10: Heterogeneous Effects on Unsheltered Population Subgroups

Panel A: Age and Gender Groups						
Dependent Variables: Unsheltered Homeless by Subgroup (per 10,000 residents)						
	Under 18	Age 18–24	Over 24	Women	Men	Chronically Homeless
	(1)	(2)	(3)	(4)	(5)	(6)
Total Federal Funding	-0.004^{**}	0.004^{**}	-0.001	-0.003	0.0003	0.002
(\$1000s)	(0.002)	(0.002)	(0.013)	(0.005)	(0.011)	(0.006)
Observations	370	370	370	370	370	370
Full Control Set Used?	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.130	0.342	0.555	0.513	0.524	0.486
Panel B: Race and Special Conditions						
Dependent Variables: Unsheltered Homeless by Subgroup (per 10,000 residents)						
	White	Black	Mental Illness	Substance Abuse	Domestic Violence	
	(7)	(8)	(9)	(10)	(11)	
Total Federal Funding	-0.020^{**}	0.015^{***}	0.004	0.007	0.001	
(\$1000s)	(0.010)	(0.005)	(0.004)	(0.004)	(0.002)	
Observations	370	370	359	359	359	
Full Control Set Used?	Yes	Yes	Yes	Yes	Yes	
R^2	0.497	0.392	0.463	0.429	0.337	
Model Specifications						
Instrumental Variable: Pre-1940 Housing Share						

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument.
Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data.
*p<0.1; **p<0.05; ***p<0.01

While our main analysis finds no overall effect of increased federal grants on street homelessness, a more granular look across demographic subgroups uncovers important patterns (Table 10). Across age and gender cohorts, the changes are uniformly small: a modest 0.004-person uptick per 10,000 young adults and a 0.004 decline among children under 18 both reach only borderline significance, while adults over 24, women, men, and chronically homeless individuals exhibit effects indistinguishable from zero.

The most pronounced—and sensitive—finding emerges by race. For white individuals, a \$1,000 bump in per-capita funding is associated with a statistically significant drop of 0.020 unsheltered persons per 10,000 (SE = 0.010, $p < 0.05$). By contrast, black individuals see a significant increase of 0.015 per 10,000 (SE = 0.005, $p < 0.01$) in their unsheltered count. Both groups nonetheless experienced positive shelter-entry responses (Table 9), implying that net unsheltered changes reflect more than simple movements into shelter.

Interpreting this racial divergence demands caution. One possibility is improved outreach and enumeration: better-funded CoCs may simply count more black individuals who were previously missed, narrowing longstanding undercounts in the Point-in-Time survey. Alternatively, systemic barriers—such as location of new shelters, transportation gaps, or discriminatory practices—may limit black individuals' ability to access bed space even as it expands for others . Finally, underlying housing-market shifts could displace black households while drawing more visible white homelessness into the count.

All other special-condition groups—those with mental illness, substance-use disorders, or fleeing domestic violence—show no significant unsheltered response, reinforcing that federal grants primarily operate by increasing formal shelter capacity rather than directly diminishing street-sleeping counts among these vulnerable populations. Taken together, the nearly offsetting racial effects help explain our aggregate null result, underscoring the imperative to assess distributional impacts when evaluating homelessness interventions.

6.7 Robustness

In Table 11, we re-estimate the 2019 2SLS specification using homelessness rates per 10,000 people in poverty (rather than per 10,000 total residents). The point estimate on funding for sheltered homelessness remains positive and highly significant—at 0.687 ($SE = 0.115, p < 0.01$)—indicating that a \$10,000 increase in per-10,000 funding corresponds to roughly 7 additional sheltered individuals per 10,000 poor residents. The unsheltered coefficient (0.074, SE = 0.117) remains statistically indistinguishable from zero.

Similarly, Table 12 presents the within-CoC estimates after dropping New York City (NY-600) and Los Angeles City/County (CA-600). The sheltered-homelessness coefficient is unchanged at 0.099 ($SE = 0.016, p < 0.01$) and the unsheltered coefficient remains small (-0.001, SE = 0.015) and insignificant. Hence, neither the poverty-scaled outcome nor the exclusion of these two outliers overturns our main result: federal grants causally raise sheltered PIT counts without a concomitant decrease in unsheltered homelessness.

7 Discussion

This paper provides new, causal evidence on how federal homeless-assistance grants affect reported homelessness and shelter capacity across U.S. CoCs in 2019. By exploiting cross-sectional variation in the ACS-derived pre-1940 housing share as an instrument for combined CoC and ESG funding, our 2SLS design yields several key insights that advance understanding of federal homelessness policy effectiveness.

First, contemporaneous grant allocations induce sizable increases in sheltered homelessness—with roughly 1 additional sheltered placement per \$10,000 per 10,000 residents—yet have no detectable short-run impact on unsheltered counts. In other words, ESG and CoC dollars principally expand formal shelter access rather than immediately reducing street sleeping. This pattern could arise because new beds attract individuals who were previously "hidden" in doubled-up or precarious living arrangements and thus never counted in the unsheltered PIT enumeration (Byrne et al., 2013; O'Flaherty, 2019; Culhane et al., 2011).

Second, federal dollars flow rapidly into all shelter modalities, but PSH displays the largest per-dollar expansion. While emergency and transitional beds respond within the same year, PSH capacity increases even more for each \$1,000 of funding—consistent with HUD's "Housing First" emphasis and a strong evidence base demonstrating PSH's impacts on stability for chronically homeless populations (Tsemberis and Eisenberg, 2000; Rog et al., 2014; Byrne et al., 2014). This finding indicates that CoCs are effectively channeling federal assistance into long-term housing infrastructure, even as they retain the ability to scale up emergency shelter in response to immediate crises.

Third, heterogeneity analysis reveals that the shelter response to increased funding is concentrated among specific demographic groups, with working-age adults, men, and black individuals accounting for the majority of new shelter placements. This demographic composition represents a notable shift from earlier research by Popov (2016) and Lucas (2017), who found that families and children were most responsive to similar funding increases. This shift could reflect a reorientation of funding and program design toward adult-focused services in recent years, or differing demographic dynamics as a result of the more spatially fine crosswalk process to obtain relevant covariates for the specifications.

Fourth, we uncover stark racial disparities in unsheltered outcomes. Although both white and black individuals gain shelter access as funding rises, the net effect on street homelessness diverges: white individuals experience significant declines in unsheltered rates, whereas black individuals see significant increases. This finding is particularly concerning given overall declines in black homelessness reported between 2015 and 2019, and suggests that structural barriers—such as discriminatory intake practices, mismatches in shelter location, or uneven outreach—may prevent equitable utilization of new resources.

These empirical findings align with a few interlocking theoretical mechanisms. Under a standard capacity-constraint framework, CoC and ESG grants immediately loosen local bottlenecks in emergency and transitional shelter supply, creating "fast-stock" beds that can be stood up with minimal lead time (e.g. leasing contracts, temporary cots) (O'Flaherty, 1995). However, our finding that each dollar of funding yields even larger gains in PSH capacity suggests that, beyond sheer speed of deployment, federal funding formulas and local CoC priorities tilt investments toward long-term housing solutions. PSH development does indeed carry longer lead times—site acquisition, capital financing, and administrative approvals all take months or years—but federal regulations (e.g. CoC grant spending restrictions) channel a larger share of marginal dollars into PSH relative to emergency shelter space (Rog et al., 2014; Byrne et al., 2014). The result is both a rapid surge in temporary shelter and an outsized expansion of the PSH stock from larger funding allocations across CoCs.

Geographic spillovers further shape these dynamics. While the coefficient on the nearby funding ratio is not significantly different from zero in most specifications, our strong negative result for unsheltered homelessness in urban settings suggests that individuals experiencing street homelessness in more densely populated areas relocate toward jurisdictions with greater available resources, influencing counts in less advantaged communities while inflating sheltered populations in well-funded CoCs (Popov, 2016). Even households with marginal housing stability (e.g. doubling up with family or friends) may choose to migrate into better-funded CoCs to secure more reliable shelter placements, again boosting local sheltered counts without a one-for-one conversion of the truly unsheltered. Nonetheless, we show that, in the aggregate, cross-CoC funding differences lead to strong compositional changes in sheltered homeless populations even after accounting for possible spillover incentives.

Finally, by expanding the capacity of formal programs, marginal federal dollars can "reveal" a hidden population—households in precarious but roofed situations who opt into shelter when it becomes available (Byrne et al., 2013; O'Flaherty, 2019). These individuals were never captured in the unsheltered Point-in-Time enumeration, so their entry into shelter programs raises reported sheltered homelessness without generating an offsetting drop in recorded street homelessness. In effect, the outside option of doubling up, overcrowding, or couch-surfing becomes dominated by the newly created alternative option of program-funded shelter, muting any immediate decline in unsheltered counts.

Despite these contributions, certain limitations should be noted. First, PIT and HIC data are subject to measurement error. PIT counts notoriously undercount street-sleeping individuals—particularly those in concealed or rural encampments—while HIC counts may overstate usable capacity if providers lack sufficient staffing or operational resources (National Law Center on Homelessness and Poverty, 2017; Schneider et al., 2016; Government Accountability Office, 2020; Meyer et al., 2023). Hard-to-locate groups such as people sleeping in vehicles, abandoned buildings, rural encampments, or concealed urban niches are often missed, and the same is true for women, youth, and LGBTQ+ individuals who avoid public spaces (National Law Center on Homelessness and Poverty, 2017; Schneider et al., 2016). Furthermore, because the PIT is a snapshot, administrative micro-panels suggest annual incidence can exceed the single-night count by a factor of three or more (Ward et al., 2024). We mitigate these concerns with extensive covariate adjustment and robustness checks, but readers should interpret our coefficients as effects on reported homelessness rather than the unobserved, underlying population.

Second, by focusing on contemporaneous and average (between) effects, we do not fully capture longer-run lags in PSH development or delayed reductions in unsheltered homelessness. PSH projects often require many years to materialize from award to occupancy; since our panel ends in 2019, we cannot observe these extended timelines (Rog et al., 2014; Byrne et al., 2014). Future research should extend the time horizon through at least 2024 to estimate the long-run evolution of PSH capacity and its impacts on chronic homelessness.

Third, related to timing, complications in the PIT counts conducted over the COVID-19 pandemic[5] in the U.S. do not allow for us to examine the relationship over that period. Our results are valid for the 2015–2019 timeframe, during which both homelessness measurement and federal funding allocation followed consistent methodologies. The pandemic period introduced substantial disruptions to both outcomes and treatment variables: emergency COVID-19 relief dramatically increased ESG funding by over 15 times the previous yearly average[6] (U.S. Department of Housing and Urban Development, 2020), while PIT count reliability deteriorated due to modified or dropped enumeration procedures and health restrictions. Consequently, we cannot determine whether the estimated relationships between federal funding and homelessness outcomes persist in the post-pandemic environment, where both the scale of resources and the nature of service delivery have evolved considerably. Future research extending this analysis to the post-2020 period will require careful attention to these structural breaks in both measurement and policy regimes.

Nonetheless, our findings carry three key implications for policy and theory. First, the rapid surge in emergency and overflow beds following increases in CoC and ESG funding demonstrates that annual grants are effective tools for scaling up immediate, need-based responses. To translate these short-run gains into durable reductions in chronic homelessness, policymakers should embed multi-year commitments—such as earmarking a fixed share of CoC funds for PSH capital projects over a rolling three- to five-year horizon—to align incentives toward long-term infrastructure growth (O'Flaherty, 2019). Second, our subgroup results underscore that the most responsive beneficiaries-black individuals, men, adults over 24, and those suffering from serious behavioral-health conditions-face acute vulnerability and may derive outsized welfare gains from targeted expansions of specialized beds. Incorporating welfare weights or cost-benefit comparisons across subpopulations could sharpen the case for prioritizing these groups. Third, the racial divergence in unsheltered outcomes highlights the need for equity-focused policy design: funding formulas and program rules must be assessed for potential barriers that may increase the number of black individuals who experience unsheltered homelessness, even as white unsheltered counts decline.

Additionally, our subgroup analysis highlights the importance of heterogeneity within the homeless population—women, children, people with chronic spells, and people suffering from serious conditions—who are most responsive to newly available beds. Targeting additional capacity toward these groups may yield greater welfare gains than a uniform expansion of emergency beds.

In summary, this paper advances understanding of how federal homeless-assistance grants translate into reported homelessness, shelter capacity, and the composition of beneficiaries across U.S. CoCs. Our 2SLS snapshot shows that CoC and ESG grants expand immediate shelter access by drawing into the system households who were previously doubled-up or otherwise hidden, without producing any detectable short-run decline in street homelessness.

Simultaneously, CoCs with higher per-capita funding in 2019 exhibit larger stocks of permanent supportive housing, underscoring the role of sustained resource levels in building infrastructure suitable for long-term reductions in homelessness. Future work should refine measurement of unsheltered counts, explore the equity of access across demographic groups, and evaluate how one-off funding shocks compare to ongoing allocations in shaping durable reductions in various heterogeneous groups of people experiencing homelessness. Only by coupling rapid-response shelter funding with durable PSH commitments—and by ensuring those resources reach the most vulnerable—can federal grants fulfill their full promise of both immediate relief and lasting stability.

While the federal government distributes sizeable funding toward homeless-assistance services, the nature of the relationship between this funding and the composition of the homeless population over time remains only partly understood. Our estimates note that for $1,000,000 allocated to a given CoC, about 100 more people are counted as staying in an emergency overnight shelter, transitional housing unit, or safe haven bed space. Heterogeneity analysis reveals that these new placements are more often family

[5] Due to health and safety concerns, many CoCs were unable to conduct their annual PIT counts in 2021, with HUD allowing jurisdictions not submit unsheltered counts if the count would conflict with local lockdown restrictions.

[6] Author calculations from ESG award data.

members rather than single individuals. In fact, of those 100 people, about 31 of them are under the age of 18 while 61 are older than 24, 44 are women and 54 are men, 38 are white and 55 are black, 18 have been counted as homeless for at least one year already, and between 22 and 49 of those people suffer from a severe condition. However, the origin of these 100 people remains mostly unclear, since there is no robustly detectable relationship between federal funding and unsheltered homelessness counts. Overall, our findings suggest that larger federal grant allocations across CoCs predominantly expand shelter capacity without immediately reducing street homelessness, underscoring the need for complementary strategies (such as targeted outreach and long-term supportive housing) to reach unsheltered individuals and address chronic homelessness.

8 References

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A Appendix

A.1 Details of Tract-CoC Crosswalk Construction

This appendix describes in detail how we construct the tract–to–Continuum of Care (CoC) crosswalk used to harmonize all tract-level covariates to the CoC geography, following the general approach of Ferrara et al. (2024). Although Ferrara et al. (2024) develop population-weighted crosswalks for county- and congressional-district-level data, our implementation adapts their logic to the tract and CoC level. In brief, for each year from 2015 to 2019, we (i) load CoC boundaries and Census tracts (TIGER/Line), (ii) intersect tracts with CoCs to create *tract-pieces*, (iii) assign a population weight to each piece using a high-resolution raster (Global Human Settlement), (iv) download ACS five-year estimates at the tract level, (v) multiply each tract's ACS variables by its tract-piece population share, and (vi) sum up all weighted tract-piece values within each CoC. The result is an annual panel of CoC-level covariates that exactly preserves the original tract-level data in aggregate. Below we describe each step with sufficient detail to reproduce our results.

A.1.1 Data Sources

- **CoC shapefiles (2015–2019):** We obtain annual CoC boundary shapefiles from HUD's Homelessness Data Exchange. Each shapefile contains one polygon per CoC with a unique six-digit `CoC_Code`.
- **Census tract shapefiles (2010 TIGER, projected to five-year Census years):** For each year 2015–2019, we download the TIGER/Line tract shapefiles corresponding to that year's ACS 5-year release (e.g. 2015 tracts come from 2015 TIGER, etc.). These are obtained via the `tigris` R package (argument `year = YEAR`, `cb = TRUE`), returning one polygon per 2010 Census tract whose boundaries are valid for the ACS reference period.
- **Population raster (Global Human Settlement, 2020 edition):** We use the GHSL population-distribution raster (`GHS_POP_E2020_GLOBE_R2020A_100m.tif`) to assign high-resolution estimates of population to each tract-piece. This raster provides estimated population counts at approximately 100 m × 100 m resolution for the year 2020, which we project into the Albers equal-area CRS (EPSG 5070).
- **ACS 5-year tract data (2015–2019):** We download tract-level five-year ACS estimates of all covariates of interest (population, poverty, housing units pre-1940, vacant units, overcrowding, rent burden, race, age, eligibility for SNAP/SSI, disability, veteran status, etc.) via the `tidycensus` R package, specifying `geography = "tract"`, `year = YEAR`, and `survey = "acs5"`. We retain only the census variables listed in Section 4.5.

A.1.2 Overall Workflow

For each year $t = 2015, 2016, 2017, 2018, 2019$, we perform the following steps:

1. **Load and preprocess CoC boundaries:**
   - Read `All_CoCs_<t>.shp` into R as an `sf` object (column `CoC_Code`), then transform to the USA Contiguous Albers equal-area CRS (EPSG 5070), and apply `st_make_valid()` to ensure valid polygons.
   - Extract the six-digit CoC identifier by taking the last six characters of `CoC_Code`, and store in a new column `id`. Call this object `coc_shp`.
   - Compute $\bigcup_{c\in C} \mathrm{CoC}_c$ (the union of all CoC polygons) and store as `coc_union` for later use in constructing "outside" pieces.
2. **Load and preprocess Census tracts:**
   - For each state in the continental U.S. $\{\mathrm{AL}, \ldots, \mathrm{WY}, \mathrm{DC}\}$, download the TIGER/Line tract shapefile (`tracts(state = st, year = t, cb = TRUE)`) and bind all states together into one `sf` (`tr_yr`). Then transform `tr_yr` into EPSG 5070 and apply `st_make_valid()`.

- At this point, `tr_yr` contains exactly the 2010 Census tracts (*GEOID*) as used by ACS for year t. We keep only the `GEOID` and the geometry in `tr_yr`.

3. **Split tracts into "inside" and "outside" CoC pieces:**

   - *Inside pieces*: Compute
   $$\text{pcs\_in} = \text{st\_intersection}\Big(\texttt{tr\_yr}, \texttt{coc\_shp}\Big),$$
   keeping the original `GEOID` and storing the intersected CoC's `id` as `coc_id`. These are all the "tract-pieces" that lie *inside* some CoC.
   - *Outside pieces*: Compute
   $$\text{pcs\_out} = \text{st\_difference}\Big(\texttt{tr\_yr}, \texttt{coc\_union}\Big),$$
   again extracting polygons. Label all of these with `coc_id = "NONCOC"`. This ensures that for each tract τ, $\Big(\text{pcs\_in}(\tau)\Big) \cup \Big(\text{pcs\_out}(\tau)\Big)$ exactly covers the entire tract.
   - Combine `pcs_in` and `pcs_out` (with identical columns) into `pieces`. Each row of `pieces` is a *tract-piece* with `GEOID`, `coc_id` $\in$ {six-digit CoC, "NONCOC"}, and a valid polygon geometry.

4. **Compute population weights via GHSL raster:**

   - Load the GHSL 100 m population raster (projected to EPSG 5070). Call this raster `gpw_proj`.
   - For each tract-piece in `pieces`, compute the total raster population via
   $$\texttt{pop\_gpw} = \text{exact\_extract}(\texttt{gpw\_proj}, \texttt{pieces}, \text{"sum"}).$$
   This yields one $\texttt{pop\_gpw} \geq 0$ per tract-piece.
   - Within each original tract (group by `GEOID`), define
   $$\texttt{pop\_share} = \begin{cases} \dfrac{\texttt{pop\_gpw}}{\sum_{\text{pieces of } \texttt{GEOID}} \texttt{pop\_gpw}}, & \text{if } \sum \texttt{pop\_gpw} > 0, \\ \dfrac{\text{area(piece)}}{\sum \text{area(all pieces of } \texttt{GEOID})}, & \text{if } \sum \texttt{pop\_gpw} = 0. \end{cases}$$
   In other words, if the GHSL raster assigns nonzero population to any piece in the tract, we use those raster-based population shares. Otherwise (e.g. water-only tracts), we revert to an area-share fallback area(piece)/area(total tract).
   - Store $\texttt{pop\_share} \in [0,1]$ for each tract-piece in `pieces`. By construction $\sum_{\text{pieces of } \tau} \texttt{pop\_share}(\tau, \text{piece}) = 1$ for every tract τ.

5. **Download and attach ACS tract variables:**

   - Via `get_acs(geography="tract", year=t, variables=acs_vars, survey="acs5", geometry=FALSE)`, retrieve the vector of ACS five-year estimates $V_{\tau,g}$ for each tract τ and each variable $g \in \{\text{pop\_total}, \text{pop\_poverty}, \ldots\}$.
   - Keep only the integer estimate columns (e.g. `pop_totalE`, `pop_povertyE`, ...) and rename them to `pop_total`, `pop_poverty`, etc. Call this data frame `acs_df`, keyed by `GEOID`.
   - Left-join `pieces` $\leftarrow$ `pieces acs_df` by `GEOID`, dropping geometry for the join. After this merge, each tract-piece has all ACS variables at the tract level, plus `pop_share`.

6. **Aggregate to CoC-level:**

   - For each $g \in$ {ACS variables}, define a CoC-level weighted sum
   $$\text{CoC}_{c,g}(t) = \sum_{\substack{\text{tract-pieces } i \\ \text{with } i.\text{coc\_id}=c}} \Big(\texttt{acs\_df}_{\tau(i),g}\Big) \times \texttt{pop\_share}_i,$$
   where $\tau(i)$ is the original tract ID for piece i.

- Record the sum for each CoC c as $\text{sum}_{c,g}(t)$, and also store $\text{total\_pop}_c(t)$. We then compute any ratios (e.g. pct_poverty = $100 \times$ pop_poverty/pop_total) as needed.
- Append $\text{CoC}_{c,\cdot}(t)$ to a list `coc_results`$[[t]]$.

7. **Diagnostics:**

   - For each year t, we compute summary diagnostics on the tract-piece population shares:

$$\texttt{diag\_stats}(t) = \Big\{\text{for each tract } \tau,\ \Big|\{\text{pieces of } \tau\}\Big|,\ \max_i \texttt{pop\_share}(i),\ \ldots\Big\},$$

   confirming that no tract's population share is degenerate (unless entire-raster zeros, then by area share) and that the median tract has a largest piece share near 0.96 (i.e. only 4% of a typical tract's population is split across multiple CoCs).

   - Save these diagnostics to `diag_results`$[[t]]$ for completeness.

After looping over $t = 2015$–2019, we bind all `coc_results`$[[t]]$ into one balanced (or nearly balanced) panel `coc_panel` with columns $\{\texttt{coc\_id}, t, \text{sum}_{c,g}(t)\}$. This final data frame contains, for each CoC–year, every ACS-derived covariate aggregated via population shares, plus any derived ratios (e.g. poverty rate, pre-1940 share, housing vacancy, rent burden, race shares, age shares, veteran share, disability share, etc.). We then merge this `coc_panel` with our outcome variables (PIT counts, HIC counts, funding, etc.) by $\{\texttt{coc\_id}, t\}$ to form the final estimation data.

At this point, `coc_panel` contains one row per {`coc_id`, `year`} with all ACS-derived covariates scaled by population shares. We then merge `coc_panel` with our outcome data (TOT PIT counts, funding, HIC counts, etc.) by {`coc_id`, `year`}. This yields the final data set used in all FE–2SLS regressions.

A.1.3 Key Validation and Diagnostics

- **Population-share diagnostics:** For each year t, we summarized $\{\max_i \texttt{pop\_share}(i)\}$ across all tract IDs. The mean largest share per tract is at least 0.96, and the minimum nonzero share is around 0.00017, confirming that (i) every tract splits no more than 25 pieces on average, and (ii) every tract has some nonzero weight in at least one CoC.

- **State-level consistency:** After constructing `coc_panel`, we aggregated total population by {state, t}, including `coc_id` = $''NONCOC''$ pieces. These state-level sums closely match the ACS state-level population counts (within 0.2%) for each year, indicating no substantial leakage or double-counting.

- **Comparison with area-only crosswalk:** In ancillary tables (not shown), we compared key covariates—poverty rate, Black population share, rent burden—aggregated via population weights versus naive area-weights (i.e. area(piece)/area(tract)). For most metropolitan CoCs, the population-weighted poverty rate is 1–2 percentage points higher than the area-weighted one, reflecting the fact that poverty clusters in dense neighborhoods. This confirms that population weights do correct meaningful within-tract heterogeneity.

A.2 Robustness: Population in Poverty Results

Table 11: Effects on Homelessness Rates Among People in Poverty

	Dependent Variables (per 10,000 people in poverty)	
	Sheltered Homeless	Unsheltered Homeless
	(1)	(2)
Total Federal Funding	0.687***	0.074
($1000s)	(0.115)	(0.117)
Black Population Share (%)	−0.848**	−2.122***
	(0.381)	(0.389)
Population Over 65 Share (%)	−0.211	−1.650
	(1.478)	(1.510)
SNAP Recipients Share (%)	3.162*	−5.097***
	(1.672)	(1.708)
SSI Recipients Share (%)	−0.666	4.820
	(4.001)	(4.088)
Poverty Rate (%)	−7.478***	−0.845
	(1.943)	(1.985)
College Education Rate (%)	−0.481	0.781
	(1.066)	(1.090)
Unemployment Rate (%)	−17.603**	28.064***
	(7.937)	(8.109)
Vacancy Rate (%)	1.099	2.112***
	(0.681)	(0.696)
Overcrowding Rate (%)	5.530	47.925***
	(6.940)	(7.091)
Rent Burden Rate (%)	4.449***	0.382
	(1.612)	(1.647)
Veteran Population Rate (%)	3.039	6.926**
	(2.736)	(2.796)
Disabled Population Share (%)	−1.537	0.412
	(3.296)	(3.367)
Nearby Funding Ratio	0.070*	0.019
	(0.037)	(0.037)
January Average Temperature	−0.730	2.337***
	(0.675)	(0.689)
January Precipitation	3.759	14.219***
	(2.426)	(2.478)
Summary Statistics		
Observations	370	370
R^2	0.401	0.549
Residual Std. Error	62.981	64.347 (df = 353)

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument. Dependent variables are homelessness rates per 10,000 people in poverty rather than per 10,000 total residents. Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data. *p<0.1; **p<0.05; ***p<0.01

A.3 Robustness: Excluding New York City and Los Angeles CoCs

Table 12: Robustness Check: Excluding New York City and Los Angeles CoCs

	Dependent Variables (per 10,000 residents)	
	Sheltered Homeless	Unsheltered Homeless
	(1)	(2)
Total Federal Funding	0.099***	−0.001
($1000s)	(0.016)	(0.015)
Model Specifications		
Full Control Set	Yes	Yes
Instrumental Variable	Pre-1940 Housing Share	
Summary Statistics		
Observations	368	368
R^2	0.404	0.536
Residual Std. Error	8.705	8.474 (df = 351)

Notes: All estimates from 2SLS regressions with pre-1940 housing share as instrument. Sample excludes New York City CoC and Los Angeles City/County CoCs to test robustness to potential outliers. Robust standard errors clustered at CoC level in parentheses. Cross-section = 2019 data. Full control set includes all demographic, socioeconomic, housing market, special population, and geographic/climate controls as shown in previous tables.
*p<0.1; **p<0.05; ***p<0.01