The Impact of Federal Homelessness Funding on Homelessness*

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Abstract

Federal spending on homelessness has increased significantly in recent years. I estimate the relationship between federal homelessness funding and homeless counts in 2011, 2013, and 2015 cross sections. I instrument for funding using a community's pre-1940 housing share, a key variable in an originally unrelated funding formula borrowed for homelessness grants. Funding increases sheltered homelessness; meanwhile, funding is unrelated to unsheltered homelessness. Lower bound estimates suggest that the minimum cost of reducing unsheltered homelessness has increased over time, from $16,400 in 2011 to $20,800 in 2013 to $50,000 in 2015. In 2013, an additional $1 thousand dollars corresponds to a .309 higher homeless rate per 10,000 people. The effect is larger for families than individuals. Funding is positively related to chronic homelessness and is unrelated to youth and child homelessness. My results suggest limitations on federal funding's ability to reduce homelessness among some of the most marginalized groups in society.

JEL codes: I38, C26

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1 Introduction

Does federal funding for homeless programs reduce homelessness? The answer has been surprisingly hard to ascertain. Nonetheless, homelessness funding has increased over 100% since 2005, exceeding $5 billion in 2013. Although recent papers have looked at the association between funding or funded services and homelessness (Moulton 2013; Byrne et al. 2014; Corinth 2017), few clear answers have emerged since funding is endogenous to the prevalence of homelessness. Popov (2016) suggests a novel strategy for estimating the causal effect of funding on homelessness: instrumenting for the exogenous variation in funding with pre-1940 housing stock, an input in the homelessness funding formula borrowed from an unrelated social program. He finds that federal funding significantly reduces unsheltered homelessness while increasing reported homelessness among families. I use a similar instrumental variable approach to estimate the relationship between funding and homelessness using a wider range of relevant covariates, accounting for outlier communities, and including a new homeless subpopulation (unaccompanied youth and children) in multiple years.

I find that funding increases the incidence of total homelessness through increases in the sheltered population. I also find that funding's negative relationship with unsheltered homelessness is tenuous at best: funding is insignificantly related to unsheltered homeless rates across three separate years using various transformations of the homeless counts. Funding is weakly positively related to chronic homelessness and is unrelated to unaccompanied youth and child homelessness. My findings suggest that federal funding is of limited success at reducing homelessness among some of the most marginalized homeless subpopulations, including unaccompanied youth and children and those sleeping rough.

I contribute to the literature on how social programs affect homelessness. Following Honig and Filer (1993), many researchers have examined the relationship between social programs, individual factors, economic conditions, and homelessness at the local and national levels.[1] Recent work has looked specifically at the associations between funding, social programs, and homelessness. Byrne et al. (2014) study the relationship between chronic (long-term unsheltered) home-

lessness and permanent supportive housing beds from 2007 to 2012. However, they identify correlation only, and they do so over a period where these data were less reliable (Lucas 2016). In the specifications that do yield a negative relationship between chronic homelessness and permanent supportive housing, the magnitude is strikingly small.[2]

In an important related paper, Moulton (2013) studies the relationship between federal homelessness funding and chronic homelessness from 2005 to 2007. He finds a negative association between funding and this subpopulation. While an important step in identifying the relationship between chronic homelessness and funding, endogeneity concerns and homeless data enumeration shortcomings during the period limit the applicability of these results.

Corinth (2017) assembles a community-level national panel of homelessness, shelter, and permanent supportive housing from 2007 to 2014. His is the first paper to use strictly within-community variation and includes a number of important non-policy covariates including median rent and weather. He finds that permanent supportive housing produces a slight decline in homelessness in the short term, but the effect is muted in subsequent years.

Popov (2016) is the first scholar to my knowledge to offer a plausible instrument for homelessness funding nationally: the relative share of pre-1940 housing stock in a community. Using cross-sectional data from 2011, he estimates the effect of homelessness funding on homeless subpopulations and on homeless program housing inventories. He finds that funding reduces unsheltered homelessness but does not reduce individual homelessness overall, potentially suggesting a desirable reallocation from streets to shelter without significant perverse incentives among individuals.[3] Though this novel approach is an important step toward establishing causality in the relationship, several important covariates were omitted—notably, measures of climate and controls for metropolitan regions (Byrne et al. 2014). More importantly, the right skew of homeless counts suggests that outliers influence the population results presented. As I document below, homeless counts are highly sensitive to the inclusion of two communities.

I combine elements of these recent approaches to robustly assess the impact of federal homelessness funding on homelessness across various homeless subpopulations using more recent data

across multiple years. Specifically, I use pre-1940 housing stock to instrument federal homelessness funding at the community level and estimate the relationship between funding and various homeless subpopulations in 2011, 2013, and 2015, controlling for numerous relevant factors. Like Moulton (2013), I estimate the relationship between funding and homelessness outcomes. In addition to a unique empirical strategy, I consider an additional subpopulation: homeless unaccompanied youth and children. My empirical strategy follows from and is similar to Popov (2016) but differs in several important ways (in addition to analyzing data from more recent years). First, I include a richer covariate list that includes additional correlates of homelessness suggested by the literature, including climate measures, disabled poverty, transient poverty, veteran poverty, multiple housing market measures, and metropolitan indicators (Byrne et al. 2013, 2014). Second, I account for the presence of two outlier communities: New York City and Los Angeles County. Homelessness is geographically concentrated, and the distribution of homelessness is highly right-skewed. I also present 2011 results for comparison with Popov (2016), showing through replication that the outlier communities have a significant impact on point estimates and that results are sensitive across years. Third, I present additional estimates for the effect of funding on homeless unaccompanied youth and children; to my knowledge, these results are novel. Finally, I present results using multiple transformations of the homeless rate.

2 Homelessness and Funding in Context

Homelessness is one of the most complex policy issues of the past three decades. Over 610,000 Americans were identified as homeless in January 2013. Almost two-thirds of the homeless were in emergency shelter or transitional housing; the remaining third were unsheltered—living in cars, abandoned buildings, outdoors, and other places not meant for human habitation. Nearly a quarter of the homeless were children and youth under age 18. Moreover, these estimates only capture the homeless at a single point in time; over 1.4 million people experienced sheltered homelessness between October 2012 and September 2013.[4]

Homelessness emerged as national policy concern in the early 1980's. Deinstitutionalization of the mentally ill left many on the streets (Lamb 1984; Baum and Burnes 1993), inciting a wave of activism and public attention. Observers began to note a shift in the demography of homelessness, from mainly older, white men with a high prevalence of mental health and substance abuse issues toward more families, youth, and minorities.

In 1987, Congress passed the McKinney-Vento Homeless Assistance Act, the nation's principal homelessness legislation. Initially, the law's major effect was to fund an explosion of emergency shelters across the country. This increase coincided with the adoption of the "linear" service approach, in which homeless individuals graduate from the streets to shelter to transitional housing and eventually into permanent subsidized or independent housing, contingent on behavioral improvements and demonstration of "housing readiness" (e.g., freedom from drug/alcohol abuse, mental stability).

In the mid-1990's, the U.S. homeless services infrastructure was divided into communities called "Continuums of Care" (CoC's). Within these regions, service providers and local government agencies coordinate to count the homeless and plan strategic responses. Most federal funding is disbursed through the CoC system.

The 2008 financial crisis brought renewed political support for homelessness programs. The Homeless Emergency Assistance and Rapid Transition to Housing (HEARTH) Act of 2009 updated the McKinney-Vento Homeless Assistance Act. The HEARTH Act offered a more detailed definition of homelessness and increased federal resources for homeless prevention, permanent supportive housing, and a coordinated data infrastructure. While emergency shelter was the most common form of homeless assistance for decades, service providers have increasingly turned to permanent supportive housing under the HEARTH Act. In 2013, there were 477,416 emergency shelter beds and 568,596 permanent supportive housing beds nationwide.

Each year, the Department of Housing and Urban Development (HUD) reports funding allocations for the main homelessness grant programs by service type. Table 1 details federal funding allocations for FY 2012 by program type. In 2013, the CoC grant and the Emergency Solutions

Grant (ESG)—the two main programs—allocated over $1.95 billion to local communities. The CoC program grant awards funding directly to CoC collaborative applicants; the funds are disbursed across nonprofit and government organizations. The ESG allocates funding directly to city, county, and state governments, who use these funds to operate homelessness programs directly or to subgrant to nonprofits. Nearly $2 billion was allocated across CoC and ESG program grants in 2012, 85% and 15% of this total respectively. The largest share of funds (52%) was for permanent supportive housing programs designed to provide homeless individuals with long-term housing stability with the support of continued, voluntary, individualized services (Rog et al. 2014). Transitional housing programs, aimed at assisting the homeless to transition from shelter into independent or permanent supportive housing, received 21% of funding. Emergency Shelter (under the ESG program grant) received about 15%. The remaining funds were allocated across various supporting programs.

3 Data and Method

Data

I gather data from various sources to construct an original, cross-section data set. Funding, bed inventories, and population counts for homelessness are reported at the CoC level; as of 2013, there were 415 CoC's. My analysis is performed at this community level.

While HUD's homelessness and bed inventory data are reported by CoC, nearly all of my covariates have to be constructed at this level. I use geospatial mapping software to assign county and local-level geographies to the appropriate CoC. I then calculate CoC-level measures for the covariates I consider by aggregating these local values to the community level. A few CoC's had to be combined to map to a single county. For instance, Chicago is is a unique CoC from the surrounding county, Cook County; I combine the homeless counts from these CoC's in order to use the county-level covariates. Additionally, certain variables are unavailable for Alaska, Hawaii, or the US territories (e.g., climate data). After obtaining all relevant covariates and combining

CoC's, I am left with cross-section of 376 communities. Summary statistics may be found in Table 2.

Homeless Counts

HUD reports annual point-in-time (PIT) counts—the best-available national data on the homeless population—in the *Annual Homelessness Assessment Report to Congress*. One night in January, social workers, volunteers, and policemen scour their communities with clipboards tallying local unsheltered homeless populations. Shelters also document client populations at this time. I use these PIT counts per 10,000 individuals in a CoC.[5]

Federal Homelessness Funding

My measure of federal homelessness funding combines HUD's CoC and ESG program grants.[6] In 2012, CoC program grant funding totaled $1.67 billion, while ESG funding totaled $286 million. I match 92% of CoC and ESG grant funds to CoC's in my panel; the remaining funds are either state-level ESG grants or in CoC's for which I lack supplementary covariate data (e.g., CoCs in the U.S. territories). My key independent variable is funding measured in thousands of U.S. dollars per 10,000 people in a CoC.

Covariates

I first construct covariates similar to Popov (2016) for comparability: white percentage; median household income; median one bedroom rent; share of population in poor or fair health; percentage of people below half of the poverty line; number of vacant housing units; and renter share who spend over 30% of income on housing. I use percentage of teen births in lieu of the percentage of births to unmarried women. Covariate sources are found in Table 2.

Building on previous research, I also include a number of important determinants of homelessness as covariates. Several scholars cite climate as a relevant factor in the distribution and extent of homelessness (Quigley 1990; Appelbaum et al. 1991; Grimes and Chressanthis 1997;

Corinth and Lucas 2017). I capture two measures of climate employed in the literature from the United States Historical Climate Network (Vose et al. 2012): average January temperature (Fahrenheit) and total precipitation (inches) for the month of January. I calculate the geodetic distance from the centroid of each CoC to each weather station and assign climate values of the minimum distance station.

Many of my demographic variables come from county-level measures available in the American Community Survey (ACS) five-year estimates. I include percentage of baby boomers: individuals between the age of 45 and 64 (Lee et al. 2003; Byrne et al. 2013, 2014). African Americans have been shown to be disproportionately represented in the homeless population (Wong et al. 1997; Metraux and Culhane 1999), while Hispanics tend to be underrepresented (Baker 1996). I include community-level black and Hispanic population shares. I also control for the share of the population who are veterans in poverty and the share of persons with a disability in poverty; these groups are over-represented in the homeless population (Metraux and Culhane 1999).

Numerous economic factors are relevant to homelessness. I calculate and include the percentage of unemployed persons (Appelbaum et al. 1991; Early and Olsen 2002; Gould and Williams 2010). Local housing market conditions are important determinants of homelessness (Honig and Filer 1993; Grimes and Chressanthis 1997; Early and Olsen 2002). I include the median rental price for a studio housing unit, the share of households with housing payments exceeding 30% of the household income, the percentage of housing units that are rented, and the number of vacant units (Byrne et al. 2014).

Many researchers have indicated a negative relationship between other social assistance and homelessness (Bohanon 1991; Troutman et al. 1999; Quigley et al. 2001). I combine federal Temporary Assistance to Needy Families (TANF) and state Maintenance of Effort (MOE) for a measure of TANF per capita social assistance. These are only available at by state, so I assign the same value to each CoC within a given state. I also include a state-level measure of per capita mental health assistance following Lee et al. (2003) and Byrne et al. (2013).[7] I also control for

the percentage of households receiving either cash assistance or food stamps (SNAPS) (Byrne et al. 2013).

Metropolitan and rural areas have markedly different homeless populations. The majority of homelessness is urban. Following Byrne et al. (2014), I use the U.S. Department of Agriculture (USDA) 2013 Rural Urban Continuum Codes, which assign a score to each county ranging from 1 (most urban) to 9 (most rural). I calculate a population-weighted CoC rural-urban score and assign an indicator variable based on that score. Scores less than or equal to three receive a "1," the rest a "0." Finally, Popov (2016) suggests that homeless families migrate to where funding is increased. I control for the share of individuals in poverty who have moved from another county or state and have lived in the area for over a year as a measure of transient poverty.

Method and Identification Strategy

I estimate how homelessness funding affects the homeless population and subpopulations. Causal relationships between public policy and homelessness outcomes have been difficult to identify since social efforts respond to the degree of homelessness in a given area. The CoC program explicitly reserves a portion of funding to communities that successfully reduce homelessness. Additionally, the funding sought is endogenous to the extent of homelessness; where homelessness is more socially costly, communities more likely organize to obtain funding, *ceteris paribus*.[8]

I use a two stage least squares approach to address endogeneity. Popov (2016) identifies pre-1940 housing stock share as an instrument for federal homelessness funding due to a peculiarity in the homelessness funding allocation process. Services are coordinated, enumerations are reported, and grants are awarded at the CoC level. CoC funding, however, is largely determined by the *entitlement* communities within its borders, i.e., metropolitan cities and urban counties eligible for the Community Development Block Grant (CDBG). Not originally intended to address homelessness, the CDBG formula was borrowed for the grants I use: the aggregated CDBG funding share of the entitlement communities within a CoC determines that CoC's share of homelessness funding.[9] The CDBG formula for entitlement community i is:

$$FundingShare_i =$$

$$\rho * max\{\underbrace{0.25Population_i + 0.25Overcrowding_i + 0.5Poverty_i}_{\text{Formula A}}, \underbrace{0.2GrowthLag_i + 0.3Poverty_i + 0.5Pre1940Housing_i}_{\text{Formula B}}\} \quad (1)$$

$Population$ refers to the entitlement community's population. $Overcrowding$ is the number of rooms occupied by more than two individuals. $Poverty$ is the number of people in poverty. $GrowthLag$ is the difference between the average entitlement community's gross population growth from 1960 to 2010 (zero if population growth exceeds the mean). $Pre1940Housing$ refers to the number of housing units built in 1939 or earlier. Each variable is calculated as the *share* relative to the sum of that characteristic across all entitlement communities. Finally, ρ is a common reduction factor so that the sum of the funding shares does not exceed one. CoC allocation shares of homelessness funding are largely based on the sum of the CDBG shares of the included entitlement communities. Significant variation in CoC-level homelessness funding is determined by the pre-1940 housing shares of entitlement communities.

Several reasons suggest that pre-1940 housing share—the aggregated pre-1940 housing share of all entitlement communities within a CoC—is plausibly exogenous to homelessness. Beginning in the 1970's, the CDBG program was originally intended to facilitate public infrastructure in aging cities. At that point, pre-1940 housing was considered a proxy for inadequate infrastructure, but the measure's relevance on this margin declined considerably over time (Richardson 2005). This led Richardson (2005, p. 48) to report, "It is pre-1940 housing that is responsible for a large number of funding anomalies." Popov (2016, p. 18) quotes a telling Senate Committee on Appropriations hearing report: "The CDBG formula has no real nexus to homeless needs." Pre-1940 housing has been criticized as a formula measure for its weak correlation with poverty (Bunce 1979). This link has weakened further as poor cities destroy their old housing and

wealthy ones renovate and restore theirs (Richardson 2005; Collinson 2014).

Since the formula is borrowed from urban renewal grants introduced in the 1970's, it is possible that the present pre-1940 housing share is correlated with pre-1940 housing share in the 1980's. The latter measure influenced CDBG grants, which likely affected housing markets (e.g., through gentrification or urban renewal). If these effects on the local housing markets are long-lasting, then my instrument could be picking up this effect on modern homelessness. Since this link would affect homelessness via the housing market, I have included numerous covariates to account for housing market conditions, including median rent, the share of vacant units, the share of rented units, and the share of households with a significant housing cost burden ($\geq 30\%$). With these, pre-1940 housing share of entitlement communities in a CoC should not capture the effects of these older grants on current homelessness.

The CDBG formula's irrelevance for homelessness has even led HUD to invite suggestions for revisions that exclude pre-1940 housing share. Furthermore, the CDBG formula relates to the relative share of the variable in entitlement communities only, which does not necessarily indicate the CoC's pre-1940 housing stock. I argue that the unique nature of the funding formula, the irrelevance of pre-1940 housing stock with respect to poverty, and the inclusion of an extensive covariate list make the use of pre-1940 housing share a reasonable, conditionally exogenous instrument for homelessness funding.

With the constructed dataset, I estimate two stage least squares regressions of the following form:

$$Homelessness_c = \beta_0 + \beta_1 HomelessFunding_c + \mathbf{X}\beta_{\mathbf{2}} + \epsilon_c \tag{2}$$

$$HomelessFunding_c = \gamma_0 + \gamma_1 Pre1940HousingShare_c + \mathbf{X}\gamma_{\mathbf{2}} + \mu_c \tag{3}$$

In my main specification, $Homelessness$ denotes the rate of homelessness per 10,000 individuals in CoC c. $HomelessFunding$ is the sum of CoC program grant and ESG grant funding in thousands of U.S. dollars per 10,000 people in CoC c. $\mathbf{X}$ is a vector of covariates that includes

the remaining four CDBG formula variables and the controls described above.

In addition to the homeless rate per 10,000 people, I present results using the rate of homelessness per 10,000 people in poverty—another common research measure (Bohanon 1991; Troutman et al. 1999; Byrne et al. 2013). I also report results using an adjusted rate of homelessness: the inverse hyperbolic sine (IHS) of the homeless rate. The natural log of the homeless rate seems an appropriate transformation, approximating the normal distribution and reducing susceptibility to outliers. But since some communities report zeros in certain subpopulations, the log transformation would result in dropping these communities—places where federal funding may be plausibly most effective.[10] The IHS transformation is an alternative to the log transformation when some observations take on zero values (Burbidge et al. 1988). The transformation is calculated as:

$$IHSrate_c = \ln(Homelessness_c + \sqrt{Homelessness_c^2 + 1}) \tag{4}$$

where $Homelessness_c$ is the rate of homelessness per 10,000 people in CoC c. The kernel density plot of total homelessness is reported by level, population rate, poverty rate, and IHS rate along with the normal distribution in Appendix 1.

First stage results appear in Table 3. Pre-1940 housing share strongly predicts funding. The relationship holds without controls (column 1), with Popov's (2016) controls only (column 2), and with my controls added in (column 3). The robust F-statistic exceeds 11 in my main specification (column 4), including all controls and excluding outlier CoC's. Furthermore, the relationship holds when breaking up the award by CoC and ESG grants (columns 5 and 6).

4 Results

Funding and Total Homelessness

Table 4 reports both ordinary least squares (columns 1-2) and two stage least squares (columns 3-6) results on the relationship between homelessness funding and the rate of total homelessness. Results are reported with robust standard errors.

All specifications yield positive statistically significant relationships. The basic OLS regression (column 1) suggests that an additional thousand dollars in federal funding per 10,000 people is associated with a $.211$ increase in a CoC's incidence of homelessness per 10,000 people. The coefficient decreases slightly ($\beta = .186$) when adding my covariate list and excluding New York City and Los Angeles (column 2). In the baseline 2SLS regression (column 3), funding and homelessness are again positively related with a point estimate of $.205$. Column 4 adds the controls from Popov (2016); this estimate is positive but smaller ($\beta = .147$) and is marginally statistically significant. Column 5 includes all covariates and New York City and Los Angeles CoC's; the point estimate on funding ($\beta = .320$) is significant at the 0.1% level. Finally, the full 2SLS model excluding these outlier CoC's is reported in column 6.

The full model suggests that an additional $1 thousand in funding per 10,000 individuals corresponds to a $.309$ person increase in the rate of homelessness. This point estimate suggests that an additional $3,236 dollars of federal funding per 10,000 people corresponds to one additional homeless person per 10,000 people in a CoC.[11]

Several intuitive results emerge in the full model covariate list. Weather plays a role: temperature positively predicts homelessness. The share of teen births, share of veterans in poverty, and unemployed share are positively related to homelessness. These variables suggest the importance of social and economic factors in explaining homelessness. The share of households receiving cash assistance or food stamps is negatively related to homelessness, indicating the importance of complementary social programs.

Funding, Shelter, and Families

In Table 5, I study the relationship between funding and homeless subpopulations using the same approach. I divide the homeless population by "sheltered" (columns 1-3) and "unsheltered" (columns 4-6), and I use total, individual, and family homeless rates within these categories.

Several features in Table 5 stand out. First, all three sheltered homelessness measures are positively related to funding. In contrast, none of the unsheltered measures is significantly related to funding, so the increase in homelessness from funding seems due to the sheltered population. Second, median rent is positively related to each of the sheltered measures but is unrelated to unsheltered homelessness. Third, climate matters differentially by group. Temperature is negatively related to the sheltered total and family populations but is positively related to all three of the unsheltered populations. A single degree increase in January average temperature corresponds to a $.39$ increase in the unsheltered rate and a $.12$ decrease in the sheltered rate. Finally, cash assistance or food stamp receipt is negatively associated with individual homelessness, both sheltered and unsheltered, and is marginally related to total unsheltered homelessness.

These results suggest important differences between sheltered and unsheltered homelessness and between individuals and families. The funding point estimate on sheltered family homelessness ($\beta = .118$) is almost twice as large as that of sheltered individuals ($\beta = .064$). The share of the population with housing burden above 30% of income is positively related to unsheltered total and individual homelessness but is unrelated to sheltered homelessness. Unemployment is positively related to all sheltered measures but only one unsheltered measure (families). Black percentage is inversely related to total and individual unsheltered homelessness but is unrelated to sheltered measures. Percentage of veterans in poverty is positively related to each unsheltered measure but is unrelated to sheltered homelessness. Marginally significant negative relationships between unsheltered family homelessness and both renter share and disabled persons in poverty are observed. Mental health expenditures per capita are marginally negatively related to unsheltered individual homelessness. Teen birth rate is positively related to total and individual homelessness for both groups. Interestingly, metro CoC's have lower total and family unsheltered

homeless rates *ceteris paribus*, but do not have lower sheltered homeless rates.

Chronic and Youth Homelessness

Table 6 reports the relationship between funding and two marginalized groups: chronic homeless and homeless unaccompanied youth and children. I report results with total, sheltered, and unsheltered dependent variables for both subpopulations.

Funding is marginally significantly related chronic homelessness (at $p > 10\%$); the magnitude is slight but positive ($\beta = .042$). For the sheltered chronic subpopulation, this relationship is about half the size ($\beta = .022$) but is significant at 5%. The unsheltered chronic coefficient is insignificant. As in the general homeless population, weather and housing conditions affect sheltered and unsheltered subpopulations differently. Temperature enters positively in the unsheltered estimate and negatively in the sheltered estimate. Median rent is positively related to sheltered chronic homelessness but is unrelated to unsheltered. Vacant housing is marginally negatively related to sheltered homelessness, but the magnitude is quite small. Significant housing burden is positively related to unsheltered homelessness. Black percentage is inversely related to the unsheltered chronic rate. Percentage of veterans in poverty corresponds to greater rates of total and unsheltered chronic homelessness. Teen births is positively related to total and sheltered chronic homelessness. Cash assistance and food stamp receipt is negatively related to all three measures of chronic homelessness.

The effect of federal funding on unaccompanied youth and children is insignificant across all three subpopulations. The percentage in poor or fair health is negatively related to sheltered homelessness. The share of population who is black is negatively related to total (10% significance) and sheltered homelessness (5% significance). Percentage of veterans in poverty is marginally positively related to total youth and child homelessness. Temperature is positively related to unsheltered youth and child homelessness and marginally related to total youth and child homelessness. Cash assistance and food stamp receipt is inversely related to the total and unsheltered rates at the 10% level.

Alternative Homelessness Measures

I report similar two-stage regression results using several different transformations of the dependent variables in Table 7. First, I show estimates using homeless rates per 10,000 people in poverty. I again use funding and CDBG formula variable rates per 10,000 people. As expected, these estimates are larger than the population rates since the number of people in poverty is smaller than the number of people generally and the homeless generally come from this economic group. Total and sheltered homelessness are positively related to funding with $p > .001$ significance. Unsheltered homelessness and funding are again unrelated. Funding is weakly positively related to individual homelessness and is positively related to family homelessness.

Next, I report results using the IHS transformation of the homeless rate described in Section 3. All of the above patterns hold. The coefficient on unsheltered homelessness is negative but again insignificant. Positive, significant coefficients are observed on total, sheltered, individual, and family homelessness.

2015 Results

To evaluate the robustness of these results across different years, I construct a cross section of 371 CoC's in 2015 following the same steps described above.[12] Table 8 reproduces the main results obtained with this dataset, where federal funding per 10,000 residents is regressed on various homeless subpopulation rates. The robust first stage F-stat for these regressions is 15.84, suggesting a still relevant instrument. I find qualitatively consistent results in 2015. Total and sheltered homelessness are positively related to funding. The coefficient on total homelessness ($\beta = .271$) is comparable to the 2013 estimate of $.309$. I again find an insignificant relationship between federal funding and unsheltered homelessness. Individual and family homelessness are positively related to funding and at $> 1\%$ significance.

The same table also reports the IHS transformation of the homeless rate as the dependent variable. Again, the results hold. Unsheltered homelessness is insignificantly related to funding. The coefficient on family homelessness is about twice as big as that on individual homelessness,

and sheltered homelessness is positively related to funding. Regressions using the poverty rate (not reported) follow the same pattern: funding increases total, sheltered, individual, and family homelessness but is unrelated to unsheltered homelessness.

5 Discussion

My results suggest that federal homeless funding has not reduced most homeless populations in recent years. Federal funding *could* reduce homelessness in several ways. As documented in Table 1, significant resources are allocated to permanent supportive housing programs. Recipients of such subsidies are no longer counted as homeless, and these programs have been shown to increase housing stability in certain contexts (Tsemberis and Eisenberg 2000; Stefancic and Tsemberis 2007). Funds allocated to these programs might reduce homelessness in the short-term; by providing a homeless individual a subsidized housing unit, funding's initial effect would decrease the homeless population one for one.

More generally, funding's impact depends on how it affects the rate of exit from homelessness relative to the counterfactual alternative (e.g., independent exit). If funding facilitates programs that increase the rate of exit, it could reduce homelessness. But the counterfactual (private) exit rate is not obviously less than the rate of exit from funded programs like permanent supportive housing, which is a long-term program by design (Corinth 2017). Previous work suggests that the homeless also respond to increased shelter quality in terms of entry and length of stay (Cragg and O'Flaherty 1999; O'Flaherty and Wu 2006). The latter possibility relates to increased *non-exit* from shelter (Lucas 2016). Exiting shelter is costly for the individual or family experiencing homelessness. If the expected benefits of remaining in shelter (e.g., increased availability of permanent housing subsidies for those in shelter or higher quality shelter) rise with funding, shelter exit may be postponed. The majority of funding was allocated to existing permanent supportive housing, transitional housing, and shelter projects; my results may suggest that expanding these traditional approaches is not obviously desirable. But although we know broadly where funding

is allocated, I cannot observe the specific program aspects that are supported by increased funding. Research on the use of federal funds and how entry and exit rates respond to increased funding across different communities and program types is necessary to parse out this mechanism.

The negative relationship between funding and homelessness can be mitigated on other several margins. Funding for emergency shelter (e.g., the majority of ESG grant funding) should not reduce short-term homelessness. One simple reason is that the sheltered population size is limited by shelter availability; increased funding may expand shelter availability, which increases the potential size of the sheltered population. Bad luck and other uncontrollable factors are important determinants of homelessness, and homelessness can be short-term and unpredictable. Thus, many homeless households have limited contact with the formal homelessness infrastructure (Culhane et al. 2011). Increased funding may facilitate this contact—and, thereby, raise homeless counts. For example, expanded bed inventory may enable shelter entry by those already homeless or precariously housed but are not captured by the counts, e.g., doubled up families may be able to enter shelter if inventory expands.[13] Individuals and families may also be able to exit unsafe housing situations (e.g., domestic violence) on account of increased funding. Another important mechanism by which funding may lead to increased local homeless enumerations is migration. Popov (2016) suggests that migration explains much of the increase in family homelessness in response to funding. Expanded outreach or increased local coordination may enable more accurate counts of unsheltered homelessness, i.e., my positive relationship may reflect an increase in *counted* rather than *actual* homelessness. Clarifying the relationship between available data (stock homeless enumerations) and actual homelessness (a flow phenomenon) is a difficult but necessary step for homelessness research as quantitative empirical analysis expands.

If federal funding increases homeless program benefits relative to other poverty subsidies, perverse incentives can potentially lead individuals to "substitute" into homelessness at the margin. Troutman et al. (1999) present evidence that federal homelessness funding was positively associated with homeless estimates during the 1980's and 1990's (when funding was mainly directed to emergency shelter and transitional housing). They attribute this to the increased benefits

of homelessness relative to non-homeless poverty. Similar assertions have been made by Culhane (1992) and Jencks (1995) in relation to emergency shelter. Lucas (2016) highlights the moral hazard associated with a federally-funded shelter and permanent supportive housing infrastructure. Furthermore, lacking clear feedback mechanisms in a nonmarket context, service providers often rely on output targets (e.g., number of individuals served), which can mitigate incentives to counteract this moral hazard.

Little is known about the role of context in creating additional, unobservable variation in homeless population attributes and service provision quality at the local level. The results here suggest that factors like climate, housing market conditions, and other support programs are potentially even more significant determinants of homelessness than is federal funding. Local culture (e.g., generosity, ideology) and ordinances (e.g., criminalization laws, housing regulations) likely influence the nature of homelessness and are worthy of future work. Relatedly, comparative research that incorporates alternatives to the mainstream responses to homelessness is sparse. Without further knowledge of these contextual factors, the nuances of the "local" nature of homelessness remain unaccounted for. Studies have compared new service models like "Housing First" to traditional shelter services and to prison and hospitalization (e.g., Tsemberis and Eisenberg 2000), but comparative work is needed to understand other alternatives for independent exit—including the role of social networks, local culture, and entrepreneurship.

Homeless counts declined by 13% from 2007 to 2015, from 647,258 to 564,708—a decline attributed entirely to unsheltered homelessness. Sheltered homelessness was slightly higher in 2015 than in 2007 and has remained relatively constant over the past decade. Thus, perhaps my most compelling result is that federal funding is unrelated to unsheltered homelessness across most specifications. Imprecise unsheltered counts are a potentially relevant explanation, as I discuss below. However, my estimates provide a useful result: a "lower bound" estimate of the relationship between federal funding and street homelessness.

Using the 95% confidence interval value on unsheltered homelessness, I estimate a minimum cost of removing one unsheltered homeless individual, which could be interpreted as a best-case

scenario of the net effect of federal dollars in reducing street homeless counts. If marginal federal funding's true effect is to reduce unsheltered homeless counts, this value provides a bound on the maximum effectiveness of that funding—the greatest plausible reduction per dollar. Interestingly, this lower bound becomes less negative in each subsequent year from 2011 to 2015. In 2011, the 95% confidence interval value is $-.061$, suggesting a minimum cost of $16,393 to achieve a one-person reduction in unsheltered homelessness. The 2013 95% confidence interval is $\beta = -.048$, so the cost is at least $20,833 to reduce the unsheltered population by one person in that year. The 2015 lower bound is $-.020$, suggesting a minimum expenditure of $50,000 to reduce the rate of unsheltered homelessness by one. Taken together, my results show an increasing minimum cost of reducing homelessness over time.[14] This is plausible given that the unsheltered homeless population has been decreasing through the period in question; the pool of remaining unsheltered homeless individuals may be becoming increasingly costly to house. Alternatively, later years could be capturing more of the long-run effect of permanent supportive housing programs. A greater share of net dollars may be allocated to maintaining existing permanent supportive housing inventories (or to emergency shelter and transitional housing inventories). If the impact of expanded permanent supportive housing inventories at reducing homeless counts diminishes over time, funding may have a more muted negative or even a positive effect on homeless counts as the long-run effect is increasingly captured (Corinth 2017).

These estimates are also consistent with several previous findings. Corinth (2017) bounds the impact of an additional permanent supportive housing bed's reduction of homelessness at a maximum of 0.72 people. Culhane et al. (2002) estimate a permanent supportive housing unit cost of $17,277 for previously homeless persons with mental illness in New York City; more broadly targeted permanent supportive housing programs in Denver and Portland involved direct costs of between $13,000 and $14,000 per person (Perlman and Parvensky 2006; Mondello et al. 2007). Overall, a $13,000 per-year cost for a single permanent supportive housing bed that reduces the homeless population by 0.72 people suggests a minimum cost of around $18,000 for a one-person reduction in homelessness via permanent supportive housing. To the extent that

marginal funds are spread across permanent supportive housing and other services, my minimum-cost estimates—which are generally higher than this figure—represent a plausible best-case scenario of the net effect of the marginal federal dollar. Note, however, that these calculations account for *direct* expenditures only. Scholars have offered fuller cost-benefit analyses of permanent supportive housing and other programs, accounting for reductions in hospital, policing, and other social service costs (Culhane et al. 2002). Such costs are much higher overall, and they are likely higher still in communities with less extensive social infrastructure (Lucas 2016).

My study also provides a novel finding in the relationship between funding and homeless youth and children. To my knowledge, no study has quantitatively assessed this relationship. While a small subset of the homeless population (45,616 individuals as of 2013), unaccompanied homeless youth and children are some of the most vulnerable and marginalized. They are often subjected to or involved in violence (Kipke et al. 1997), survival sex (Greene et al. 1999), and health and mental health challenges (Yates et al. 1988). 2013 was the first year that unaccompanied youth and children were explicitly enumerated in the PIT counts, suggesting a lack of targeting to this subgroup until recently. This may help explain the non-relationship between funding and unaccompanied homeless youth and children.

Differences from Previous Research

A natural discussion point for these results pertains to the observed differences between the present findings and Popov (2016). While our similar approaches yield some consistent results, a notable difference arises regarding unsheltered homelessness. Popov (2016) finds a sizeable impact of federal funding on unsheltered homeless counts in 2011; I find no relationship in 2013 or in 2015 using the unsheltered homeless rate.

To help understand these differences, I create a third cross-section dataset for 2011 to replicate Popov's results. I obtain CoC-level data on funding, homeless counts, and all of the covariates employed by Popov (2016) and the present study for 376 communities. Table 9 reports my results using homeless populations rather than rates (following Popov). Using his controls,

I qualitatively replicate the two main findings of interest here: an increase in total homelessness and a decrease in unsheltered homelessness. My total homelessness point estimate is well within a standard deviation: 0.587 compared to his 0.733. My unsheltered homelessness estimate is qualitatively consistent with his, although it is smaller (-0.243 compared to -0.458).

Tables 9 also reveals the sensitivity of these population-level results to the inclusion of Los Angeles and New York City. Together, New York City and Los Angeles accounted for 14% of the total counted homeless in 2011, with 51,123 and 34,622, respectively. While 95% of New York City's homeless population is sheltered, over half of Los Angeles' homeless population is unsheltered. This suggests that population-level regressions may be influenced by these outliers; indeed, that is the case. After excluding these two communities, total homelessness becomes statistically insignificant and the magnitude is dramatically diminished. The coefficient remains insignificant and actually flips sign after adding my controls.

I also compare my estimates of the relationship between homeless rates and funding in 2011 to Popov's 2016 in Table 10. I find a negative but insignificant relationship between funding and the total homeless rate; Popov estimates a positive but insignificant rate that is within a standard deviation of my estimate. Once outliers are excluded and controls added, the relationship again becomes positive, significant, and consistent with my other year estimates ($\beta = 0.218, p > .01$). My unsheltered replication estimate is larger than his (-0.182 compared to -0.090) and is statistically significant. After making the described changes, the coefficient again becomes positive and insignificant.

To attempt to further understand this sensitivity, I present similar, population-level results for both total and unsheltered homelessness for 2013. Appendix Table 11 reports these results. I first present results that only differ from Popov (2016) in year. Then, my controls are added. Lastly, I drop New York City and Los Angeles. I do this for total and unsheltered homelessness.

A similar pattern emerges. Using the controls found in Popov (2016), the initial point estimate on total homelessness is larger than the 2011 estimate and is statistically significant (column 1, $\beta = 0.917$). The magnitude decreases when New York City and Los Angeles are excluded, and

decreases further when my controls are added (columns 2 and 3). The initial unsheltered estimate is negative, qualitatively similar to 2011, and statistically significant at the 10% level. After dropping outliers, the statistical significance disappears (column 5); the estimate changes little after adding my controls (column 6).

Limitations

Several limitations are inherent. One concern is data quality. HUD's annual PIT estimates are very noisy but have improved over time.[15] My 2013 and 2015 data are likely reliable than previous years; yet, they are still subject to both benevolent and self-interested error, the extent of which could be considerable.[16]

Thus, one explanation for the insignificant relationship between unsheltered counts and funding is that these counts may be unreliable. Sheltered homelessness depends on shelter availability, making it relatively straightforward to enumerate. Unsheltered homeless estimates involve scouring the community to identify individuals who often do not want to be found, as qualitative investigations indicate (Williams 2011). The measurement error of unsheltered counts is likely a relevant source of attenuation bias. While improving the accuracy of homeless counts is a federal priority, these counts undoubtedly involve a degree of uncertainty. If communities that receive more funding also perform more thorough or better coordinated street counts, this could bias estimates either upward or downward: more individuals might be identified, but less individuals may be double-counted. No obvious means of identifying such a bias exists, but it is not implausible.

Attenuation bias may also be relevant for funding. My data capture funding awards; expenditures may be higher or lower if funds are carried over from previous years or left unspent in the present year. The annual PIT homelessness counts are stock data by construction, and do not address the flow of homelessness. For many, homelessness is a short-term, stochastic phenomenon (O'Flaherty 2004).[17] Without comparable measures of in- and out-flow of homelessness, sorting out the mechanisms by which funding affects homelessness across communities is difficult. Furthermore, my estimates capture the short-term relationship between funding and

homelessness. If shelter, transitional housing, and other supportive services are more stabilizing in the long-term, causing reductions in homelessness, funding could be more effective than the present estimates suggest. But Corinth (2017) notes that permanent supportive housing may actually be *less* effective in the long-run, and his empirical results suggest that emergency shelter and transitional housing increase homeless counts in the long-run.[18]

A final limitation concerns the relationship between federal funds and other homelessness expenditures (e.g., other federal programs, state and local governments, private foundations). The CoC and ESG grants are not the only source of federal funding for those at risk of homelessness. For instance, Housing Opportunities for Persons with Aids (HOPWA), Low Income Housing Tax Credit (LIHTC), and Section 8 Housing Vouchers allocate significant public resources to individuals who are, were, or could become homeless. The multiplicity of partially overlapping programs could be another source of attenuation bias in my estimates. Beyond the federal level, this funding may crowd out private and local public spending on efforts that would have successfully reduced homelessness. Conversely, complementarities between federal and effective private spending may exist. The nature of the resulting impact, however, depends also on the *content* of complementary (or crowded out) spending. If federal funding leads private groups to increase expenditure on food, blankets, and other assistance to those on the street, more individuals may be incentivized to obtain these benefits. Alternatively, federal expenditure may to increased local investment in effective services and programs. There is no way to assess the relationship between these funding sources or of the programs funded by the associated changes in local spending. Identifying these relationships would contribute to our understanding of the full impact of federal funding.

6 Conclusion

I construct multiple cross sections to estimate the relationship between federal homelessness funding and homelessness. Following Popov (2016), I instrument for funding using a commu-

nity's share of entitlement community pre-1940 housing. Funding increases homelessness through the sheltered population and is unrelated to street homelessness. Funding increases family relative to individual homelessness, may increase chronic homelessness, and is unrelated to unaccompanied child and youth homelessness. My results hold qualitatively in 2011, 2013, and 2015 and are consistent using homeless rates, rates per 10,000 people in poverty, and inverse hyperbolic sine transformed rates. Federal funding may provide value on margins other than reducing the homeless population (e.g., enabling more people to escape dangerous or unsanitary housing conditions). But my results suggest limitations on the ability of federal funding to reduce homelessness among some of the most marginalized groups in society.

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Notes

[1]For an excellent review of this work, see Byrne et al. (2013).

[2]One model estimates that a 244 unit increase in PSH corresponds to a 17 person reduction in chronic homelessness; a second estimates that the same increase corresponds to only 2.4 fewer chronically homeless individuals for a community of 600,000 people. They find no relationship between unsheltered chronic homelessness and lagged permanent supportive housing—an indication of the long-term relationship.

[3] Popov (2016) also estimates a positive relationship between funding and total homelessness, suggesting that funding increases the local homeless population. He attributes this affect largely to migration effects among homeless families.

[4]Even this is an underestimate by some definitions, such as the European Federation of National Organisations Working with the Homeless (FEANTSA) European Typology of Homeless and housing exclusion (ETHOS) definition of homelessness. That definition also includes insecure (e.g., threats of eviction or domestic violence) and inadequate (e.g., overcrowded or unsanitary) housing situations. By this definition, homelessness affects a far broader set of individuals.

[5]The distribution of homelessness is highly right-skewed; this is one reason why gross homelessness population numbers are less commonly used in analysis (Byrne et al. 2013). Population rates are still fairly right-skewed, although less extremely than total homeless measures. To address this, I also report results using adjusted rates of homelessness described below. Finally, I report results using the total homeless population for comparability with Popov (2016) and the rate of homelessness per 10,000 individuals in poverty following others in the literature (Troutman et al. 1999; Byrne et al. 2013, 2014).

[6]These grants are generally paid from October of the award year through September of the following year, so a percentage of FY 2013 funding was disbursed after the counts in January. Thus, I use FY 2012 funding awards and 2013

PIT counts. For the 2015 results, I use FY 2014 funds. For the replication cross section (2011), I use 2011 funding for comparability with Popov (2016).

[7]Florida and New Mexico did not report for fiscal year 2013, so the fiscal year 2012 amount was used.

[8]As discussed above, CoC program grant funding *eligibility* is determined by the formula, while ESG funding is allocated directly proportionately to it. Thus, there is leeway for endogeneity to matter in spite of the formula.

[9]The CDBG formula share identifies community eligibility for funding; 75% of funding is allocated on the basis of this eligibility. The remaining 25% is allocated on the basis of non-entitlement community shares and other considerations. HUD is also able to adjust funding shares such that communities have sufficient funding to renew ongoing programs; if this "Annual Renewal Demand" is higher than eligible share, the Annual Renewal Demand value is used.

[10]Adding an arbitrary constant would solve this selection at the cost of creating other distortions (e.g., in the variable's variance).

[11] Moulton (2013) estimates a first-year cost of about $55,000 to move one chronic homeless individual out of homelessness. My estimate suggests that such an expenditure may increase homelessness, potentially among other subgroups. The mechanisms for the increase require future research.

[12]The only thing I borrow from the 2013 dataset is the CDBG formula variables and the rural urban scores. I could not obtain more recent CDBG entitlement values. Following the geospatial mapping approach above, I assigned counties and weather stations using 2015 CoC geographies. As with the 2013 dataset, I include prior year funding (FY 2014) and exclude New York and Los Angeles. Some CoC geographies change from year to year, which explains the change in number from 2013.

[13]Several definitions of homelessness (e.g., the FEANTSA ETHOS definition) include doubling up as a form of homelessness.

[14]An additional explanation for this is that the later years in my sample rely on more recent data and are thus less correlated with prior funding. The CDBG formula allocations used for my 2011 cross section relied on 2000 Census data, but the FY 2012 CDBG formula relied on data from the ACS five-year estimates and 2010 Census (Joice et al. 2011). More recent ACS data were used in 2015 alongside the 2010 Census. If 2011 formula variables were more correlated with previous funding efforts, then those results could capture some of that funding's effect. But I find a much larger difference from 2013 to 2015, which both rely on 2010 Census data, than from 2011 to 2013 (when the decennial Census change occurs). The latter point estimates are fairly comparable, suggesting that the increasing minimum cost estimates are not due to weakening correlation with prior funding.

[15]Major localities like Los Angeles and Detroit faced major methodological inconsistencies that led to spurious estimates in the mid-2000's (HUD 2009). HUD has invested heavily in educating local practitioners and establishing common enumeration methodologies since then, so data have improved over time (HUD 2014).

[16]One scholar notes that HUD's PIT counts have become "a high stakes numbers game" (Williams 2011). Lucas (2016)

discusses these data shortcomings and the unreliability of these data as well as the rent-seeking implications of the government's imposition of common definitions and counting methodologies for measuring homelessness.

[17]HUD has charged CoC recipients of federal funding to document aggregate shelter usage patterns via internal databases called Homelessness Management Information Systems (HMIS). Unfortunately, HMIS data are generally not publicly available, nor are they comparable at this stage. Popov (2016) acquires some of these data for 2011 and finds evidence of family migration toward CoC's with greater funding.

[18]The short-run effect of permanent supportive housing allocated to a homeless individual is a one-person reduction in the homeless population. But if that individual's exit rate from permanent supportive housing is slower than his or her counterfactual exit without permanent supportive housing, the long-run effect on the homeless counts will be less than one-for-one—and approaches zero under certain assumptions (Corinth 2017, p. 79).

Table 1: CoC and ESG Award Funding by Program, 2012

Award Component	Projects (#)	Awards ($)	Share (%)
Permanent Supportive Housing	4231	$1,027,500,308	52%
Rapid Re-housing	84	$13,232,856	<1%
Transitional Housing	2171	$417,457,781	21%
Supportive Services Only	816	$126,697,977	6%
HMIS	447	$43,175,120	2%
Safe Haven	124	$33,158,892	2%
CoC Planning Projects	211	$12,025,263	<1%
CoC Program Total	8,084	$1,673,248,197	85%
ESG Program	360	$286,000,000	15%
Funding Total		$1,959,248,197	100%

Source: US Department of Housing and Urban Development 2012

Table 2: Summary Statistics (2013)

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Homeless Rates*						
Total Homeless	376	19.528	19.997	2.023	159.091	HUD (2013)
Sheltered Homeless	376	12.429	10.956	1.506	102.572	HUD (2013)
Sheltered Individuals	376	6.955	6.106	.398	51.407	HUD (2013)
Sheltered Families	376	5.474	6.029	0	58.285	HUD (2013)
Unsheltered Total	376	7.098	15.963	0	147.654	HUD (2013)
Unsheltered Individuals	376	5.601	12.196	0	130.062	HUD (2013)
Unsheltered Families	376	1.498	6.293	0	94.02	HUD (2013)
Chronic Homeless	376	3.666	5.116	0	37.348	HUD (2013)
Sheltered Chronic	376	1.474	2.056	0	25.284	HUD (2013)
Unsheltered Chronic	376	2.192	4.265	0	34.553	HUD (2013)
Homeless Youth/Children	376	1.653	2.913	0	35.422	HUD (2013)
Sheltered Youth/Children	376	.856	.829	0	7.586	HUD (2013)
Unsheltered Youth/Children	376	.797	2.693	0	34.44	HUD (2013)
Funding ($K)*						
CoC Grant	376	52.127	53.365	.737	453.672	HUD (2012)
ESG Grant	376	3.687	5.744	0	48.407	HUD (2012)
Total Funding	376	55.814	57.987	.737	490.484	HUD (2012)
Covariates						
Precipitation (January)	376	3.091	2.693	.1	17.54	USHCN (2013)
Temperature (Jan. Avg.)	376	37.005	12.949	6.6	71.8	USHCN (2013)
Median Rent ($)	376	662.99	203.68	400	1311	HUD (2013)
Median Household Income ($K)	376	54.760	14.224	33.060	122.238	ACS (2013)
TANF per capita ($K)	376	5.374	11.25	.031	76.201	HHS (2013)
Mental Health Exp. per capita ($)	376	131.116	74.367	32.77	345.36	Kaiser (2013)
White (%)	376	77.506	13.371	21.286	97.541	ACS (2013)
Black (%)	376	11.976	11.917	.352	64.186	ACS (2013)
Hispanic (%)	376	11.873	12.788	.8	81.58	ACS (2013)
Veterans in Poverty*	376	51.043	20.858	11.248	120.175	ACS (2013)
Babyboomers (%)	376	24.205	2.799	13.541	33.967	ACS (2013)
Cash Assistance/SNAPS HH (%)	376	12.938	4.469	2.928	26.221	ACS (2013)
Extreme Poverty (%)	376	6.521	2.22	1.533	21.488	ACS (2013)
Unemployed (%)	376	4.804	1.071	1.829	8.343	ACS (2013)
Disabled in Poverty*	376	268.739	103.767	35.776	567.071	ACS (2013)
Transient in Poverty*	376	118.103	52.518	17.221	338.77	ACS (2013)
Poor or Fair Health (%)	376	14.971	3.727	6.89	32.00	CHR (2013)
Housing Burden >30% Income	376	14.056	4.5	5.643	31.289	ACS (2013)
Vacant Housing Units (K)	376	42.638	62.091	2.466	598.821	ACS (2013)
Renter (%)	376	29.169	7.967	10.903	61.547	ACS (2013)
Metro	376	.766	.424	0	1	USDA (2013)
CDBG Formula Vars						
Population Share	376	.198	.351	0	3.79	Census (2010)
Overcrowded Share	376	.222	.842	0	12.71	ACS (2009)
Growth Lag	376	.282	.916	0	10.535	Census (1960, 2010)
Poverty Share	376	.203	.426	0	4.541	ACS (2009)
Pre-1940 Housing Share	376	.212	.631	0	9.74	ACS (2009)

*Per 10,000 people.

Table 3: First Stage Results

Dependent variable:†	Total Award (ESG + CoC)				CoC Award	ESG Award
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-1940 housing share†	9365.55***	8597.92***	9026.49***	9090.67***	8372.22**	718.45***
	(2552.96)	(2409.01)	(2712.26)	(2640.92)	(2524.20)	(172.34)
Popov (2016) Controls	No	Yes	Yes	Yes	Yes	Yes
My Controls	No	No	Yes	Yes	Yes	Yes
Outlier CoC's	Yes	Yes	Yes	No	No	No
N	376	376	376	374	374	374
F-stat	13.46	12.74	11.08	11.85	11.00	17.38

*** $p < 0.001$. Robust standard errors in parentheses.
†Per 10,000 people in a CoC.

Table 4: Funding and Total Homelessness

	OLS	OLS	IV	IV	IV	IV
Funding ($K)†	0.211***	0.186***	0.205***	0.147*	0.320***	0.309***
	(0.048)	(0.034)	(0.048)	(0.071)	(0.092)	(0.084)
White (%)		0.184		0.331**	0.179	0.227
		(0.217)		(0.112)	(0.222)	(0.219)
Poor or Fair Health (%)		-0.388		-0.458	-0.028	-0.081
		(0.517)		(0.397)	(0.507)	(0.507)
Median Rent ($)		0.022*		0.046***	0.020*	0.016
		(0.010)		(0.011)	(0.010)	(0.010)
Median Household Income ($K)		0.050		-0.460**	-0.016	0.064
		(0.181)		(0.146)	(0.194)	(0.181)
Housing Burden >30% Income (%)		1.239		1.347*	1.291	1.533
		(1.172)		(0.549)	(1.102)	(1.110)
Extreme Poverty (%)		0.573		1.578	0.593	0.785
		(1.016)		(1.132)	(1.021)	(1.014)
Teen Births (%)		3.240*		3.072*	3.142*	3.516*
		(1.381)		(1.376)	(1.435)	(1.419)
Vacant Housing Units (K)		-0.016		0.001	0.000	-0.016
		(0.013)		(0.012)	(0.016)	(0.014)
Temperature (Jan. Avg.)		0.275*			0.254*	0.271*
		(0.133)			(0.128)	(0.127)
Precipitation (January)		-0.309			-0.151	-0.169
		(0.393)			(0.342)	(0.340)
Black (%)		-0.248			-0.258	-0.224
		(0.222)			(0.227)	(0.223)
Hispanic (%)		0.053			0.018	0.065
		(0.136)			(0.140)	(0.138)
Babyboomers (%)		0.524			0.391	0.263
		(0.744)			(0.776)	(0.770)
Disabled in Poverty (%)†		-0.001			-0.024	-0.019
		(0.021)			(0.027)	(0.026)
Transient in Poverty (%)†		0.031			0.023	0.025
		(0.025)			(0.024)	(0.024)
Veterans in Poverty(%)†		0.195*			0.219**	0.229**
		(0.078)			(0.080)	(0.079)
Unemployed (%)		3.060*			2.989*	3.265*
		(1.363)			(1.335)	(1.345)
Renter (%)		-0.007			-0.188	-0.353
		(0.486)			(0.520)	(0.519)
Cash Assistance/SNAPS HH(%)		-0.761$^{\gamma}$			-0.644	-0.894*
		(0.444)			(0.468)	(0.425)
TANF per capita ($K)		0.147			0.078	0.093
		(0.141)			(0.135)	(0.131)
Mental Health Exp. per capita		-0.018			-0.018	-0.018
		(0.014)			(0.014)	(0.014)
Metro		-2.660			-3.728	-3.810
		(2.629)			(2.800)	(2.743)
N	376	374	376	376	376	374
R^2	0.229	0.474	0.229	0.369	0.421	0.434

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: CDBG formula variables are included in all specifications. Results in columns 2, 4, 5, and 6 also include population quintile indicator controls (4).

Table 5: Funding and Sheltered vs. Unsheltered Homelessness

Dependent variable†	Sheltered Homeless			Unsheltered Homeless		
	Total	Individuals	Families	Total	Individuals	Families
Funding ($K)†	0.183***	0.064**	0.118***	0.127	0.062	0.064
	(0.044)	(0.021)	(0.032)	(0.089)	(0.054)	(0.046)
White (%)	0.199	0.101	0.098	0.027	-0.024	0.051
	(0.138)	(0.070)	(0.082)	(0.174)	(0.134)	(0.066)
Poor or Fair Health (%)	-0.449	-0.347*	-0.102	0.369	0.243	0.126
	(0.278)	(0.158)	(0.165)	(0.446)	(0.348)	(0.175)
Median Rent ($)	0.018**	0.009*	0.009**	-0.003	-0.004	0.001
	(0.006)	(0.005)	(0.003)	(0.008)	(0.006)	(0.004)
Median Household Income ($K)	-0.093	-0.060	-0.034	0.157	0.153	0.004
	(0.097)	(0.066)	(0.050)	(0.152)	(0.113)	(0.066)
Housing Burden >30% Income (%)	-0.565	-0.182	-0.383	2.098*	1.767*	0.331
	(0.695)	(0.376)	(0.418)	(0.953)	(0.813)	(0.326)
Extreme Poverty (%)	-0.581	-0.110	-0.470$^{\gamma}$	1.365	0.730	0.635
	(0.471)	(0.334)	(0.261)	(0.931)	(0.504)	(0.553)
Teen Births (%)	1.262$^{\gamma}$	1.026*	0.235	2.254$^{\gamma}$	1.301$^{\gamma}$	0.954
	(0.668)	(0.432)	(0.379)	(1.286)	(0.768)	(0.712)
Vacant Housing Units (K)	-0.004	-0.002	-0.002	-0.012	-0.004	-0.008
	(0.005)	(0.003)	(0.003)	(0.013)	(0.007)	(0.007)
Temperature (Jan. Avg.)	-0.123*	-0.026	-0.097**	0.394***	0.259***	0.135*
	(0.056)	(0.030)	(0.035)	(0.119)	(0.077)	(0.058)
Precipitation (January)	-0.015	0.010	-0.025	-0.154	-0.052	-0.101
	(0.185)	(0.107)	(0.113)	(0.295)	(0.198)	(0.156)
Black (%)	0.112	0.046	0.066	-0.336*	-0.244$^{\gamma}$	-0.093
	(0.166)	(0.080)	(0.104)	(0.166)	(0.128)	(0.069)
Hispanic (%)	0.103	0.015	0.088	-0.038	-0.025	-0.013
	(0.088)	(0.042)	(0.056)	(0.121)	(0.092)	(0.050)
Babyboomers (%)	-0.095	0.105	-0.199	0.358	0.859$^{\gamma}$	-0.501
	(0.289)	(0.170)	(0.173)	(0.731)	(0.490)	(0.376)
Disabled in Poverty (%)†	0.017	0.012	0.005	-0.036	-0.016	-0.020$^{\gamma}$
	(0.014)	(0.007)	(0.009)	(0.024)	(0.018)	(0.010)
Transient in Poverty (%)†	0.025	0.005	0.020	-0.000	-0.000	-0.000
	(0.021)	(0.011)	(0.013)	(0.020)	(0.014)	(0.009)
Veterans in Poverty(%)†	0.039	0.024	0.014	0.190**	0.123**	0.067$^{\gamma}$
	(0.046)	(0.027)	(0.029)	(0.067)	(0.046)	(0.036)
Unemployed (%)	1.777*	0.729$^{\gamma}$	1.048*	1.489	0.462	1.026$^{\gamma}$
	(0.705)	(0.402)	(0.411)	(1.174)	(0.758)	(0.564)
Renter (%)	0.303	0.253	0.050	-0.656	-0.328	-0.328$^{\gamma}$
	(0.322)	(0.197)	(0.174)	(0.412)	(0.314)	(0.189)
Cash Assistance/SNAPS HH(%)	-0.313	-0.326*	0.013	-0.580$^{\gamma}$	-0.566*	-0.014
	(0.264)	(0.133)	(0.172)	(0.351)	(0.279)	(0.152)
TANF per capita ($K)	-0.043	-0.018	-0.026	0.136	0.198	-0.061
	(0.107)	(0.044)	(0.069)	(0.163)	(0.158)	(0.044)
Mental Health Exp. per capita	-0.002	-0.001	-0.001	-0.016	-0.017$^{\gamma}$	0.001
	(0.010)	(0.005)	(0.006)	(0.011)	(0.009)	(0.005)
Metro	0.891	0.812	0.078	-4.701$^{\gamma}$	-2.395	-2.306$^{\gamma}$
	(1.403)	(0.818)	(0.807)	(2.500)	(1.514)	(1.346)
N	374	374	374	374	374	374
R^2	0.463	0.485	0.277	0.371	0.427	0.130

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: Results also include CDBG formula variables and population quintile indicators (4).

Table 6: Chronic Homeless and Unaccompanied Youth and Children

Dependent variable†	Chronic Homeless			Youth and Children		
	Total	Sheltered	Unsheltered	Total	Sheltered	Unsheltered
Funding ($K)†	0.042$^{\gamma}$	0.022**	0.020	0.030	0.006	0.025
	(0.023)	(0.007)	(0.021)	(0.022)	(0.004)	(0.020)
White (%)	0.059	0.072$^{\gamma}$	-0.013	-0.019	-0.009	-0.009
	(0.066)	(0.040)	(0.049)	(0.045)	(0.008)	(0.043)
Poor or Fair Health (%)	0.022	-0.077	0.099	0.114	-0.047*	0.161
	(0.154)	(0.071)	(0.124)	(0.121)	(0.023)	(0.115)
Median Rent ($)	0.005$^{\gamma}$	0.004*	0.001	-0.001	0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Median Household Income ($K)	0.048	0.019	0.030	0.007	-0.011	0.018
	(0.051)	(0.022)	(0.042)	(0.034)	(0.008)	(0.032)
Housing Burden >30% Income (%)	0.260	-0.243	0.503$^{\gamma}$	0.270	-0.012	0.282
	(0.360)	(0.190)	(0.300)	(0.293)	(0.043)	(0.286)
Extreme Poverty (%)	0.232	0.095	0.137	0.181	-0.012	0.193
	(0.268)	(0.124)	(0.233)	(0.130)	(0.050)	(0.121)
Teen Births (%)	0.731*	0.310$^{\gamma}$	0.421	0.334	0.136	0.198
	(0.358)	(0.159)	(0.314)	(0.246)	(0.111)	(0.217)
Vacant Housing Units (K)	-0.004	-0.002$^{\gamma}$	-0.002	0.001	-0.000	0.001
	(0.003)	(0.001)	(0.003)	(0.002)	(0.000)	(0.002)
Temperature (Jan. Avg.)	0.081**	-0.023*	0.104***	0.026$^{\gamma}$	-0.004	0.031*
	(0.028)	(0.011)	(0.027)	(0.015)	(0.005)	(0.014)
Precipitation (January)	0.017	-0.024	0.042	0.008	0.018	-0.010
	(0.088)	(0.045)	(0.086)	(0.040)	(0.018)	(0.035)
Black (%)	-0.059	0.058	-0.117*	-0.080$^{\gamma}$	-0.021*	-0.058
	(0.067)	(0.044)	(0.050)	(0.043)	(0.009)	(0.040)
Hispanic (%)	0.022	0.038*	-0.016	-0.039$^{\gamma}$	-0.006	-0.033
	(0.031)	(0.018)	(0.028)	(0.023)	(0.006)	(0.021)
Babyboomers (%)	0.152	0.027	0.125	0.160	0.007	0.153
	(0.197)	(0.060)	(0.181)	(0.145)	(0.034)	(0.139)
Disabled in Poverty (%)†	-0.003	0.004	-0.007	-0.006	0.000	-0.006
	(0.007)	(0.003)	(0.006)	(0.004)	(0.002)	(0.004)
Transient in Poverty (%)†	0.005	0.007	-0.002	-0.001	0.001	-0.002
	(0.006)	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)
Veterans in Poverty(%)†	0.073***	0.013	0.060***	0.023$^{\gamma}$	0.008	0.015
	(0.020)	(0.010)	(0.018)	(0.012)	(0.005)	(0.010)
Unemployed (%)	0.585	0.228	0.356	0.205	0.026	0.179
	(0.362)	(0.178)	(0.295)	(0.219)	(0.058)	(0.203)
Renter (%)	0.053	0.143	-0.089	-0.038	0.005	-0.042
	(0.163)	(0.096)	(0.122)	(0.114)	(0.020)	(0.110)
Cash Assistance/SNAPS HH(%)	-0.307**	-0.089$^{\gamma}$	-0.217*	-0.130$^{\gamma}$	-0.011	-0.119$^{\gamma}$
	(0.107)	(0.053)	(0.093)	(0.072)	(0.026)	(0.065)
TANF per capita ($K)	0.040	0.003	0.037	0.024	0.012	0.012
	(0.027)	(0.020)	(0.028)	(0.019)	(0.007)	(0.017)
Mental Health Exp. per capita	-0.000	0.001	-0.002	-0.002	-0.000	-0.002
	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)
Metro	-0.739	0.222	-0.961	-0.527	0.027	-0.554
	(0.656)	(0.276)	(0.595)	(0.411)	(0.181)	(0.354)
N	374	374	374	374	374	374
R^2	0.455	0.351	0.421	0.231	0.234	0.211

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: Results also include CDBG formula variables and population quintile indicators (4).

Table 7: Federal Funding and Alternative Homelessness Measures (2013)

Dependent variable:	Homeless rate per 10,000 in poverty					IHS rate per 10,000 people				
	Total	Sheltered	Unsheltered	Individuals	Families	Total	Sheltered	Unsheltered	Individuals	Families
Funding ($K)†	1.821***	1.182***	0.639	0.800$^{\gamma}$	1.021**	0.006**	0.006**	-0.003	0.004$^{\gamma}$	0.010**
	(0.553)	(0.257)	(0.502)	(0.417)	(0.315)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)
N	374	374	374	374	374	374	374	374	374	374
R^2	0.420	0.424	0.376	0.475	0.081	0.508	0.495	0.503	0.551	0.265

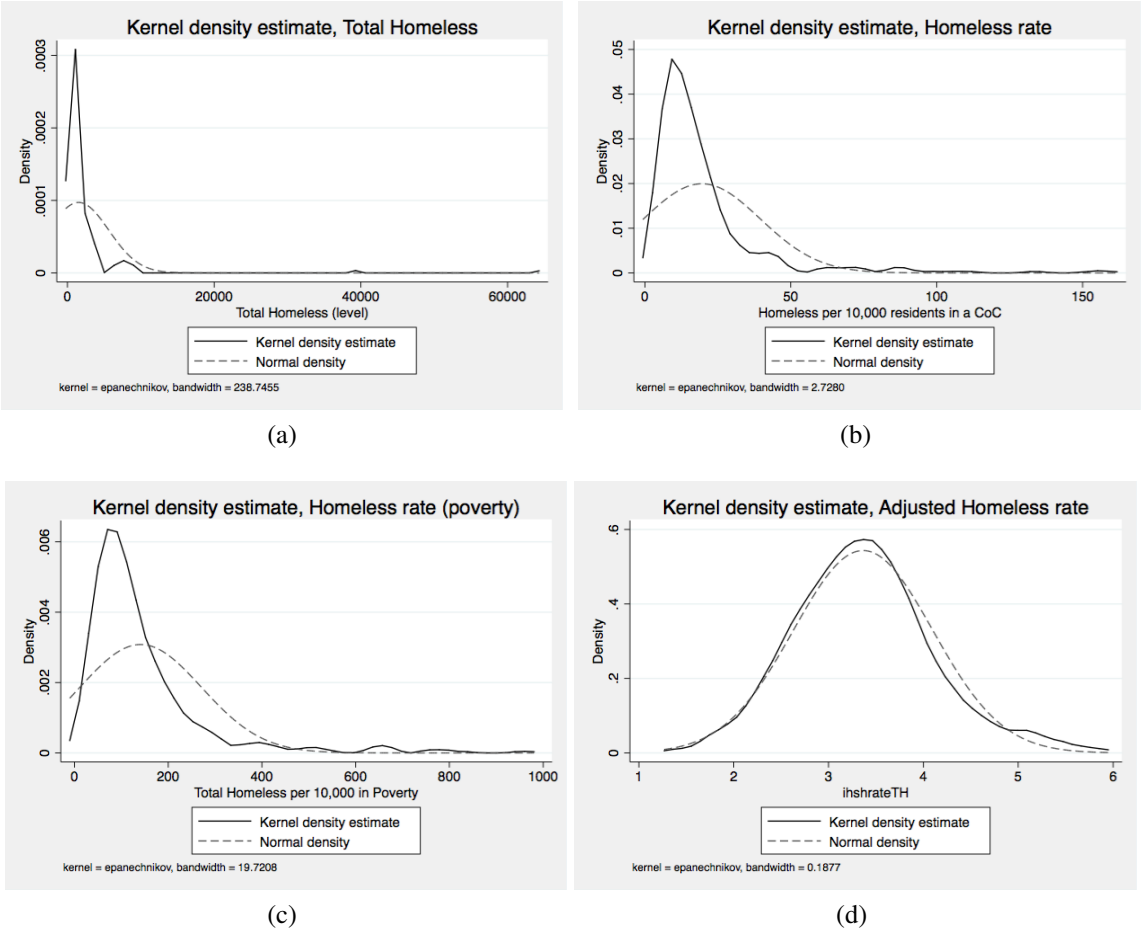
$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: Results include all controls shown above, including the CDBG formula variables and population quintile indicators (4).

Table 8: Federal Funding and Homelessness (2015)

Dependent variable:	Homeless per 10,000 people					IHS rate per 10,000 people				
	Total	Sheltered	Unsheltered	Individuals	Families	Total	Sheltered	Unsheltered	Individuals	Families
Funding ($K)†	0.271***	0.186**	0.085	0.127**	0.144**	0.006**	0.005*	-0.001	0.005$^{\gamma}$	0.010***
	(0.055)	(0.062)	(0.054)	(0.046)	(0.044)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
N	371	371	371	371	371	371	371	371	371	371
R^2	0.514	0.422	0.547	0.597	0.084	0.553	0.516	0.624	0.585	0.294
F-stat	15.841	15.841	15.841	15.841	15.841	15.841	15.841	15.841	15.841	15.841

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: Results include all controls shown above, including the CDBG formula variables and population quintile indicators (4).

Appendix 1: Distribution of Homeless Count and Transformations, 2013



(a) (b)

(c) (d)

Figure 1: Kernel density estimates of PIT count and transformations, 2013

Appendix 2: Replication Tables

Table 9: Popov (2016) Replication, FY 2011 (Levels)

Dependent var:	Total Homelessness				Unsheltered Homelessness			
	Popov (2016)	My estimates			Popov (2016)	My estimates		
Funding ($K)	0.733*	0.587**	0.044	-0.009	-0.458*	-0.243*	-0.116$^{\gamma}$	-0.126*
	(0.310)	(0.206)	(0.068)	(0.065)	(0.185)	(0.102)	(0.061)	(0.056)
Added Controls		No	No	Yes		No	No	Yes
Outlier CoC's		Yes	No	No		Yes	No	No
N	360	376	374	374	360	376	374	374
R^2		0.785	0.691	0.724		0.555	0.418	0.486
F-stat		20.676	32.971	29.365		20.676	32.971	29.365

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
Notes: Results with "Added Controls" include all controls described above with 2011 values. Disabled in poverty, veterans in poverty, and extreme poverty share relied on 2013 ACS data. Rural Urban Continuum data for Metro indicator based on 2013 score.

Table 10: Popov (2016) Replication, FY 2011 (Rates)

Dependent var:	Total Homelessness				Unsheltered Homelessness			
	Popov (2016)	My estimates			Popov (2016)	My estimates		
Funding ($K)†	0.064	0.010	0.005	0.218***	-0.090*	-0.182*	-0.171*	0.064
	(0.045)	(0.089)	(0.090)	(0.065)	(0.045)	(0.092)	(0.087)	(0.063)
Added Controls		No	No	Yes		No	No	Yes
Outlier CoC's		Yes	No	No		Yes	No	No
N	360	376	374	374	360	376	374	374
R^2		0.317	0.303	0.536		-0.015	0.006	0.420
F-stat		17.694	18.672	16.027		17.694	18.672	16.027

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.
†Rate per 10,000 people in a CoC.
Notes: Results with "Added Controls" include all controls described above with 2011 values. Disabled in poverty, veterans in poverty, and extreme poverty share relied on 2013 ACS data. Rural Urban Continuum data for Metro indicator based on 2013 score.

Table 11: Sensitivity of Population-Level Results (2013)

Dependent variable:	Total Homeless			Unsheltered Homeless		
	(1)	(2)	(3)	(4)	(5)	(6)
Award ($K)	0.917**	0.132*	0.099*	-0.162$^{\gamma}$	-0.022	-0.024
	(0.336)	(0.055)	(0.048)	(0.093)	(0.043)	(0.031)
Popov Controls	Yes	Yes	Yes	Yes	Yes	Yes
My controls	No	No	Yes	No	No	Yes
Oultier CoC's	Yes	No	No	Yes	No	No
N	376	374	374	376	374	374
R^2	0.560	0.712	0.751	0.648	0.414	0.529

$^{\gamma}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.