Homeless Programs and Social Insurance*

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Abstract

Each year, over 1.5 million Americans rely on homeless programs for overnight shelter. Despite robust federal funding for this critical part of the social safety net, more than 200,000 remain unsheltered on any given night. In this paper, I quantify behavioral responses to program generosity to study the tradeoffs inherent in expanding homeless assistance. I utilize a new, national dataset on sheltered and unsheltered homeless populations and exploit differential distribution of federal homeless assistance grants across communities. An outdated formula sets each region's funding eligibility, inadvertently generating exogenous variation in homeless assistance. Program providers use the resulting marginal funds to add beds in both individual and family programs. Homeless individuals and families, however, have very different characteristics and behavioral patterns. I find that greater individual program generosity reduces unsheltered homelessness without drawing others into the local homeless population. A permanent $100,000 annual increase in homeless assistance decreases the size of the unsheltered population by 35 individuals, and all of the individuals who utilize marginal beds would otherwise be unsheltered. The effects of family program expansions are quite different. More generous funding helps house otherwise unsheltered families while also drawing in a larger homeless family population (73 additional people in families for every $100,000). I show that this increase is primarily driven by homeless families migrating to communities with greater funding. These results illuminate the policy responsiveness of homeless populations and shed light on the efficacy of homeless assistance funding. (**JEL Classification Codes**: H53, H75, I38, R23)

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I Introduction

Each year, over 1.5 million Americans rely on homeless programs for overnight shelter.[1] These programs provide beds and services, and they act as a last resort for many of the most impoverished individuals and households in the United States. This assistance is expensive, and homelessness remains a visible and controversial societal problem. Despite robust federal funding for homeless assistance, over 200,000 on any given night are without any shelter at all, sleeping in the streets, their cars, or other places not meant for human habitation.[2]

Some argue this is because current programs are simply not generous enough. These advocates call for greater funding, often arguing that the best way to combat homelessness is to simply provide entire housing units to those in need at little or no cost. Others argue that the needs of homeless households cannot be met by traditional programs. Skeptical policy makers worry that more generous funding may hinder housing independence for households on the margin of homelessness, without actually addressing the obstacles of those sleeping on the streets.[3]

This debate mirrors the central tradeoff inherent in any social insurance or anti-poverty program. On the one hand, greater generosity helps smooth consumption in face of adverse events. On the other, program expansions incur costs by distorting households' incentives. Though economists have studied behavioral responses to social insurance generosity in many contexts, no prior work has explored the quantitative importance of these forces across programs that serve the homeless. This paper is the first attempt to estimate the causal effect of homeless assistance funding on the size, composition, and behavior of homeless populations.

I study homeless assistance in the context of federal grants, administered by the Department of Housing and Urban Development (HUD), which fund the vast majority of homeless program providers. These grants are distributed regionally across the United States to administrative and geographic units called "Continuums of Care" (CoCs).[4] An outdated formula sets each CoC's

[1] Annual Homeless Assessment Reports to Congress, 2010-2014

[2] Point In Time Count Data, 2011, 2013

[3] In a recent reiteration of this debate, the New York Times solicited op-eds on the topic of expanding homeless program generosity from a series of housing policy experts in February 2015. The resulting titles included Sam Tsemberis' "It's Fiscally Sensible and the Right Thing to Do" and Howard Husock's "Offering Housing Could Increase Demand for It."

[4] I describe the structure and geography of Continuums of Care in Section III.

funding eligibility, inadvertently generating exogenous variation in homeless assistance funding. Using this variation, I find that the unsheltered homeless respond to program generosity, and federal funding successfully reduces unsheltered homelessness on the margin. Areas that receive more funding also have (all else equal) larger homeless populations. I show, however that homeless families (households with children) explain this entire effect, largely because homeless families migrate to regions with more generous programs. Funding has no effect on the total number of individuals (single adults) experiencing homelessness.

In Section II, I describe the unique data sources that make this analysis possible. National homelessness data are now collected in two ways. First, all households entering or exiting homeless programs that receive any federal funding anywhere in the United States respond to a standardized survey. Through this process, service providers gather information on demographics, income, government benefit receipt, and residence prior to entry. Second, each CoC enumerates its sheltered and unsheltered homeless populations every other year, administering short surveys to unsheltered homeless people to ascertain basic demographics. I construct a dataset using aggregated reports of both types of records, along with federal funding data and a broad set of relevant covariates.

In Section III, I use these data to document stylized facts about homeless households and patterns in homeless program utilization. Service providers operate separate programs for single individuals and families, and the data reveal that homeless individuals and families have quite different characteristics.[5] Moreover, the cultural stereotype of a homeless person is not at all a representative depiction of those who utilize homeless programs. I show that families account for nearly 40 percent of the homeless population at a point in time, and many of those who enter homeless programs have very short homeless spells. Together, these households comprise a vulnerable and important subset of the population, yet there is very little evidence documenting their behavioral responses to policy and program generosity. I conclude Section III by providing the relevant institutional details of homeless programs and homeless assistance funding in the United States today.

Section IV begins by outlining a conceptual framework to clarify how the behavior of vulnerable households maps onto community-level observables in the data. I then describe my empirical

[5] In the homeless services sector, families are defined as households that include children or a pregnant woman. Individuals are single adults and households without children. I adopt this terminology throughout the paper.

strategy. The key ingredient for identification is a particular variable in the formula that determines each community's homeless assistance funding eligibility: each community's share of the housing stock that was built before 1940. This variable remains in the formula for historical and political reasons, though it is widely accepted to no longer predict poverty and economic outcomes. Today, occupants of housing built before 1940 are neither more nor less likely to be in poverty than those in newer buildings.[6] Nevertheless, this measure of housing stock age is one of the strongest predictors of homeless assistance funding. I use pre-1940 housing as an instrumental variable for federal homeless assistance funding in the cross section of CoCs.

I present the full set of results in Section V. I first demonstrate that service providers use marginal homeless assistance funding to expand program capacity. An additional $100,000 in annual federal homeless assistance funding supports 152 additional beds across a wide variety of programs. Specifically, communities that receive more generous funding allocations offer more space in emergency shelters and permanent supportive housing units for chronically homeless individuals. Potentially unsheltered individuals and families both respond by entering programs. A $100,000 increase in a community's annual federal funding provides a roof over the heads of 46 people who would otherwise be unsheltered on a given night.

Marginal funding improvements do not change the size of the individual homeless population. The total size of a community's overnight homeless family population, however, grows by 73 people if the community receives an additional $100,000 annually for homeless assistance. I show that homeless family migration explains at least two-thirds of this effect; areas with more generous funding serve more families *who became homeless elsewhere*. Finally, I provide evidence that substitution away from social support networks may also affect this margin. Areas with disproportionately greater funding see more families entering programs who were previously relying on family and friends for shelter and support.

I address threats to identification and perform a series of falsification tests, which I motivate with the homeless assistance funding formula. The formula dictates that pre-1940 housing stock does *not* determine funding allocation within one particular group of communities. I use these communities to directly test my assumed exclusion restriction on a subset of my data. If pre-1940

[6] I discuss threats to identification the the validity of the exclusion restriction in detail throughout Section IV and Appendix Section C

housing is spuriously correlated with homeless program outcomes in a systematic way, one would expect this reduced form correlation to hold across communities whose funding is unaffected by housing age. This is not the case. I find that pre-1940 housing only predicts outcomes when it is tied to funding allocations.

The empirics illuminate the tradeoffs associated with redistributing federal funds towards homeless assistance. I begin Section VI by exploring these insights in the context of an optimal social insurance model. I modify the Chetty (2006, 2008) framework to accommodate an additional behavioral margin that is important in this setting – response along the sheltered/unsheltered margin, conditional on homelessness. The framework yields a modified Baily-Chetty formula for the optimal level of homeless assistance funding.

I argue that the benefits of expanding homeless assistance for individuals likely outweigh the costs. On the one hand, homeless assistance accomplishes its stated goal of providing a roof over the heads of those who would otherwise be unsheltered. On the other hand, my estimates suggest that there is little scope for moral hazard under current institutions, even though communities use funds to expand generous permanent supportive housing programs for single adults. This finding begins to fill a gap in the discussion surrounding the effectiveness of permanent supportive housing, because prior work does not address the potential effects of provision on non-targeted populations. I use the social insurance framework to clarify the assumptions under which marginal homeless assistance funding expansions are unambiguously welfare-improving.

I then discuss two policy implications of the family migration results. First, correctly anticipated migration can mitigate local government incentives to fund homeless programs. If local governments only want to provide services to their own residents, migration increases the cost of doing so. Future work can explore this issue further to determine if federal subsidies can help local areas internalize the positive externalities of homeless program funding on nearby areas' citizens. Second, removing inequities in the funding formula may help families avoid moving costs, which may be especially harmful for children (Oishi and Schimmack 2010). Section VII provides some closing thoughts and suggests directions for future work.

This work advances what has, to date, been an important but relatively small literature on the economics of homelessness.[7] The majority of the economics literature commenting on homelessness has asked which economic and demographic variables predict rates of point-in-time homelessness across metropolitan areas in the United States. Notable examples includes Honig and Filer (1993), Elliot and Krivo (2001), Quigley et al. (2001), and Fargo et al. (2013). For a helpful summary of this literature, see Byrne et al. (2012). Like these studies, I predict rates of homelessness in the cross-section. I add, however, policy-relevant causal inference of the primary funding channel in the sector. Program evaluation studies accompanying rollouts of new homeless programs have quantified observed effects on targeted households (See, for example, Sandowski et al. (2009), Leopold and Ho (2015), and Stergiopoulos et al. (2015)).[8] This paper complements these studies by studying outcomes at the community-level, which enables examination of potential unintended effects. I also build upon recent work examining rates of homelessness as an outcome in a quasi-experimental setting. Evans, Sullivan, and Wallskog (2016) document that emergency financial assistance reduces the incidence of homeless shelter entry. O'Flaherty, Goodman, and Messeri (2014) study the effects of a homeless prevention program's roll out in New York City, and Jackson and Kawano (2014) argue the Low Income Housing Tax Credit curtails county-level homelessness. To my knowledge, however, this paper is the first national exploration of traditional homeless assistance funding effects. More broadly, this study adds a new, important context to the large and central literature exploring individual and household responses to social insurance and anti-poverty programs.[9]

II Data Sources

Though homeless assistance has been an important topic for many years, reliable homeless population data are a relatively new phenomena. I utilize several data sources to construct a nationally representative dataset of sheltered and unsheltered homeless populations, federal homeless funding, and relevant covariates.

[7] Sociologists and social psychologists have devoted much more attention to topics surrounding homelessness.

[8] The Department of Housing and Urban Development's *Family Options Study* also presents a randomized controlled trial exploring the differential effects of referring homeless families to various types of homeless programs.

[9] A full review of this literature is well beyond the scope of this paper. Some widely cited examples, however, include Meyer (1990), Gruber (1997), Hopenhayn and Nicolini (1997), Autor and Duggan (2003), Chetty (2006, 2008), Hansen and Imrohoroglu (2007), French and Song (2014), and Maestas, Mullen, and Strand (2015).

Broadly speaking, service providers and communities collect data on homeless populations in two ways. First, each person entering or exiting any homeless program that is eligible for federal funding responds to a survey, typically administered by program employee or volunteer.[10] This survey is detailed, asking each household about its demographics, sources of income, living situation prior to program entry, destination upon program exit, and government benefit receipt. Respondents provide identifying information, so individuals' and households' utilization can be tracked over time. Moreover, the questions are standardized across the U.S.[11] Each Continuum of Care (CoC) maintains a database of these responses, and the resulting data are called Homeless Management Information System, or HMIS, data. These data provide detailed information for *sheltered* homeless populations.

The second way in which communities learn about homelessness is by enumerating *unsheltered* homeless populations. Every other year, each CoC is required to count its unsheltered homeless residents on a particular night in the last week of January.[12] This process is called the Point In Time, or PIT, count. The lead agency in the CoC recruits a small army of volunteers, who methodically survey the city, counting and interviewing people they find sleeping on the street, in cars, in abandoned buildings, or anywhere else not meant for human habitation. Enumerators ask basic demographic questions of homeless individuals and families that they encounter to determine if they are chronically homeless, disabled, or military veterans.

Both types of records are aggregated to produce the homeless data sources I use in my analysis – the Point In Time Count Data and the Local Area Annual Homeless Assessment Report Data.[13] The PIT data provide a CoC-level snapshot of sheltered and unsheltered homelessness, while the AHAR data specify annual CoC-level utilization of homeless programs by demographic type. I merge both data sources with federal homeless assistance grant data. These data, along with

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[10] According to 2011 HUD Annual Homeless Assessment Report Data, slightly over 86% of all homeless program beds benefitted from federal funding and participated in gathering these data.

[11] HUD publishes and requires communities to comply with specific data standards. See: https://www.hudexchange.info/resources/documents/HMIS-Data-Standards-Manual.pdf.

[12] These counts are held in late January because the weather is typically cold then, and homeless populations are most likely to seek shelter. Thus, the count of the total (sheltered and unsheltered) population is more accurate because sheltered populations are easier to count (i.e. via local HMIS data).

[13] The Department of Housing and Urban Development makes the aggregate CoC-level PIT counts publicly available. The Local Area Annual Homeless Assessment Report Data were previously public, but data from recent years are no longer available to researchers.

covariates from a variety of other data sources, comprise the information at the core of my analysis.

In the next section, I also present summary statistics that I generate from program entry- and exit-level HMIS data for 2013–2014 in Santa Clara County, California.[14] While these data are specific to one area, they provide detailed information about homeless utilization patterns. I use these data to illustrate stylized facts about homeless populations, provide context, and motivate the heterogeneity that I explore with aggregate, national data later in the paper. Appendix A provides a description of all variables and more details on how I construct the dataset.

III Homelessness and Homeless Programs in the United States

III.A Who is Homeless in the United States?

Modern day homelessness became a widespread, visible, and controversial issue in the early 1980s. At this time, homelessness grew from a problem concentrated in a few small, urban "skid row" neighborhoods, to a nation-wide phenomenon (Jencks 1994).[15] Researchers explored numerous hypotheses as to why this was taking place. Many pointed to deinstitutionalization of state-run mental health facilities (Lamb 1984, Applebaum 1987). Others argued that a diminishing social safety net, declining marriage rates, housing market changes, and the crack epidemic may have been to blame (Jencks 1994).

Over the past decade, the size of the homeless population in the United States has been relatively stable, and a diverse group of people experience homelessness each year. Table 1 describes the characteristics of the national homeless population in January 2011. The top panel describes the stock of homelessness on a single night in January. These aggregate statistics inform an understanding of homelessness in three critical ways. First, aggregate homeless demographics differ dramatically from cultural and media stereotypes of the homeless. These generalizations are rooted in early hypotheses linking homelessness to deinstitutionalization and tend to associate homelessness with chronically homeless, unsheltered individuals (Min 1999).[16] Table 1 shows, however, that

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[14]I thank Community Technology Alliance, the non-profit that manages Santa Clara County's HMIS database, for generously providing these data.

[15]Political commentators and the media began to report on the issue but assumed that the increase in people living on the streets was a temporary side effect of the 1981-1982 recession. When the recession ended, however, homelessness remained on an upward trajectory.

[16]Min (1999) writes, "In the past decade, no single subject has been put under a microscopic examination like

only 12 percent of the homeless population on a given night falls into this demographic. In fact, less than a fifth of the homeless population is chronically homeless.[17] Over a third of the population is comprised of families.

Second, a staggering number of those who are homeless in the United States are unsheltered. When the count was conducted in late January 2011, over 200,000 people were sleeping in a place not meant for human habitation, as shown in Table 1. This rate is likely to be even higher in warmer seasons, when cold-weather shelters are not operating.

Finally, families and individuals experiencing homelessness tend to have very different characteristics. In particular, families are less likely to be unsheltered or chronically homeless than their individual counterparts. Only 17 percent of people in families were unsheltered during the Point In Time count, and only five percent of families were chronically homeless. In stark contrast, 46 percent of individuals were unsheltered, and 19 percent of individuals were deemed chronically homeless.

Homeless program utilization data mirrors this dichotomy between individual and family homeless households. The lower panel in Table 1 shows the number and characteristics of those utilizing homeless programs in the 2011 AHAR sample. Those in families are far less likely to be disabled or to have served in the military. The data also show, however, that both groups migrate at roughly the same rate. Approximately 25 percent of individuals utilizing homeless programs did so in a different CoC from the one in which they became homeless; about 28 percent of families moved across CoC boundaries during a homeless spell. In Section V, I provide evidence on whether this migration is directed towards areas of greater homeless program funding.

In Table 2, I use the Santa Clara County HMIS data to present a more detailed description of characteristics for individual adults and those in family households. Adults who enter family shelters with children tend to be significantly younger than those in programs for individuals. The median age of individuals in the data is 46, compared to only 32 for adults accompanied by children. Adults in families are more likely to be women; single mothers comprise a large share of adults in family shelters. In contrast, less than a quarter of those in individual programs are women.

the issue of homelessness... The image of the homeless, however, has not been entirely accurate. They have been portrayed as drunk, stoned, crazy, sick, and drug abusers by the media and by many social science researchers."

[17] Chronic homelessness follows the official HUD definition; one is chronically homeless if he or she has a disabling condition and has either been homeless for over a year or had four or more homeless episodes in the past three years.

As noted in the national data, adults accompanied by children are also less likely to have veteran status or a physical or mental disability. They are more likely than their counterparts in individual shelters to be earning income at the first moment they enter a program. To compare utilization frequency, I classify an adult as having only a single homeless event if he or she has only one shelter spell in my data.[18] Adults in families are almost fifty percent more likely to experience only one shelter spell, conditional on entering a homeless shelter, throughout 2013 and 2014.

Prior social psychology literature has also documented that homeless households are very heterogeneous in their duration of homelessness, and the characteristics of the chronically homeless differ dramatically from those utilizing programs for short periods of time (Kuhn and Culhane 1998, Fargo et al. 2013). I validate these stylized facts by partitioning homeless adults in Santa Clara County into those who have one emergency shelter spell and all others. Table 2 shows the substantial heterogeneity in how long people utilize homeless programs. Contrary to the cultural stereotype, more than half of all adults in the period enter an emergency shelter once, stay for a median duration of less than two weeks, and do not return in my sample period.[19]

Single entry and multiple entry households have quite different characteristics. Those with only one homeless spell tend to be younger, and they are more likely to be women. Those with multiple entries, on the other hand, are more likely to receive disability benefits from the government, and they are only two-thirds as likely to be employed when entering a program.

These demographic and utilization differences motivate my analysis of heterogeneous effects across household types and chronic homeless status. Throughout my analysis, I will explore how responses to federal funding differ for individuals vs. families and chronic vs. non-chronic homeless households along each relevant margin. More broadly, these data collectively reiterate that the homeless population in the United States is very diverse, and quite different from both the visibly homeless population and the cultural archetype of homelessness.

[18] If one leaves a shelter and returns within a week, I classify that as a single homeless spell.

[19] Of course, those who I classify as "Single Entry" households may return to the homeless service sector but in a different region.

III.B Programs Available to Homeless Households Today

The majority of homeless programs provide in-kind shelter to those who are unable to secure other means of housing, and more often than not, they are operated by non-profit agencies.[20] The most common first option for a homeless family is an emergency shelter, often referred to as a homeless shelter. These shelters offer beds and typically few supportive services. Shelters vary tremendously in their rules and quality. They do not typically specialize in assisting certain homeless subpopulations or addressing particular needs, though shelters for families with children do operate separately from those serving individuals. Individual shelters tend to situate many beds in a large open space, while family shelters provide each family with a separate room. As a result, family shelters tend to face greater capacity constraints and maintain waitlists. Shelters account for about a third of all homeless program beds. Many people, however, cycle through these beds, and as a result, shelters serve 70 percent of those utilizing homeless programs each year.

One typically cannot stay in an emergency shelter indefinitely. After some time, households are referred to programs with more intensive services.[21] Traditionally, this has meant moving to a transitional housing program. Transitional housing provides a wide array of services alongside in-kind shelter. Depending on household needs, these services can range from substance abuse treatment to job search assistance. If these services cannot help a household attain housing independence, the next step is permanent supportive housing. As the name implies, this program is meant as a permanent solution, whereby an individual or family is given an entire apartment and access to supportive services.[22]

The popularity of permanent supportive housing has grown tremendously in policy circles over the past few years.[23] A collection of studies, including Culhane, Metraux and Hadley (2002) and Flaming, Mantsunaga, and Burns (2009), have argued that giving the most vulnerable chronically homeless individuals free apartments actually *saves* communities money through reductions in emergency room and jail utilization. These studies help bolster the popularity of the "Housing First" model, which advocates providing housing to homeless households before providing additional

[20]Programs in several large cities, such as New York and Philadelphia, are notable exceptions. These are largely city-run programs.

[21]Individual shelters often have thirty or sixty day limits.

[22]Households do not always follow the intended sequential flow through these programs.

[23]The Department of Housing and Urban Development's homeless assistance priorities reflect this trend.

services.[24] To my knowledge, there is no prior evidence on whether such programs reduce the incidence of independent housing, employment, or family reunification.

III.C Homeless Program Funding and Continuum of Care

Federal tax dollars support homeless programs through a series of Housing and Urban Development grants, collectively referred to as McKinney-Vento grants.[25] The largest of these grants is the Continuum of Care (CoC) Program Grant, which distributes nearly $2 billion dollars for homeless programs annually.[26] The Emergency Solutions Grant distributes an additional $250 million for emergency shelters and associated services. Together, these grants are a predominant funding source for homeless programs in the United States. I describe the structure of the grants in more detail in Appendix B.

Service providers do not apply for these funds individually. Rather, HUD has asked service providers and relevant local government agencies to band together to form "Continuums of Care," or CoCs. Each Continuum of Care is both a geographic and administrative unit. Today, there are 415 Continuums of Care in the U.S, and Figure 1 shows a map of their borders. Continuums of Care range in size from a metropolitan area (i.e. Chicago, New York City), to a county (i.e. Santa Clara County), to a collection of counties (i.e. Southwest Pennsylvania, which is a CoC comprised of seven counties).

The Continuum of Care is my primary unit of analysis. As administrative units, CoCs have three primary functions. First, all organizations within a Continuum of Care's boundaries collectively apply for CoC funding as a "collaborative applicant." The Department of Housing and Urban Development distributes the awarded funds to the Continuum of Care through a lead agency, and that lead agency, in turn, distributes funding to each service provider and local government entity that requested funds as a part of the continuum. Second, CoCs have a planning role. The agencies and organizations within a Continuum of Care together coordinate services and decide

[24] For more information on the Housing First approach, see the National Alliance to End Homelessness website's description at http://www.endhomelessness.org/pages/housing_first.

[25] These grants still bear the name of the original McKinney-Vento Homelessness Assistance Act of 1987.

[26] The exact amount is determined annually through negotiation of the Appropriations Committee's Transportation, Housing, and Urban Development Funding Bill.

on community goals and priorities for homeless services.[27] Finally, each Continuum of Care is responsible for maintaining data on its local homeless populations.

The mean (median) CoC receives $3.2 milllion ($1.6 million) in federal homeless assistance funding. Continuum of Care Grants are competitive grants, but as I discuss in further detail in next section, the level of funds that each Continuum of Care is eligible to apply for is determined by a formula.[28] HUD did not create this formula with homeless assistance grants in mind. Instead, the formula was adopted from a different HUD program, the Community Development Block Grant, which provides funds for infrastructure and public property maintenance and acquisition. The Emergency Solutions Grant is an entitlement grant, where the funds are allocated by the Community Development Block Grant formula directly. This formula, and the funding inequities it generates, drive my empirical strategy.

IV Conceptual Framework and Empirical Strategy

I study the effects of homeless assistance generosity on residentially unstable populations in the context of federal grants. These grants are not the only source of homeless program funding available to homeless service providers. Homeless programs benefit from state and local government funds, as well as private philanthropy, and the interaction of these funding streams with homeless outcomes is ripe for future research. Federal grants, however, occupy a very important role in the sector, essentially expanding or contracting the amount of funds available to fight homelessness at the local level. Studying the ways in which these funds translate to outcomes informs us about both behavioral responses and funding efficacy. The regional distribution of federal grants allows for the study of non-targeted population effects, which are critical for evaluating potential negative incentive effects. Moreover, the optimal level of federal grant funding is, in and of itself, a very important policy instrument about which we have little empirical evidence.

I therefore construct an empirical strategy using CoC-level data and policy variation in federal grant generosity. Before detailing estimation and identification, I first outline a simple conceptual

[27] The latest McKinney-Vento Act reauthorization states, "The Continuum is responsible for coordinating and implementing a system for its geographic area to meet the needs of the homeless population and subpopulations within the geographic area."

[28] Many previously funded programs are eligible for renewal each year, which can augment a CoC's level of funding eligibility. In certain years, CoCs may also be eligible for bonuses that are not tied to the funding formula.

framework, which describes how community outcomes are informative about household behavior among vulnerable populations.

IV.A Conceptual Framework

The benefits and unintended consequences of expanding homeless assistance generosity depend on the behavioral responses of targeted and non-targeted populations. To learn about these responses, I employ an empirical strategy that mimics the following thought experiment in the cross section of CoCs.

Suppose there are two identical, nearby communities, A and B. They have identical characteristics, $\theta^A = \theta^B$, and receive identical grant funding allocations, $x^A = x^B$. The two communities have the same population, $n^A(x^A, \theta^A) = n^B(x^B, \theta^B)$. In each community, $j \in \{A, B\}$, the population is partitioned into those who are homeless, $l^j(x^j, \theta^j)$, and those who are housed, $h^j(x^j, \theta^j)$. Moreover, each community's homeless population is divided among those who are unsheltered $l_u^j(x^j, \theta^j)$, and those who are sheltered in homeless programs, $l_s^j(x^j, \theta^j)$, so $l_u^j(x^j, \theta^j) + l_s^j(x^j, \theta^j) = l^j(x^j, \theta^j)$. For each community:

$$n^j(x^j, \theta^j) = l_u^j(x^j, \theta^j) + l_s^j(x^j, \theta^j) + h^j(x^j, \theta^j) \tag{1}$$

What happens if community B is awarded an increase in homeless assistance funding? Service providers in community B will be able to improve the availability and/or quality of their programs, and these changes may affect households' location choices.[29] I can decompose any subsequent change in community B's homeless program utilization:

$$\frac{dl_s^B(x^B, \theta^B)}{dx^B} = \frac{dl^B(x^B, \theta^B)}{dx^B} - \frac{dl_u^B(x^B, \theta^B)}{dx^B} \tag{2}$$

If unsheltered homeless residents of community B (the targeted population) are responsive to marginal program improvements, they will start utilizing homeless programs, such that $\frac{dl_u^B(x^B, \theta^B)}{dx^B} < 0$. The larger this magnitude, the more effective homeless assistance grants will be at sheltering people on the margin and insuring against adverse shocks.

If only the targeted population's behavior is elastic with respect to funding, no one will be drawn

[29] This is assuming there is not perfect crowd out of local homeless program funding. I verify this assumption in the following section by demonstrating that federal funding has a significant effect on program capacity.

into homeless programs, meaning $\frac{dl^B(x^B,\theta^B)}{dx^B} = 0$. If, on the other hand, funding increases the size of the local homeless population, this effect can be driven by two distinct behavioral margins. Equation 1 implies:

$$\frac{dl^B(x^B, \theta^B)}{dx^B} = \frac{dn^B(x^B, \theta^B)}{dx^B} - \frac{dh^B(x^B, \theta^B)}{dx^B} \tag{3}$$

The "additional" people in the homeless population must have either migrated in response to the funding change or substituted away from local housing or reliance on family and friends. In either case, these behavioral responses inflate the marginal cost of reducing unsheltered homelessness at the local level.

More generally, as I discuss in detail in Section VI, responses along each of these margins delivers unique normative implications. The goal of my empirical strategy is to use community-level data on homeless populations to identify each one.

IV.B Empirical Strategy

Quantifying these behavioral responses requires variation in grant funding across regions that is unrelated to the size of homeless populations and programs. This poses a challenge because federal funding is typically targeted specifically to regions with greater need. I overcome this obstacle by exploiting inequities generated by the Continuum of Care funding eligibility formula.

Shortly after homeless assistance grants were introduced, HUD tied the total amount of funding that each CoC is eligible to apply for to an old formula for a different HUD program, the Community Development Block Grant.[30] This grant was signed into law in 1974 to provide communities with funds for a wide range of infrastructure needs. Despite well-known inequities in the repurposed formula (Richardson 2005), it is still used to distribute CoC grants today.

Homeless assistance grants are calculated at the level of an *entitlement community*.[31] These entitlement communities include medium to large cities and certain counties. Once the appropriations bill determines the level of funding for homeless assistance grants, the formula allots a share

[30]This formula drives funding allocations for both the Continuum of Care Program Grant and the Emergency Solutions Grant. The Emergency Solutions grant, however, is an entitlement grant, so these funds are allocated directly based on the formula. Most of the funds flow through the Continuum of Care program grant, for which the formula determines the amount of funding that each CoC is eligible to apply for.

[31]This is due to historical reasons. The Department of Housing and Urban Development awards The Community Development Block Grant to entitlement communities.

of the budget to each entitlement community. The funds that each CoC is eligible for are the sum of funds allocated across all entitlement communities within the CoC.[32]

Equation 4 shows the homeless assistance grant formula. It dictates that an entitlement community's share of available funding is a function of five variables from the decennial U.S. Census.[33] Each variable is expressed as a share of the total across all entitlement communities.

$$
\begin{aligned}
&FundingShare = \\
&\qquad k \max \Big\{ \underbrace{0.25 PopulationShare + 0.5 PovertyShare + 0.25 OvercrowdedShare}_{\textbf{Formula A}}, \\
&\qquad\qquad \underbrace{0.2 GrowthLagShare + 0.3 PovertyShare + 0.5 Pre1940\,HousingShare}_{\textbf{Formula B}} \Big\}
\end{aligned} \tag{4}
$$

Using these variables, the formula computes two weighted averages.[34] These two computations are referred to as Formula A and Formula B. The formula's interim funding allocation for each community is the larger of the two. Communities with a larger Formula A share are commonly referred to as "Formula A communities," and likewise for Formula B.[35] Of course, if these allocations were implemented, more than 100 percent of the total funding could be disbursed, so each community's funding is reduced pro-rata (by factor k) until the shares available to all entitlement communities add up to one.[36] These allocations are then aggregated to the CoC-level to determine funding eligibility.

A substantial portion of funding disbursement relies on a region's pre-1940 housing share, and I use this formula component as an instrumental variable for homeless assistance funding. Both policy analysts and grant recipients have argued that this measure of housing stock age is unrelated to homeless outcomes and should not be used to distribute funding (See Richardson 2005).[37] Today,

[32] For example, the Santa Clara County Continuum of Care is eligible for the sum of the formula-determined funds of the eight entitlement communities within its boundaries – Cupertino, Gilroy, Milpitas, Mountain View, Palo Alto, San Jose, Santa Clara, and Sunnyvale.

[33] As of FY 2013, the American Community Survey became the primary source for the formula variables.

[34] Overcrowded units are those with more than two people per bedroom. The growth lag measures the rate at which an entitlement community's population growth since 1960 lags that of the average entitlement community. Communities that have grown at a faster than average rate receive a growth lag value of zero.

[35] Approximately half of all entitlement communities are Formula A communities.

[36] The pro-rata reduction in 2011 was 16%, so $k^{2011} = 0.82$

[37] Even as I write this paper, HUD's Office of Policy Development & Research is working on designing a new

the vast majority of pre-1940 housing is occupied by households well above the federal poverty line, but the variable remains in the formula for historical reasons.[38] In the following section, I discuss the origin and plausibility of the instrument in more detail and address identification concerns.

The pre-1940 housing instrument allows me to study how outcomes vary with exogenous grant funding differentials in the cross section of CoCs. Using data from 2011,[39] I run regressions of the form

$$\begin{aligned} y_c &= \beta_0 + \beta_1 HomelessAssistance_c + \mathbf{X_c}\boldsymbol{\beta_2} + \epsilon_c \\ HomelessAssistance_c &= \delta_0 + \delta_1 Pre1940HousingShare_c + \mathbf{X_c}\boldsymbol{\delta_2} + \nu_c \end{aligned} \tag{5}$$

where c denotes a Continuum of Care, $\mathbf{X_c}$ is a vector of CoC-level controls,[40] and y_c reflects outcomes such as the number of unsheltered, total, or migrating homeless people in a CoC.[41]

The coefficient of interest in these regressions, β_1, should not be interpreted as the effect of a one-time grant funding shock. CoCs that receive higher grant levels due to the funding formula do so each year. My empirical strategy speaks to how outcomes vary with funding in steady state, comparing similar communities who continually receive unequal grant allocations. This variation teaches us about long-run effects of funding expansions and contractions, accounting for outcomes that may evolve slowly, such as capacity expansion or migration. This feature does, however, have the limitation that the magnitudes I estimate likely do not reflect effects of short-term spending fluctuations.

I find a strong first stage. As I show in Table 3, pre-1940 housing share has strong predictive power for a CoC's eventual grant funding. The estimates imply that if the median CoC demolishes half of its pre-1940 housing, all else equal, the community loses $300,000 in grant funding for homeless programs.

formula.

[38]According to the 2000 Census, which was used to determine CoC eligibility in 2011, 84 percent of pre-1940 housing units were occupied by tenants above the federal poverty line.

[39]According to HUD staff and several Continuum of Care directors, HMIS data was not reliable prior to 2011. Thus, 2011 is the single year for which I can confidently merge together all available datasets.

[40]This vector includes CoC program formula variables, CoC-level median income, vacancy rate, median one-bedroom rent, share of the population that identifies as white, and share of the population in poor health. In addition, I add dummy variables for CoC population quartiles. Controlling for population in other ways does not significantly affect the results.

[41]I present results from alternative specifications in Appendix D.

IV.C Addressing Identification Concerns

A natural concern with this empirical strategy is that pre-1940 housing prevalence is correlated with community factors that directly affect homelessness outcomes. If this were the case, my exclusion restriction would fail, and I would incorrectly attribute a spurious correlation to causal effects of federal grants. In this setting, however, I can construct a direct test of my exclusion restriction using a subset of the data. Equation 4 implies that across Formula A communities, pre-1940 housing actually does not affect funding allocations, conditional on all other formula variables. If pre-1940 housing is a relevant factor for homeless behavior or programs, however, the instrument should predict outcomes across these communities as well, generating a significant reduced form effect. In Section V, I show that this is not the case. Pre-1940 housing only predicts homelessness outcomes when it affects funding.

This falsification exercise only offers a partial test. Formula A communities have, on average, low amounts of pre-1940 housing, so I can only rule out pre-1940 housing's direct effect over part of the variable's support.[42] One may still worry that among communities with especially old housing, those with more pre-1940 housing units differ systematically in ways that affect rates of homelessness.

To explore this concern, I examine how communities with different pre-1940 housing levels differ on observables related to poverty and economic activity. Housing built before 1940 is no more likely to be occupied by households in poverty.[43] Figure 2 shows a scatter plot of pre-1940 housing per capita and a HUD measure of housing affordability across CoCs in 2011. There is no significant relationship between pre-1940 housing and rent burdens.

I present a series of additional regressions and correlations in Appendix C. Areas with differing levels of per-capita pre-1940 housing have similar rates of new construction and incoming migration.[44] Areas with more pre-1940 housing do not have more substandard housing, and social

[42]Though the sample of Formula A communities is not representative, the falsification test estimates are not biased because Formula A status is determined solely by observable covariates. Note that the standard Heckman Correction term is proportional to the correlation between the error in the estimating equation and the error in the selection equation, but in this case, there is no error in the selection equation. As a result, $\mathbb{E}[y|X, \text{Formula A}] = X\beta + \mathbb{E}[u|X, \text{Formula A}] = X\beta + \mathbb{E}[u|X]$, because Formula A status yields no information over and above the known covariates. Thus, the reduced form can be estimated consistently using OLS.

[43]Calculation using 2011 American Community Survey data.

[44]I use newly issued residential building permits in 2011 as a measure of new construction.

welfare program take-up is similar across pre-1940 housing levels.[45] These results suggest that despite building age, pre-1940 housing is not associated with community decline. Instead, 1940 appears to be a sufficiently distant and arbitrary cutoff.

So why is this variable responsible for distributing homeless assistance? Pre-1940 housing's effect on funding is a relic from the repurposed Community Development Block Grant formula. That program was largely intended to support infrastructure, which could feasibly be more costly in communities with older housing (Bunce 1979). This relevance is absent in the formula's application to homeless assistance. The Senate Committee on Appropriations in 2000 went so far as to write "The CDBG formula has no real nexus to homeless needs."[46]

Moreover, the original motivation for including pre-1940 housing in the Community Development Block Grant formula back in the 1970s was largely political. The Community Development Block Grant consolidated several pre-existing HUD programs, and the pre-1940 housing variable was added as the hold harmless clause for these prior programs was expiring, in part, to shift funds in a way that ensured no community lost too much funding relative to prior programs. In Bunce's (1979) evaluation of the formula, he writes, "The political advantages of the dual formula [i.e. a formula with pre-1940 housing and growth lag] are (1) it partially offsets the effects of the hold harmless phase-down [...] and (2) it avoids creating a new class of entitlement city losers." Bunce (1979) goes on to write "The disadvantage [of the dual formula, with pre-1940 housing and growth lag] of course is the lower correlation with the poverty dimension." Even when the formula was introduced, those who advocated for it acknowledged that pre-1940 housing had no systematic association with poverty-related outcomes.[47]

Ultimately, I argue it is unlikely that the identifying variation conflates the effects of grant funding with relevant, systematic differences across communities with varying housing stocks. I show that pre-1940 housing share is conditionally uncorrelated with homeless program capacity

[45] Substandard housing units are those with inadequate plumbing or kitchen facilities. I measure social welfare program take-up by the fraction of those in poverty receiving food stamps and the fraction of those in poverty receiving SSI.

[46] See Senate Report 106-410.

[47] I cannot separately identify the effects of homeless assistance and Community Development Block Grants because their award levels are based on the same formula. I consider it unlikely that my estimates are driven by CDBG funding, rather than the funds that directly target homelessness, but this hypothesis is impossible to test empirically. To the extent that CDBG funding affects homelessness, my results can be interpreted as the joint effect of a dollar of homeless assistance alongside the proportional CDBG allocation.

and utilization *across Formula A communities*, for which pre-1940 housing does not affect funding. Moreover, pre-1940 housing does not appear to be correlated with observable economic outcomes. Instead, the variable remains in the formula for historical and political reasons, with its original intended purpose lacking current relevance. The institutional context and available evidence suggest that pre-1940 housing is a valid instrument for homeless assistance funding.

V Results

V.A Homeless Assistance Funding and Program Capacity

As program funding becomes more generous, service providers add beds. Table 4 shows the effects of grant funding on program capacity across various types of programs (Panel A). I estimate that areas with $100,000 in additional funding provide 152 additional "year-round-bed equivalents," across all programs.[48]

Of course, not all beds are created equal. Columns (2)-(7) in Panel A of Table 4 report how the 152 marginal beds are distributed across program types. In 2011, marginal homeless assistance funding was not spent on transitional housing.[49] Instead, communities and service providers spend marginal grant funds on emergency shelter expansions (for both individuals and families) and permanent supportive housing for individuals. Individual permanent supportive housing expansions are particularly interesting because the effects of such programs are at the core of many debates surrounding solutions for chronic homelessness.

There are many channels through which program generosity might manifest, but capacity expansions are particularly important for several reasons. First, the fact that funding increases capacity must mean that federal homeless assistance funds do not fully crowd out local government funds or philanthropic donations. In fact, the low implied marginal cost of a bed (in terms of federal funds) suggests that significant *crowd in* is possible. Second, surveys of unsheltered individuals cite lack of bed availability as a primary culprit for unsheltered homelessness.[50] Finally, a local increase in

[48]Year-round bed equivalents is a measure that accounts for seasonal beds. A bed operating year-round receives a value of one. A bed in a cold weather shelter, on the other hand, operating only in the winter receives a value of 0.25.

[49]This result is consistent with the rise in popularity of the "Housing First" approach, which advocates rehousing households as an alternative to receiving supportive services in transitional housing.

[50]For example, in a 2013 survey of 265 unsheltered homeless people in Santa Clara County, two-thirds cited a lack

the number of beds or available programs is a salient change, which both targeted and non-targeted populations potentially respond to.

V.B Homeless Assistance Funding and Unsheltered Homelessness

Who occupies the marginal program beds? Unsheltered populations may respond to changes in program generosity or capacity by entering shelters or permanent supportive housing units. If they do, then the marginal beds are very valuable, providing a basic human need to those those who would otherwise go without a roof over their head. If the behavior of unsheltered populations is relatively inelastic, on the other hand, federal grants will be ineffective at combating unsheltered homelessness.

I find that the unsheltered do respond to homeless assistance generosity by entering homeless programs. Table 4 shows that an additional \$100,000 in grant funding leads to 46 people utilizing homeless programs who would otherwise be unsheltered at a point in time (See Panel B). This estimate implies that, taking local behavioral responses as given, the federal government could reduce the average probability that a homeless person is unsheltered by 5% at a cost of \$10 per homeless person.

To complement this average estimate, I explore heterogeneous responses by chronic homeless status and household type. I find that those on the margin are comprised of both chronically and temporarily homeless households. Of the 46 people lifted out of unsheltered homelessness by a \$100,000 annual increase in funding, 14 are chronically homeless. Moreover, both individual and family households are less likely to be unsheltered when homeless program funding is more generous. As greater funding expands capacity in both individual and family programs, the targeted populations – otherwise unsheltered households – utilize both sets of beds.

V.C Homeless Assistance Funding and Total Homelessness

Increasing local homeless program generosity may also increase the total size of the local homeless population if those outside the local homeless population exhibit an elastic location response. I test for this effect and present the results in Table 4, Panel C. I find that a \$100,000 increase in local

of bed availability as the reason they were unsheltered.

grant funding leads to 73 more people entering the local homeless population at a point in time. Taken together with the results from the previous section, this estimate implies that an additional $100,000 in homeless assistance funding induces 119 people to enter homeless programs. For every five people who enter programs in response to regional funding increases, two would have otherwise been part of the local unsheltered homeless population. The other three must be entering homeless programs from a housing situation or immigrating from another region.

To dig deeper, I explore how the effect of funding on total homelessness varies across homeless subpopulations. I find that funding has no effect on the total number of homeless individuals. Increases in program generosity successfully house unsheltered individuals without drawing more individuals into the local homeless population. This result implies that permanent supportive housing availability, despite its controversial generosity, does not attract individuals to local homeless programs. Instead, I find that all those drawn into the local homeless population by increased funding are in non-chronically homeless families. These results beg the question – where would these marginal families locate if the program beds were not available?

V.D Funding, Migration, and Prior Residence

Several distinct behavioral margins may drive the effect of funding on total family homelessness. Families could migrate across CoC boundaries in pursuit of available homeless programs, substitute away from family and friends as program generosity changes, or reduce search effort for independent housing. Each of these behaviors could explain the larger homeless family populations in regions with greater funding, all else equal. Each behavior, however, generates a different normative implication, so policy ramifications depend critically on the relative empirical importance of these margins.

First, I explore migratory responses to funding using the Annual Homeless Assessment Reports (AHAR) data, which enumerate the number of individuals and families utilizing programs in each responding CoC who became homeless elsewhere. Migration concerns occupy a great deal of airtime in local homeless program funding debates, yet there is no prior empirical evidence linking homeless migration to homeless assistance policy. Table 5 reports the effects of homeless grant funding on total annual utilization and gross migration of individuals and people in families. Homeless individuals do not migrate to areas with greater homeless program funding, but homeless families do. An additional $100,000 in local grant funding attracts about 85 people in homeless families utilizing local services throughout the year who became homeless in a different CoC. Using the same AHAR sample, I find that an additional $100,000 in grant funding leads to 138 more people in families utilizing shelters throughout the year. Thus, the migration effect is large enough to explain over 60 percent of the annual increase in family shelter utilization in response to funding.[51] Increased family utilization is driven entirely by those in emergency shelters, which is consistent with the evidence in Table 4.[52]

What explains the few remaining families unaccounted for? Unfortunately, I currently lack the data to directly estimate the counterfactual residence type for families that are drawn into the homeless population by generous homeless funding. I can, however, offer suggestive evidence by exploring how the composition of residence prior to homelessness varies across areas with more or less plentiful funding. The AHAR data categorizes homeless individuals and households by what category of residence they inhabited immediately prior to checking into a homeless program. The reporting categories are: unsheltered homelessness, another homeless program, staying with family and friends, rental housing, owned housing, hospital or substance abuse treatment facility, hotel/motel, jail, and other/unknown. To get a sense of where marginally homeless families may locate in the absence of program bed availability, I ask how the number of people reporting each of these prior residence types varies with funding generosity.

Figure 3 displays the results of the nine regressions, one for each prior residency type. I plot the coefficient representing the effect of $100,000 in local funding on the total number of people utilizing homeless programs throughout the year. The largest effect size corresponds to people in families who were staying with family and friends prior to entering a program. This suggests that families likely substitute away from relying on family and friends when local funding for homeless programs is greater. The only other sizable (though not statistically significant) effect corresponds to families moving from rented housing to homeless programs. Of course, this results does not

[51] Recall, this same funding increase led to 83 more people in families utilizing programs at a point in time. Of these marginal people in families, approximately 15 percent would have been unsheltered in the absence of additional funding. Assuming that this relative magnitude is consistent throughout the entire year, family migration accounts for 70 percent of the effect of funding on total local homelessness.

[52] Emergency shelters also account for the majority of greater individual program utilization in areas with greater funding. The point estimates in Table 5 imply that funding has a positive effect on individuals' permanent supportive housing utilization, consistent with capacity effects in Table 4, though I lack the power in the AHAR sample to reject a null effect.

imply that these families would have remained in rented housing in the absence of greater program funding. Rather, it could be that when program capacity is available, families are more likely to move from rental housing to homeless programs instead of first transitioning to staying with family and friends or unsheltered locations. In any case, these results highlight the residence transitions that warrant further investigation with more granular data in the future.

V.E Falsification Tests and Robustness

I run a series of falsification tests to assess the validity of my instrument and empirical approach. A unique feature of the formula design allows me to directly test my exclusion restriction (i.e. pre-1940 housing share does not affect homeless sector outcomes) on the subset of communities whose funding does not reflect variation in the instrumental variable. Across Formula A communities, the formula assigns funding based solely on the population share, poverty share, and overcrowded unit share. If pre-1940 housing, however, predicts rates of homelessness, we should expect it to do so for these communities as well. I test for this possibility by estimating the reduced form effect of pre-1940 housing on shelter capacity, unsheltered homelessness, and total homelessness in Formula A CoCs. Table 6 presents the results of these tests; I find that pre-1940 housing has no predictive power for outcomes of interest when it has no effect on grant funding.

VI Homeless Assistance Policy Implications

To formally explore the normative implications of my parameter estimates, I adapt the Chetty (2006) social insurance framework for the setting of homeless assistance funding. For my purposes, this framework delivers two key benefits. First, the model illustrates and clarifies the key tradeoff in social insurance provision in this context. Second, the framework shows how the estimates can inform local welfare analysis. I first outline a simple version of the model. Appendix E discusses how and when the results can be generalized or extended. Then, I use the model to interpret my empirical findings.

VI.A A Social Insurance Model of Homeless Program Funding

At the core of the static model, a benevolent social planner chooses a homeless assistance benefit level to maximize a utilitarian social welfare function, taking population behavioral response into account.[53] Each person in the population, indexed by $i \in I$, faces uncertainty over whether or not he or she encounters a homeless spell. That is, everyone faces one of two potential states of the world: a housed state and a homeless state. Let e_i denote the probability of being housed. One's behavior affects whether or not he or she falls into homelessness, so effort, exerted at a cost of $\psi(e_i)$, determines one's high-state probability, e_i.

Current institutions do not give cash to those experiencing homelessness. Instead, homeless programs use homeless assistance funding to provide services and in-kind overnight shelter. As a result, no one is guaranteed support, and with over a third of the homeless population unsheltered on any given night,[54] capacity constraints are a first order concern. To account for this unique setting in the model, I assume that a per-capita benefit b is used to provide shelter with some probability $s_i(b)$ in the homeless state. This probability implicitly depends on both the agent's behavior and capacity constraints. Homeless assistance funding is financed by a tax in the housed state, $\tau(b)$, and the planner's budget constraint dictates that $\mathbb{E}[e_i\tau(b)] = \mathbb{E}[(1-e_i)b]$.[55] Upon normalizing the size of the population to one, I use the notation in Section IV to rewrite the constraint as $h\tau(b) = (1-h)b$, where $h = 1-l$ denotes the fraction of the population that is housed. Taxes on the housed equal assistance expenditures for the homeless.

In the housed state, agents consume housing, a_h, and a composite good c_h.[56] I assume that agents earns a wage w_h when housed, so non-housing consumption in the high state equals $c_h = w_h - pa_h - \tau(b)$, where p is the price of a unit of housing.[57] One who is homeless but sheltered

[53] Throughout, I take the private insurance market failure as given. There is no private insurance against homelessness, except of course in cases of natural disasters. Such a market would likely suffer from tremendous adverse selection.

[54] Calculation using 2011 Point In Time Count Data.

[55] In reality, unlike in the case of unemployment insurance, there is no one-to-one mapping from the state of the world to taxes in this setting. Nevertheless, households are more likely to pay taxes in housed states of the world.

[56] The social planner's problem is unaffected by whether or not agents are assigned a_h in the high state or choose housing optimally. If everyone automatically consumes some level of housing, $\tilde{a_h}$, upon the realization of a housed state, the problem becomes analogous to the case of a single consumption good (so long as $p\tilde{a_h} < w_h$). If agents choose housing optimally in the housed state, they are indifferent between the marginal unit of housing and other consumption, so the effect of the marginal benefit increase on high state utility is second order.

[57] I assume that the agent has no assets in the static model, but extending the model to account for assets does not

in a homeless program consumes the bundle (c_l^s, a_s). In a state of unsheltered homelessness, one consumes (c_l^u, a_u). Each agent has the same smooth utility function, $u(c, a)$, which is strictly concave in both arguments.

With this setup, I can write the agent's problem. Taking the tax rate, price of housing, and homeless assistance benefit level as given, each person simply chooses effort to maximize:

$$\max_{e_i \in (0,1)} V(e_i) = e_i u(c_h, a_h) + (1 - e_i)[s_i u(c_l^s, a_s) + (1 - s_i) u(c_l^u, a_u)] - \psi(e_i) \tag{6}$$

Each agent's optimal effort level ensures:

$$u(c_h, a_h) - [s_i u(c_l^s, a_s) + (1 - s_i) u(c_l^u, a_u)] = \psi'(e_i) \tag{7}$$

At the optimum, everyone equates the expected utility benefit from exerting an additional unit of effort with that effort's marginal cost.

The social planner takes this effort response into account when setting the optimal benefit level. Intuitively, raising the benefit level increases the likelihood of homelessness (by lowering the utility difference between the housed and homeless states) but increases the likelihood of being sheltered conditional on being in a homeless state. Formally, the utilitarian planner solves:

$$\begin{aligned} \max_b W(b) &= h\left[u(w_h - pa_h - \tau(b), a_h)\right] + (1 - h)\left[\frac{l_s(b)}{l} u(c_l^s, a_s) + \frac{l_u(b)}{l} u(c_l^u, a_u)\right] - \mathbb{E}\left[\psi(e_i)\right] \\ \text{s.t. } & h = \mathbb{E}[e_i(b)] \end{aligned} \tag{8}$$

By differentiating the planner's objective function and employing a convenient and natural normalization,[58] I arrive at a simple Baily-Chetty formula. At the optimal level of homeless assistance funding, it must be that

$$\left(\frac{\frac{-dl_u(b)}{db}[u(c_l^s, a_s) - u(c_l^u, a_u)] - u_1(c_h, a_h)}{u_1(c_h, a_h)}\right) = \left(\frac{b}{l(1 - l)}\right) \frac{dl(b)}{db} \tag{9}$$

This equation mirrors the classic optimal social insurance formula (Baily 1978, Chetty 2006,

affect any results or conclusions. Prices are assumed exogenous and held fixed throughout.

[58] As in Chetty (2006), I normalize the welfare gain from a \$1 increase in the size of the social insurance program by the welfare gain from an additional \$1 in the housed state.

2008) but accounts for an additional behavior margin that is important in the homeless assistance setting: the degree to which funding reduces unsheltered homelessness on the margin.[59] The expression is not written in terms of primitives, but rather elasticities that are themselves a function of the benefit level. These elasticities illustrate the key tradeoff balanced in an optimally set social insurance policy. The left hand side of Equation 9 illustrates the marginal benefit, through consumption smoothing and relaxation of capacity constraints. The degree to which marginal funding reduces unsheltered homelessness is $\frac{dl_u(b)}{db}$. This responsiveness is taken into account to arrive at the normalized utility gain from being homeless but sheltered as opposed to unsheltered, $\left(\frac{\frac{-dl_u(b)}{db}[u(c_l^s,a_s)-u(c_l^u,a_u)]-u_1(c_h,a_h)}{u_1(c_h,a_h)}\right)$. The right hand side of Equation 9 reflects the marginal cost of raising the benefit level. The behavioral response (via a reduction in the agent's search effort) reduces the funds available for redistribution across states.

This basic intuition is fairly general, despite the strong assumptions in the model I present. I discuss key assumptions and more general variants of this model in Appendix E.

VI.B Lessons for Federal Homelessness Assistance

The social insurance framework illustrates the federal government's tradeoff in providing homeless assistance, and my empirical strategy explores the marginal costs and benefits with current institutions. The framework and empirics together allow me to specify the assumptions needed to make unambiguous welfare statements and clarify how future work can fill the gaps as new data become available.

Perhaps the most straightforward and striking empirical result is that expansions of homeless programs for individuals successfully shelter people without attracting those who would otherwise find housing on their own. Funding reduces rates of unsheltered homelessness among individuals, so $\frac{dl_u(b)}{db} < 0$. Funding has no effect on the total size of the individual homeless population. This result could not hold if homeless assistance funding significantly altered incentives, discouraging search for housing, employment, treatment, or family reunification, so $\left(\frac{b}{l(1-l)}\right)\frac{dl(b)}{db} = 0$.

As long as $\frac{-dl_u(b)}{db}[u(c_l^s, a_s) - u(c_l^u, a_u)] > u_1(c_h, a_h)$ (i.e. shelter is sufficiently desirable), the

[59] While I discuss the formula in the context of homeless programs, the approach here can be generally useful for analyzing social insurance programs with capacity constraints. In these settings, one must account for the degree to which funding relaxes capacity constraints.

benefit of transferring an additional dollar from the housed state to a homeless assistance program for individuals outweighs the cost. If the marginal utility of consumption is higher in a homeless state than in a housed state, this inequality will hold whenever, $\frac{-dl_u(b)}{db}[u(c_l^s, a_s) - u(c_l^u, a_u)] > [l_s u_1(c_l^s, a_s) + l_u u_1(c_l^u, a_u)]$.[60] In other words, as long as providing shelter (and associated services) is preferable to simply redistributing cash to the homeless population, increasing homeless assistance funding for individual programs will be welfare improving.

In practice, many homeless programs being debated today are targeted towards individuals, especially those individuals who are chronically homeless. Early rollouts of permanent supportive housing have been largely aimed at reducing chronic, unsheltered homelessness among individuals.[61] Proponents of permanent supportive housing argue that providing individuals with nearly free apartments and services actually saves communities money. To support this claim, they point to a series of studies that compare indirect societal costs of unsheltered homelessness individuals to the cost of permanent supportive housing.[62] Such studies, however, could not account for the potential effects of permanent supportive housing availability on non-targeted populations. If permanent supportive housing draws many new people into the local homeless population by adversely affecting incentives, such programs are unlikely to succeed and improve welfare. I find no evidence that this is the case.[63] This result yields support for those arguing that permanent supportive housing, and the "Housing First" approach more broadly, are cost-effective.

Families respond to homeless assistance funding along a number of behavioral margins, making local welfare evaluation for family program generosity more complex. On one hand, family program expansions provide shelter to some families who would otherwise be unsheltered. This

[60] This follows from the concavity of the utility function.

[61] In 2010, for example, the United States Interagency Council on Homelessness released the first federal strategic plan to combat homelessness, and the first goal set forth in the plan was to end chronic homelessness by 2015 through expansion of permanent supportive housing. As I document in Table 1, the unsheltered homeless population is comprised primarily of individual households. Concurrently, many areas including New Orleans, San Francisco, and Denver have written or renewed ten-year plans to fight homelessness, with permanent supportive housing provision as a key feature.

[62] See, for example, Culhane, Metraux and Hadley (2002) and Flaming, Burns, and Matsunaga (2009). This type of study has been consistently replicated across many U.S. communities; see `http://www.endhomelessness.org/blog/entry/study-data-show-that-housing-chronically-homeless-people-saves-money-lives#.VkIyNtaJndk` for a comprehensive survey. Societal costs include the direct cost of homeless programs along with emergency room costs, jail operation costs, and locally provided supportive services.

[63] An important caveat is that my estimates are local to those communities who choose to expand permanent supportive housing if they become eligible for additional funding.

finding is surprising given that so few families are unsheltered to begin with. On the other hand, program expansions draw more families into the local homeless population. This response should not necessarily be interpreted as moral hazard. In the context of the social insurance model, moral hazard costs manifest as reductions in the likelihood of paying into the system. Homeless assistance funding may increase the size of the local homeless population without changing the likelihood of a household paying taxes.

In fact, I find that in areas with more (exogenously determined) homeless assistance funding, the majority of marginal family beds are occupied by those who would be homeless in a different region but for that funding. These *already homeless* families migrate in search of available beds, and these households would still be homeless in the absence of the marginal funding. The fact that they move to areas with generous programs is not evidence of moral hazard in the context of the social insurance model.

Finally, I present evidence that family homelessness often lives on the border between private social support networks and publicly funded programs. As homeless programs expand, more families move from living temporarily or permanently with family members and friends to residing in shelters. Even though these moves are incremental improvements upon a form of existing, informal private insurance, these families still benefit from the availability of shelters. To conduct sharp welfare analysis, future work should document the effect of these transitions on income and employment. Though beyond the scope of the model, it is also worth noting that shouldering family and friends of struggling families with the burden of housing them is a very regressive policy because income and opportunity are correlated within social networks.[64]

VI.C Implications of Homeless Family Migration

Thus far, I have focused the policy discussion on the optimal level of federally funded homeless assistance. The finding that families migrate in response to funding differentials generates two policy implications beyond just the *level* of benefits. First, homeless household migration can mitigate local government incentives to provide homeless services. In fact, qualitative evidence suggests

[64] See, for example, Verbrugge (1997), Mardsen (1987), Louch (2000), Yamaguchi (1990) and McPherson, Smith-Lovin, and Cook (2001). A branch of Sociology explores social resource theory to explain the the correlation of income, educational attainment, and job market outcomes within social networks.

that it certainly does. The prospect of attracting homeless residents from nearby areas occupies many city council meetings discussing homeless program funding and expansions. In the presence of migration, local funding for homeless programs exerts a positive externality on residentially unstable populations in nearby areas. Local governments potentially do not internalize these benefits, and therefore do not provide services optimally. Future work can explore the quantitative importance of this under-funding and propose mechanisms to allow local governments to internalize the entirety of program benefits. Pigouvian federal subsidies that reimburse CoCs for assisting migrant homeless households provide a theoretical solution, though their implementation could be hampered by adverse incentives to misreport data and selectively admit migrating households.

Second, migration implies that the *distribution* of federal homeless assistance is suboptimal. Though funding inequities underlie my identification strategy, they lead to migration costs for families that search for available beds. Moving is likely to be especially costly for children whose schooling and environment are disrupted. If funding tracked area need more closely, many homeless families could avoid these moving costs.[65]

VII Concluding Thoughts

In this paper, I show that federal grant funding for homeless programs affects homeless behavior and outcomes across a variety of important margins. Regions with exogenously higher homeless program grant funding have greater capacity across both individual and family programs. The marginal beds in individual programs are all occupied by those who would otherwise be unsheltered. Marginal beds in family programs are occupied by a collection of families who would otherwise be either unsheltered, living (and likely homeless) in a different region, or supported by family and friends. Taken together, these results provide new and needed evidence on both the effectiveness of homeless program funding and behavioral responses of homeless populations.

More generally, I show that homeless populations' behavior is elastic with respect to homeless policy along a number of critical margins. This behavior-based inquiry informs a new approach for homelessness literature. Homeless interventions have been, more often than not, justified on

[65]If areas are heterogeneous in the types of services or programs that they offer, regional sorting of homeless populations may be welfare improving even if moving costs are exerted. In practice, however, families appear to move to areas with available shelter beds, which do not typically have many services provided alongside them.

grounds of fiscal externalities or pure paternalism. Homeless populations are capable of responding to incentives and relocating in search of better services and opportunities. By studying their behavior, choices, and constraints, social scientists and policy makers can collaborate to create more effective and efficient policies.

This paper, however, only represents the tip of the iceberg for research exploring the economics of homelessness. Future work can address how homeless funding can or should be targeted effectively to various subpopulations. Moreover, we lack strong empirical evidence on the long-term effects of homeless spells. Even more basic unanswered questions involve how other programs in the social safety net can or should help households avoid homelessness in the first place. The homeless population data I use in this paper can be used to further our understanding of the connections between social insurance programs and markets. How do changes in disability insurance generosity or welfare generosity affect rates of homeless spells? How does the changing labor market affect the composition of households using homeless programs? This area is ripe for future research that will inform how policies affect the most marginalized members of society.

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Table 1: Homelessness in United States, 2011

	Individuals	Persons in Families	Total
Point In time Data (Population Snapshot)			
All homeless	357,481	217,880	575,361
Unsheltered	166,121	36,782	202,903
Chronically Homeless	94,904	11,334	106,238
Unsheltered & Chronically Homeless	68,074	8,715	76,789
National AHAR Data (Annual Sample)			
Sheltered	638,233	385,173	1,023,406
Disabled	278,072	32,573	310,645
Veterans	79,621	3,410	83,031
Migrating	165,770	108,188	273,958

Notes: This table presents counts of homeless people in the United States from two sources: the Point In Time counts and the Annual Homeless Assessment Report. Sheltered persons are those residing overnight in emergency shelters, transitional housing programs, or permanent supportive housing programs. Unsheltered persons are those in the PIT count spending the night in a place not meant for human habitation. Chronic homelessness follows the official HUD definition; one is chronically homeless if he or she has a disabling condition and has either been homeless for over a year or had four or more homeless episodes in the past three years. Those deemed migrating are those who check into programs in a different Continuum of Care from the one they became homeless in.

Table 2: Santa Clara County Emergency Shelter Demographics, 2013-2014

By Household Type

	Individuals	Adults in Families
Median Age	46	32
Single Entry	57%	83%
Female	22%	72%
Disability	48%	18%
Veteran	13%	2%
Earned Income	22%	40%
SSI/SSDI	30%	9%

By Number of Entries

	Single Entry	Multiple Entry
No. of People	4,705	3,259
Leave Within Two Weeks	68%	36%
Median Age	43	47
Female	31%	19%
Disability	39%	53%
Veteran	11%	13%
Earned Income	28%	19%
SSI/SSDI	25%	30%

Notes: The table tabulates characteristics of adults in Santa Clara County emergency shelters by household type and the number of sheltered homeless spells. "Single Entry" denotes an adult that only appears to have one sheltered homeless spell in the data. An observation is an adult who entered or exited a homeless shelter in some HMIS-participating program in 2013 or 2014. If one leaves a shelter and returns within a week, I classify that as a single continuing homeless spell. Missing variables are dropped from the calculation of percentages.

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

Panel A: All Continuums of Care

	(1) Grant Funding ($Mil)	(2) Grant Funding ($Mil)
Pre1940HousingShare	4.710***	6.467***
	(1.424)	(1.296)
Funding Formula Variables	✓	✓
All Controls		✓
N	367	367
F-Stat	42.76	51.67
R-Squared	0.939	0.948

Panel B: AHAR Sample

	(1) Grant Funding ($Mil)	(2) Grant Funding ($Mil)
Pre1940HousingShare	3.910***	5.580***
	(1.372)	(1.767)
Funding Formula Variables	✓	✓
All Controls		✓
N	302	302
F-Stat	27.20	33.76
R-Squared	0.958	0.966

Notes: Regressions report the first stage effects of a CoC's pre-1940 housing share on its homeless assistance grant funding. An observation is a Continuum of Care in 2011. Top panel reports the first stage from IV regressions using PIT data outcomes. The lower panel reports the first stage statistics from IV regressions using AHAR data, such as those studying migration or program utilization by prior residence. Grant funding, measured here in millions of dollars, is the sum of Continuum of Care Program funds and Emergency Solutions Grant funds. Pre-1940 housing share ranges from zero to 100. The funding formula variables (entitlement community population share, poverty share, overcrowded unit share, and growth lag share are all measured as shares across all entitlement communities in the United States). Other controls include dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. See Appendix A for a full description of sources. F-Stat refers for the first stage F-Statistic on pre-1940 housing. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Homeless Outcomes and Funding

Panel A: Capacity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Emergency Shelter		Transitional Housing		Permanent Supportive Housing	
	Total Beds	Individual	Family	Individual	Family	Individual	Family
Grants ($K)	1.518***	0.263***	0.761***	0.031	-0.000	0.413***	0.050*
	(0.430)	(0.081)	(0.272)	(0.019)	(0.030)	(0.100)	(0.027)
Formula Variables	✓	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,597	271	261	218	260	280	250
N	367	367	367	367	367	367	367

Panel B: Unsheltered Homelessness

	(1)	(2)	(3)	(4)	(5)
	Unsheltered Total	Unsheltered Chronically Homeless	Unsheltered Short Term	Unsheltered Individuals	Unsheltered Persons in Families
Grants ($K)	-0.458**	-0.141*	-0.316**	-0.353**	-0.105**
	(0.185)	(0.073)	(0.123)	(0.156)	(0.044)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Mean of Dep. Variable	561	177	384	441	120
N	360	360	360	360	360

Panel C: Total Homelessness

	(1)	(2)	(3)	(4)	(5)
	Homeless Total	Homeless Chronically Homeless	Homeless Short Term	Homeless Individuals	Homeless Persons in Families
Grants ($K)	0.733**	-0.158*	0.891**	0.009	0.724**
	(0.310)	(0.083)	(0.367)	(0.089)	(0.303)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,507	289	1,218	937	569
N	360	360	360	360	360

Notes: Regressions report results of IV estimates of homeless assistance grant funding on (a) capacity, (b) number of unsheltered homeless enumerated in PIT counts, and (c) total number homeless (unsheltered and residing in overnight programs) enumerated in PIT counts. An observation is a Continuum of Care in 2011. Capacity is expressed in year-round bed equivalents (i.e. a shelter bed operating only in winter receives a value of 0.25). Someone is deemed chronically homeless (Column 2 in Panels B and C) if he or she has a disabling condition and has either been homeless for over a year or has been homeless four or more times in the past three years. Controls include the CoC program formula variables (all available in 2000 Census), as well as dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Total Annual Utilization and Migration in Response to Funding

Panel A: All Programs

	(1)	(2)	(3)	(4)
	Individuals		People in Families	
	Total	Migrating	Total	Migrating
Grant ($K)	0.743**	-0.015	1.384**	0.846**
	(0.325)	(0.123)	(0.635)	(0.415)
Formula Variables	✓	✓	✓	✓
All Controls	✓	✓	✓	✓
Mean of Dep. Variable	1,983	543	1,208	358
N	251	251	251	251

Panel B: Emergency Shelters

	(1)	(2)	(3)	(4)
	Individuals		People in Families	
	Total	Migrating	Total	Migrating
Grant ($K)	0.573**	-0.052	1.382**	0.839**
	(0.276)	(0.101)	(0.678)	(0.423)
Formula Variables	✓	✓	✓	✓
All Controls	✓	✓	✓	✓
Mean of Dep. Variable	1,368	399	710	263
N	251	251	251	251

Panel C: Permanent Supportive Housing

	(1)	(2)	(3)	(4)
	Individuals		People in Families	
	Total	Migrating	Total	Migrating
Grant ($K)	0.129	0.036	-0.019	0.010
	(0.113)	(0.022)	(0.039)	(0.008)
Formula Variables	✓	✓	✓	✓
All Controls	✓	✓	✓	✓
Mean of Dep. Variable	284	50	178	28
N	251	251	251	251

Notes: Regressions report results of IV estimates of HUD Homeless Assistance Grant funding on total number of people using homeless programs throughout the year, as well as the subset of those people that became homeless in another CoC. The outcome variables are enumerated in the Local Area Annual Homeless Assessment Report data. An observation is a Continuum of Care in 2011. The top panel includes those in all programs. Panel B restricts to emergency shelters while Panel C restricts to those in Permanent Supportive Housing Units. Controls include the CoC program formula variables (all available in 2000 Census), as well as dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Falsification Tests

Panel A: Capacity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Emergency Shelter		Transitional Housing		Permanent Supportive Housing	
	Total Beds	Individual	Family	Individual	Family	Individual	Family
Pre-1940 Units	-0.006	0.003	-0.003	-0.004	-0.004	0.003	-0.001
	(0.009)	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)
Communities	A Only	A Only	A Only	A Only	A Only	A Only	A Only
Formula Variables	✓	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,345	235	163	238	262	280	176
N	153	153	153	153	153	153	153

Panel B: Unsheltered Homelessness

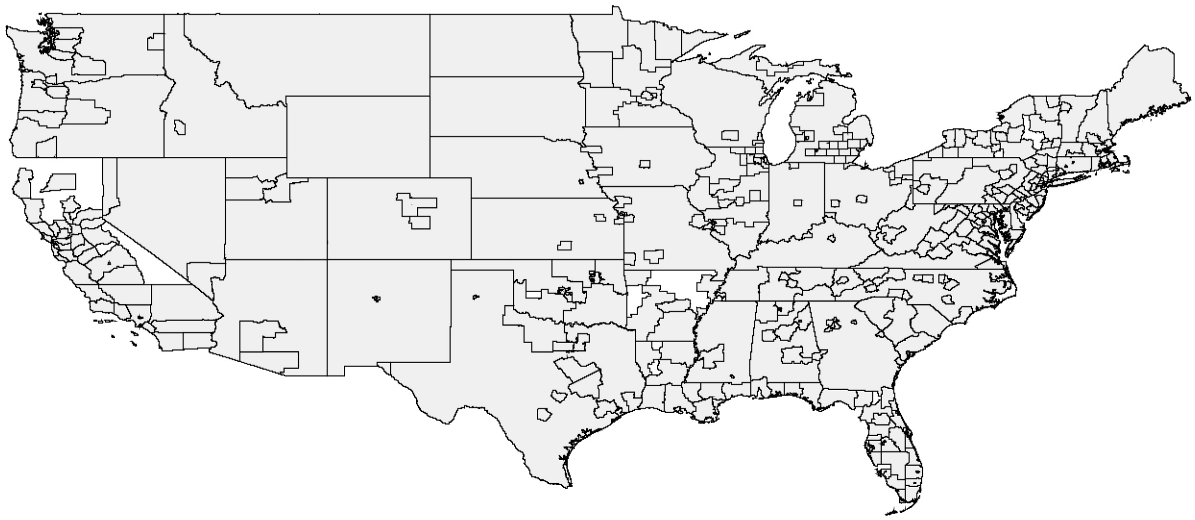
	(1)	(2)	(3)	(4)	(5)
	Unsheltered Total	Unsheltered Chronically Homeless	Unsheltered Short Term	Unsheltered Individuals	Unsheltered Persons in Families
Pre-1940 Units	-0.020	-0.004	-0.016	-0.015	-0.006
	(0.015)	(0.005)	(0.010)	(0.014)	(0.004)
Communities	A Only	A Only	A Only	A Only	A Only
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Mean of Dep. Variable	734	222	512	595	139
N	153	153	153	153	153

Panel C: Total Homelessness

	(1)	(2)	(3)	(4)	(5)
	Homeless Total	Homeless Chronically Homeless	Homeless Short Term	Homeless Individuals	Homeless Persons in Families
Pre-1940 Units	-0.020	-0.003	-0.017	-0.013	-0.008
	(0.018)	(0.005)	(0.015)	(0.018)	(0.005)
Communities	A Only	A Only	A Only	A Only	A Only
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,559	328	1,231	1,076	482
N	151	151	151	151	151

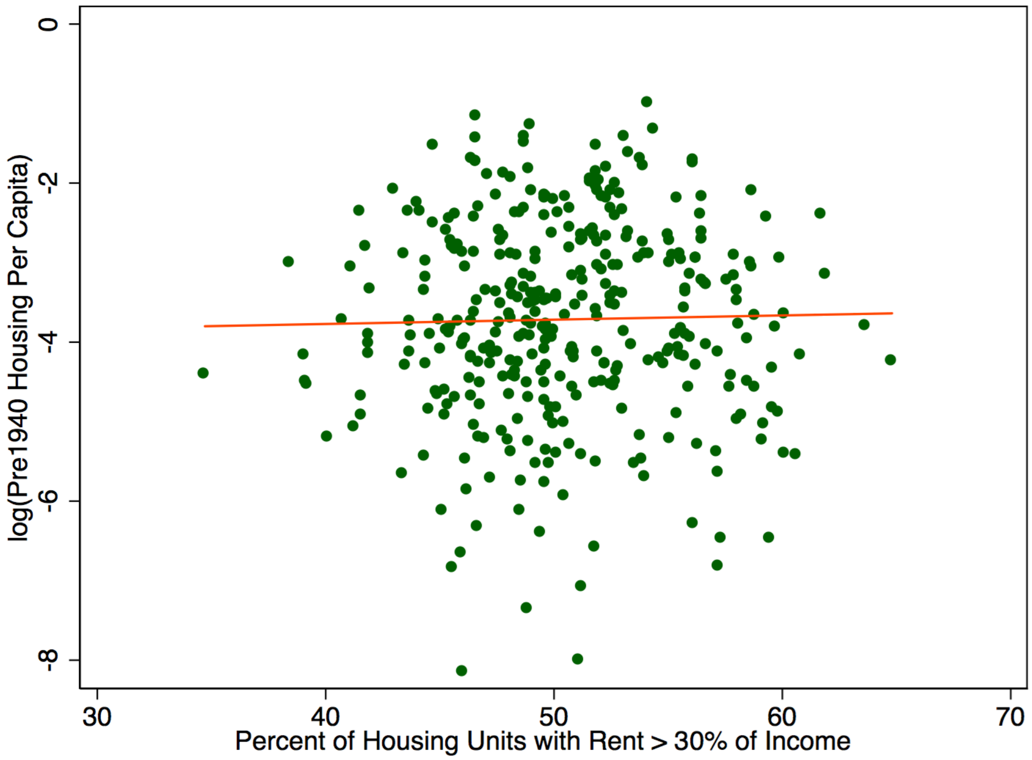
Notes: Regressions report OLS estimates of HUD homeless assistance grant funding on (a) capacity, (b) number of unsheltered homeless enumerated in PIT counts, and (c) total number homeless (unsheltered and residing in overnight programs) enumerated in PIT counts. An observation is a Continuum of Care in 2011 comprised entirely of "Formula A" communities. Capacity is expressed in year-round bed equivalents (i.e. a shelter bed operating only in winter receives a value of 0.25). Someone is deemed chronically homeless (Column 2 Panels B and C) if he or she has a disabling condition and has either been homeless for over a year or has been homeless four or more times in the past three years. Controls include the CoC program formula variables (all available in 2000 Census), as well as dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Map of CoCs, 2013



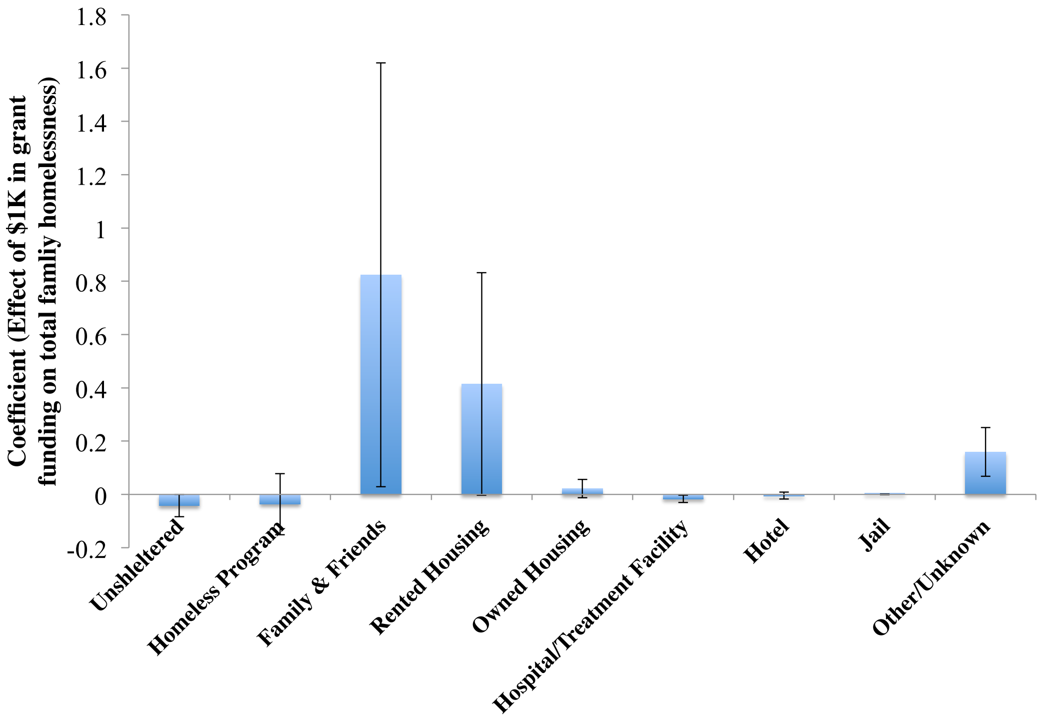
Notes: This is a map of the 415 Continuum of Care regions throughout the United States in 2013. I generate the map from the Department of Housing and Urban Development's shapefile, available at `https://www.hudexchange.info/coc/gis-tools/?filter_ToolType=Tool&filter_Year=2014&filter_State=&program=CoC&group=GIS`. White regions represent the few areas not covered by a Continuum of Care.

Figure 2: Housing Stock Age & Housing Affordability



Notes: This chart presents a scatter plot of per-capita pre-1940 housing (on a log scale) against the share of housing units for which rent exceeds thirty percent of occupant income, along with a linear trend-line. Each observation is a Continuum of Care. The pre-1940 housing measure denotes per-capita residential housing built before 1940, as reported in the 2000 Decennial Census. This variable is the measure of housing stock age that enters the homeless assistance grant formula at the entitlement community level. The housing affordability measure is reported in the 2009 American Community Survey. The trendline represents the unweighted best linear prediction, and its estimated slope is statistically indistinguishable from zero (0.005 with a standard error of 0.014).

Figure 3: Funding & Family Homelessness By Prior Residence Type



Notes: This chart plots coefficients and associated 95% confidence intervals for nine separate IV regressions. The outcome variable in each regression is the number of people in families utilizing homeless programs throughout the year in a CoC whose prior residence is denoted by the relevant category. An observation is a CoC in the 2011 AHAR sample. In each regression, pre-1940 housing share is used as an instrument for federal homeless assistance grant funding. All available controls, including population quartile dummies, are used as covariates in each regression.

Appendix (For Online Publication)

A Data Sources and Construction

To study responses to homeless assistance generosity, I construct a nationally representative dataset of sheltered and unsheltered homeless populations, homeless assistance funding, and relevant covariates. The core of my data originates from two sources.

The first source is CoC-level Point In Time (PIT) count data. Every other year, each Continuum of Care counts both its sheltered and unsheltered homeless population in the last week of January.[66] The resulting CoC-level data offer a comprehensive snapshot homelessness throughout the United Sates on a single night.

The second source is the set of Local Area Homeless Assessment Reports. Each person entering or exiting any homeless program that is eligible for federal funding responds to a survey, typically administered by program employee or volunteer.[67] The resulting records are referred to as Homeless Management Information Systems (HMIS) data. These data are aggregated to the Continuum of Care (CoC) level to create Local Area Annual Homeless Assessment Reports.

These national data, along with covariates from various other data sources, comprise the information at the core of my analysis. In order to document more detailed patterns in homeless program utilization, I also present summary statistics generated from program entry- and exit-level HMIS data in Santa Clara County.[68] While these data are specific to one area, they contain great detail that illustrate stylized facts about homeless populations and motivate the heterogeneity that I explore in the paper. In this Appendix Section, I describe each data source, and how I construct the datasets I use in the analysis.

[66] These counts are held in late January because the weather is typically cold then, and homeless populations are most likely to seek shelter.

[67] According to 2011 HUD Annual Homeless Assessment Report Data, slightly over 86% of all homeless program beds benefitted from federal funding and participated in gathering this data.

[68] Community Technology Alliance maintains this database for Santa Clara County's Continuum.

A.1 Point In Time Count Data

In odd calendar years, each Continuum of Care submits its count of both sheltered and unsheltered homeless individuals and families on a particular night in late January as part of the Continuum of Care Program Grant application process.[69] HUD, in turn, makes these PIT Count data publicly available, providing the most accurate available snapshot of the entire U.S. homeless population at a single point in time.

I utilize this CoC level data in my analysis to study cross-sectional differences in unsheltered and sheltered rates of homelessness. I drop the observations corresponding to U.S. territories, and I am left with 413–417 observations per year.[70] For each CoC, I observe the number of individuals and persons in families that are homeless and unsheltered, utilizing a homeless shelter, utilizing a transitional housing program, or residing in permanent supportive housing on a given night. For each of these aggregate measures, the surveys that accompany the data collection enable me to observe the number of people who are mentally or physically disabled, veterans of the U.S. military, or chronically homeless. One is chronically homeless, according to the survey and HUD's official definition, if he or she has a disabling condition and has either been homeless for over a year or has had more than four homeless spells in the past three years.

Communities take great care to ensure that these data accurately represent the size and scope of their local homeless population, and this count is not at all a small or haphazard effort. The Department of Housing and Urban Development distributes a detailed methodology guide to assist CoCs.[71] Each CoC recruits a large number of volunteers to assist with this process, spreading out over the city and prioritizing areas where service providers know homeless households reside. Los Angeles' CoC used as many as 6,000 volunteers in 2015.[72] As a result, the counts are stable over time, suggesting a relatively high signal to noise ratio despite the inherent difficulty in counting unhoused populations (See Figure A1).

[69] The unsheltered count is the result of the aforementioned effort to survey places not meant for human habitation. The sheltered count is primarily conducted by aggregating HMIS data on that same night.

[70] In 2011, there were 415 CoCs in the United States. The number of CoCs differs slightly from year to year because small CoCs sometimes merge or split.

[71] A recent guide and implementation tools are available at `https://www.hudexchange.info/resource/4036/point-in-time-count-methodology-guide/`.

[72] "Three nights and thousands of homeless to be counted on L.A. County's streets," *Los Angeles Times Editorial*, January 12, 2015.

A.2 Local Area Annual Homeless Assessment Report Data

In addition to conducting the PIT counts, a sample of communities is also responsible for submitting annual summaries of their HMIS data to the Department of Housing and Urban Development.[73] The Department of Housing and Urban Development uses these summaries to produce the Annual Homelessness Assessment Report (AHAR), which it then presents to the U.S. Congress. This report is responsible for providing an estimate of the total number of people utilizing homeless services in the United States. The underlying CoC-level data underlying this estimate are the Local Area Annual Homeless Assessment Reports, which enumerate sheltered individual and family populations in emergency shelters, transitional housing programs, and permanent supportive housing. Unlike the PIT data, AHAR Data represent unduplicated counts of all people checking into programs throughout the course of the government's fiscal year.[74]

For each participating CoC, program type, and household type (*i.e.* individuals vs. people in families) these data specify the share of homeless persons falling in each demographic group, veteran status, disability status, and age category. Moreover, the data break down the number of homeless people in each program by prior residence type. For example, the data specify the number of people in families who checked into emergency shelters throughout the course of the year were staying with family and friends immediately prior to entering the shelter. Critically, these data also indicate what share of households in each program became homeless outside the boundary of the Continuum of Care whose programs they utilize. This variable provides a nation-wide measure of homeless populations' gross migration. The AHAR data also provide national information on program capacity.

I drop any observation where the entire CoC is not responsible for reporting data.[75] I am left with data for 251 CoCs in 2011, which is considered the most reliable year of currently available data. Not all service providers participate in collecting HMIS data.[76] All service providers do,

[73] All major metropolitan areas are always included in the sample of communities whose data are collected. For detailed information about how the sample of reporting communities is selected, see Section C at https://www.hudexchange.info/resources/documents/2012-AHAR-Volume-2-Data-Collection-and-Analysis-Methodology.pdf.

[74] The U.S. federal government fiscal year runs from October 1 to September 30.

[75] There are several instances of certain communities, but not others, being sampled within a CoC. I drop all of these cases so as not to conflate utilization levels with reporting levels.

[76] Programs that do not receive, and do not wish to receive, federal homeless assistance funding are not required to maintain HMIS data.

however, submit their capacity information. Fortunately, the share of beds in each region that are not tied to HMIS data is both small and uncorrelated with the outcomes that I study.[77] In alternative specifications, I account for HMIS non-participation, which does not alter the patterns I describe in the paper.

A.3 Homeless Program Grant Data

HUD publishes their final, awarded homeless assistance grant amounts for each Continuum of Care. These data also specify which providers receive funding through the lead agency in each Continuum of Care. This level of detail not only ensures a transparent process, but also provides insight into how funds are being distributed at the local level. I add together funding from the CoC Program grant and the Emergency Solutions Grant to arrive at a total level of federal homeless assistance for each CoC.[78] The mean (median) CoC receives $3.2 million ($1.6 million) in homeless program grants. I am able to match all but six CoCs in the PIT data, and all of the CoCs in the AHAR sample, to their awarded grant funding.

A.4 Data Sources for Covariates

I merge homeless population and homeless assistance funding data to a variety of relevant CoC-level covariates. The variables that enter the CoC funding formula are available in the decennial U.S. Census. I match all but 48 CoCs in the PIT data to their funding formula variables, and these 48 remaining regions only account for three percent of all homeless assistance funding. I am able to match the entirety of the AHAR sample. Table A1 shows all of the covariates that I employ and their sources. My final nationally-representative dataset includes funding information and all relevant covariates for 367 CoCs in the PIT data (251 in the AHAR sample).

[77] The correlation between HMIS participation and migration is 0.048 ($p = 0.480$).

[78] I treat these two programs together because the identifying variation that I use to arrive at my estimates is the same across the two programs. I elaborate my empirical strategy in Section 5.

A.5 Santa Clara County HMIS Data

According to the most recent PIT count, Santa Clara County has the eighth largest homeless population across all Continua of Care in the U.S.[79] Though I do not claim the region is nationally representative, I use Santa Clara County HMIS Data to present descriptive statistics and motivate my analysis of two key dimensions of heterogeneity in the homeless population: household type and homeless duration. Each record in these data corresponds to a program entry or exit, with individual identifiers that can link both individuals and households across events. At every program entry or exit, an employee or volunteer records demographics, residence prior to entry, exit destination, government benefits, and income sources. Across all program types and services in 2013–14, these data include over 205,000 observations from over 21,000 people. To compare outcomes and demographics within program type, however, I tabulate summary statistics for the 9,571 adults that entered an emergency shelter at least once in 2013–2014. The HMIS data standards have changed over time, but the most recent version is available at `https://www.hudexchange.info/resources/documents/HMIS-Data-Standards-Manual.pdf`.

B Detailed Description of Homeless Assistance Grants

The two primary homeless assistance grants are the Continuum of Care Program grant and the Emergency Solutions Grant. These programs date back to the McKinney-Vento Homeless Assistance Act of 1987, though their current regulations were enacted into law through the Homeless Emergency Assistance and Rapid Transition to Housing Act of 2009 (HEARTH Act). In paper's analysis, I aggregate these two sources of funding to make use of the common identifying variation underlying both grants.

B.1 Continuum of Care Program Grant

The HEARTH Act regulation states that:

> "The Continuum of Care program is designed to promote community-wide goals to end homelessness; provide funding to quickly rehouse homeless individuals (including

[79] Santa Clara County also has very high HMIS-participation across providers. Over 95% of program beds are accounted for in HMIS data. All Santa Clara County emergency shelter beds participate in collecting HMIS data.

unaccompanied youth) and families while minimizing trauma and dislocation to those persons; promote access to, and effective utilization of, mainstream programs; and optimize self-sufficiency among individuals and families experiencing homelessness."[80]

At the heart of this program are the Continuum of Care Program Grant and the rules defining the scope and purpose of Continuums of Care throughout the United States.

The Continuum of Care Grant is a competitive, matching grant. Each Continuum submits one collaborative application on behalf of all the service providers in that region. The applications specify the programs requesting funding and provide a series of performance metrics for programs seeking funding renewals. The scoring criteria are made public each year during the application process, and the Department of Housing and Urban Development (HUD) conducts the final scoring and award determination.

Communities must match 25 percent of all awarded funds, and HUD verifies each Continuum's match before disbursing funds.[81] Once funds are awarded, they can cover any of the following (deemed eligible costs): "Continuum of Care planning activities, Unified Funding Agency costs, acquisition, rehabilitation, new construction, leasing, rental assistance, supportive services, operating costs, HMIS, project administrative costs, relocation costs, and indirect costs."[82]

B.2 Emergency Solutions Grant

The Emergency Solutions Grant (ESG) is the second largest federal homeless assistance grant, distributing $270 million in the most recent fiscal year.[83] Its current form and regulations emerged from the HEARTH Act, as it replaced the pre-existing (and similar) Emergency Shelter Grants program. The transition took place in 2011 (the year of my analysis), and funding was doled out in two portions. Technically, the first allocation was transferred under the Emergency Solutions Grant, but the funding amounts and allocations were identical, so this does not pose problems for interpreting my results.

[80]Federal Register Vol. 77 No. 147, July 31, 2012.

[81]The match can either take the form of cash or in-kind provision of goods or services whose cash value is sufficient to cover the match.

[82]Federal Register Vol. 77 No. 147, July 31, 2012. "HMIS" refers to costs associated with collecting or managing the local Homeless Management Information Systems database.

[83]The total ESG distribution is typically about 15% of the CoC Program Grant distribution.

The ESG differs from the CoC Program grant in three key ways. First, the ESG has a unique (though overlapping) set of eligible activities. Communities may spend ESG funds on five program components: street outreach, emergency shelter, homeless prevention, rapid re-housing assistance, and HMIS. Second, ESG funds are awarded directly to designated entitlement communities, rather than Continuum of Care lead agencies. The Continuum of Care planning process, however, necessitates coordination among all providers throughout the Continuum of Care, so I analyze the effects of funding at that level. Finally, ESG is an entitlement grant, so the formula directly determines the allocation of funds for each community.

B.3 Continuum of Care Program Formula

The formula used to determine Continuum of Care funding eligibility and Emergency Solutions Grant entitlement is based on the Community Development Block Grant formula. This formula determines an allocation share for each community and Continuum of Care based on five variables: population, overcrowding, growth lag, poverty, and pre-1940 housing.[84]

I describe the general structure of the formula in Section IV, but there are three features of the formula that I omit in the main body of the paper because they do not substantially affect my analysis. First, the CoC formula is calculated separately for two types of communities: so called "ESG entitlement communities" and all other entitlement communities.[85] Once some funds are allocated to U.S. territories, seventy-five percent of the available remaining funds are allocated to ESG entitlement communities and twenty five percent are allocated to all remaining communities. Then, the formula is applied separately to each group.

Second, some ESG funds are allocated to state governments. If a community is entitled to fewer than 0.05 percent of the total available funds, its allocation is automatically given to its state's government. The state can then allocate these funds as it sees fit across its regions and communities. These funds account for a very small fraction of total homeless assistance funding,

[84]Each variable is calculated as a fraction of the total across all entitlement communities. Overcrowded units are those with more than one person per room. Growth lag is defined as the difference between the current population and the population the community would have obtained if it had grown at the rate of the average entitlement community since 1960. Communities with above average growth from 1960-present receive a growth lag value of zero.

[85]ESG entitlement communities are a subset of all entitlement communities, as determined by the initial regulations surrounding the Community Development Block Grant. Approximately one third of all Community Development Block Grant entitlement communities are also ESG entitlement communities.

and I lack the data to trace these funds to their final destination, so I do not include these state allocations in my analysis.[86]

Finally, service providers in each community are able to renew certain funding allocations each year, depending on HUD funding priorities and scoring guidelines. Thus, some communities simply apply for all their renewal projects, regardless of funding determined by the formula. I treat any discrepancies between renewal eligibility and formula funding allocation as unobserved, idiosyncratic error in my first stage.

C Exclusion Restriction Validity

The empirical strategy's key identifying assumption is that pre-1940 housing is conditionally independent of unobservables that affect homelessness outcomes. As I discuss in Section 4, a unique feature of the homeless assistance grant allocation formula allows me to conduct a partial test of this exclusion restriction. I show that pre-1940 housing share is conditionally uncorrelated with homeless program capacity and utilization *across Formula A communities*, for which pre-1940 does not affect funding.

While these results are reassuring, they correspond to only a partial test. Formula A communities mechanically have, on average, lower levels of pre-1940 housing than their Formula B counterparts. Thus, the test does not rule out that unobservables across regions with particularly high levels of pre-1940 housing affect the behavior of service providers and impoverished households directly. I argue that the prior formula research, the arbitrary and distant age cutoff, and the lack of correlation with relevant observable community characteristics do not support such a story.

The original Community Development Block Grant formula did not include pre-1940 housing. In 1974, when HUD introduced the program, only Formula A was used to distribute funds. Then, in 1979, the Carter Administration proposed adding the Formula B component, which included the pre-1940 housing and growth lag variables (Bunce 1979).

The motivation was largely political. The Community Development Block Grant program replaced and consolidated several pre-existing HUD programs, and the Formula A calculation im-

[86]If state governments purposely distributed their ESG allocations in a way that was directly informed by the inequities in the formula, this would bias my IV results. Given the magnitude of the funds in question, however, the quantitative consequences would likely be small.

plicitly shifted funds away from certain older cities that had received large funding allocations in the 1960s. At first, the Community Development Block Grant allocations included a hold harmless clause – communities would receive no less than they had been entitled to under previous programs. In 1979, however, this clause expired, and addition of Formula B was proposed to mitigate the re-allocation of funds. HUD acknowledged that the inclusion of the pre-1940 housing variable weakened the formula's ability to target funds towards economically disadvantaged areas, even then. Bunce (1979) writes in his evaluation of the current Community Development Block Grant formula,

> "The political advantages of the dual formula [i.e. a formula with pre-1940 housing and growth lag] are (1) it partially offsets the effects of the hold harmless phase-down [...] and (2) it avoids creating a new class of entitlement city losers. [...] The disadvantage [of the dual formula, with pre-1940 housing and growth lag] of course is the lower correlation with the poverty dimension."

The other justification for including pre-1940 housing as a variable in the Community Development Block Grant formula was that infrastructure was plausibly more expensive to maintain and replace in older cities. Bunce (1976) noted that areas with an older housing stock had more substandard housing, lacking adequate plumbing and kitchen facilities, which was a reasonable proxy for the cost of public infrastructure repair.

Over time, however, this relationship has faded. Today, a very small fraction of the inadequate housing that worried regulators in the 1970s still stands. Figure A2 shows that housing units with inadequate plumbing facilities are few, far between, and uncorrelated with pre-1940 housing prevalence in the community.

Nevertheless, a natural identification concern is that areas with older housing stocks tend to be declining communities, conditional on income, and that declining communities have fundamentally different populations or attitudes towards homelessness. I offer up two tests to address this concern. First, I ask whether areas with more pre-1940 housing have different rates of new construction. If pre-1940 is a measure of age that correlates with community decline, we should observe fewer new, residential building permits in areas with more pre-1940 housing. Table A2 presents the results, showing that this is not the case. Pre-1940 is a poor predictor of new residential construction.

Figure A3 also shows that pre-1940 housing per capita does not predict incoming migration flows in the cross-section of Continuums of Care. If areas with greater pre-1940 housing shares were declining communities, we would expect fewer households to move there each year. This is simply not the case. The seventy year old cutoff appears to be sufficiently distant in time, so as to not predict which communities are rising or declining.

D Robustness in Alternative Specifications

In this section, I explore robustness of the main results. First, I ask whether the responses and effects that I document hold within region. Pre-1940 housing prevalence is not uniform across the United States. The Northeast and Midwest, in particular, have older housing stocks, on average, simply because cities in those regions tend to be older. Thus, a potential concern in my empirical strategy is that the identifying variation conflates homeless assistance funding effects with unobserved inter-regional differences.

I investigate this possibility by adding Census region fixed effects to my primary specifications.[87] The resulting regressions rely on identification from *within-region* variation in pre-1940 housing because the fixed effects absorb regional level differences. Table A3 present the estimates, which are very similar to those I discuss in Section V. The qualitative story remains the same, though the effect of funding on unsheltered homelessness is slightly attenuated.

Next, I explore whether my results are robust to specifications in which I use per-capita measures of relevant variables. Though I control flexibly for population size in my main specifications, I present these results to alleviate worries that the relevant effects conflate homeless funding with CoC size. I show the estimates in Table A4. The patterns I describe in Section V hold up. Funding expands capacity, shelters those who would otherwise be unsheltered, and draws short-term homeless families into the local homeless population.

[87]There are four main Census regions: West, Midwest, South, and Northeast.

E Assumptions in the Social Insurance Framework

E.1 Accommodating Richer Behavioral Models

The social insurance framework is fairly simple on the surface, but as Chetty (2006) argued, it implicitly accounts for a wide array of possible behavioral responses to social insurance generosity. Changes in homeless assistance might, in principle, affect housing choices, labor supply, precautionary savings, and a variety of other margins. These responses are captured, however, in the sufficient statistics that appear in the Baily-Chetty formula. Greater precautionary savings, for example, might allow for households to continue making rent payments while suffering adverse income shocks. This effect would manifest as a change in $\frac{dl(b)}{db}$. The precautionary savings response to homeless assistance would have a second order effect on utility because optimizing households would be indifferent between the marginal dollar saved and the marginal dollar spent. In this way, the framework can account for any number of relevant behavioral margins that households optimize over.

E.2 Fiscal Externalities

These margins can, however, affect the optimal benefit level if they impose costs on the planner's or government's budget constraint. If, for example, the government collected an income tax in addition to the stylized lump-sum tax in the model, labor supply responses would affect income tax revenue. Similarly, if homeless assistance funding affects household savings, capital tax revenues may rise or fall as well. Chetty and Finkelstein (2013) show how such fiscal externalities affect general optimal social insurance formulae. In this setting, one would need to estimate the responses of tax revenue to homeless assistance generosity through all appropriate channels (labor supply, savings, etc.) because changes in the planner's budget constraint are first order elements of the Baily-Chetty formula. With this context, however, these responses are likely to be negligible in practice.

On the other hand, prior literature has argued that fiscal externalities associated with unsheltered homelessness are significant. Flaming, Mantsunaga, and Burns (2009), for example, report evidence of greatly increased utilization of emergency health care and corrections facilities among unsheltered homeless individuals. If providing shelter to homeless households on the margin reduces the tax burden funding public health care or jails, this benefit should be taken into account when optimally setting homeless assistance benefit levels.

One can extend the framework for account for these externalities. Suppose that unsheltered homeless individuals incur per-capita cost ν through utilization of other government programs. The lump sum tax that individuals pay in the high state must finance this expenditure in addition to the homeless assistance benefit, b. The planner's budget constraint now becomes, $h\tau(b) = (1-h)b + l_u\nu$. Solving the planner's first order condition as in Section VI, I find a Baily-Chetty formula that internalizes the fiscal externality

$$\frac{\frac{-dl_u(b)}{db}[u(c_l^s, a_s) - u(c_l^u, a_u) - u_1(c_h, a_h)}{u_1(c_h, a_h)} = \left(\frac{b}{l(1-l)}\right)\frac{dl(b)}{db} + \frac{b\nu}{l}\left[\frac{dl_u(b)}{db} + \frac{l}{1-1}\frac{dl(b)}{db}\right] \tag{10}$$

The right hand side includes an extra term, not present in Equation 9, that accounts for the benefit that homeless assistance has through reduction of unsheltered government resource utilization.

E.3 Critical Assumptions and Future Work

The modified social insurance framework is flexible in many ways, but two critical assumptions are worth noting and discussing further. First, the derivation of the optimal benefit level formula assumes away any general equilibrium effects. As the planner varies homeless assistance on the margin, housing and labor market characteristics are held fixed. If, for instance, homeless assistance alters housing prices or wages, the partial equilibrium effects I estimate do not tell the full story. Exploring the interaction between homeless program provision and prices throughout the local economy is thus an important and interesting direction for future research.

A second key assumption is perfect and consistent optimization. The framework's ability to accommodate behavioral margins with sufficient statistics relies on the envelope theorem, which requires that agents are both (1) able to realize the appropriate indifference conditions and (2) making decisions that the social planner wishes to emulate. Both of these assumptions are questionable, especially when the population in question suffers from high rates of mental disability. Again, this tension is both an important caveat for current work and opportunity for future work. We know very little about frame-dependent decision-making and behavioral biases among homeless populations. With a better understanding of behavior, the growing literature on behavioral welfare analysis can inform normative analyses of homeless policy and social insurance more broadly.

Appendix Table A1: Covariates at the Continuum of Care Level

Variable	Source
CoC Funding Formula Variables	
Entitlement community population	2000 Census
Poverty rate	2000 Census
Overcrowded units	2000 Census
Growth lag	2000 Census
Number of housing units built before 1940	2000 Census
Other Covariates	
Median 1-bedroom rent	HUD 50th Percentile Rent Estimates
Total CoC Population	American Community Survey
Median household income	American Community Survey
Share of population that is white	American Community Survey
Share of vacant housing units	American Community Survey
Share of units with rent > 30 percent of income	American Community Survey
Share of population in extreme poverty	American Community Survey
Share of population with fair or poor health	County Health Rankings
Share of births to unmarried women	Community Health Status Indicators

Notes: Entitlement community population refers to the population within each CoC living in a designated Community Development Block Grant entitlement community. An overcrowded unit is defined as one with more than two people per bedroom. Growth lag is a measure of how slowly a community's population has grown since 1960. One is defined as living extreme poverty if he or she earns less than half of the federal poverty line. I thank the Homelessness Analytics Initiative for aggregating several of these variables to the CoC-level.

Appendix Table A2: New Residential Construction Permits and Pre-1940 Housing

	(1) New Permits	(2) New Permits
Pre1940 Housing	59.433	-25.526
	(780.747)	(797.031)
Population Controls	✓	✓
All Controls		✓
N	322	322

Notes: Regressions report the OLS estimates of a CoC's pre-1940 housing share on its newly issued residential construction permits in 2011. An observation is a Continuum of Care in 2011. Outcome variable taken from U.S. Census Building Permits Survey. Controls include dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A3: Alternative Specifications: Regional Fixed Effects

Panel A: Capacity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Emergency Shelter		Transitional Housing		Supportive Housing	
	Total Beds	Individual	Family	Individual	Family	Individual	Family
Grants ($K)	1.499***	0.260***	0.738***	0.035**	0.009	0.408***	0.049*
	(0.419)	(0.079)	(0.263)	(0.017)	(0.028)	(0.100)	(0.026)
Formula Variables	✓	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓	✓
Region Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,597	271	261	218	260	280	250
N	367	367	367	367	367	367	367

Panel B: Unsheltered Homelessness

	(1)	(2)	(3)	(4)	(5)
	Unsheltered	Unsheltered	Unsheltered	Unsheltered	Unsheltered
	Total	Chronically Homeless	Short Term	Individuals	Persons in Families
Grants ($K)	-0.325***	-0.100**	-0.226***	-0.247**	-0.078***
	(0.116)	(0.048)	(0.077)	(0.100)	(0.028)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Region Fixed Effects	✓	✓	✓	✓	✓
Mean of Dep. Variable	561	177	384	441	120
N	360	360	360	360	360

Panel C: Total Homelessness

	(1)	(2)	(3)	(4)	(5)
	Homeless	Homeless	Homeless	Homeless	Homeless
	Total	Chronically Homeless	Short Term	Individuals	Persons in Families
Grants ($K)	0.621***	-0.111**	0.733***	0.045	0.577***
	(0.214)	(0.055)	(0.248)	(0.064)	(0.202)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
Region Fixed Effects	✓	✓	✓	✓	✓
Mean of Dep. Variable	1,507	289	1,218	937	569
N	360	360	360	360	360

Notes: Regressions report results of IV estimates of HUD homeless assistance grant funding on total number of homeless people enumerated in PIT counts. An observation is a Continuum of Care in 2011. Capacity is expressed in year-round bed equivalents (i.e. a shelter bed operating only in winter receives a value of 0.25). Someone is deemed chronically homeless (Column 2 in Panels B and C) if he or she has a disabling condition and has either been homeless for over a year or has been homeless four or more times in the past three years. Controls include the CoC program formula variables (all available in 2000 Census), as well as dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent. Region fixed effects correspond to the four primary Census regions: west, midwest, south, and northeast. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A4: Alternative Specifications: Per-Capita Effects

Panel A: Per-Capita Capacity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Emergency Shelter		Transitional Housing		Supportive Housing	
	Total Beds	Individual	Family	Individual	Family	Individual	Family
Grants ($ per capita)	0.319***	0.042***	0.073***	0.027**	0.026**	0.110***	0.041***
	(0.064)	(0.011)	(0.027)	(0.012)	(0.010)	(0.033)	(0.014)
Formula Variables	✓	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓	✓
N	367	367	367	367	367	367	367

Panel B: Per-Capita Unsheltered Homelessness

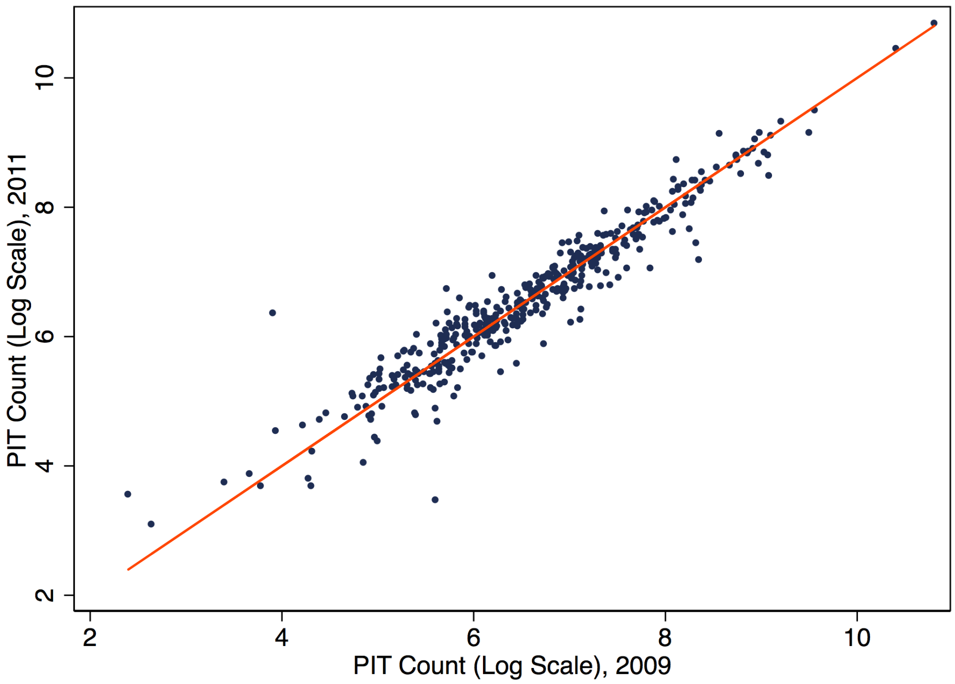
	(1)	(2)	(3)	(4)	(5)
	Unsheltered Total	Unsheltered Chronically Homeless	Unsheltered Short Term	Unsheltered Individuals	Unsheltered Persons in Families
Grants ($ per capita)	-0.090**	-0.032*	-0.058**	-0.061*	-0.029*
	(0.045)	(0.019)	(0.028)	(0.035)	(0.017)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
N	360	360	360	360	360

Panel C: Per-Capita Total Homelessness

	(1)	(2)	(3)	(4)	(5)
	Homeless Total	Homeless Chronically Homeless	Homeless Short Term	Homeless Individuals	Homeless Persons in Families
Grants ($ per capita)	0.064	-0.009	0.073**	-0.010	0.074**
	(0.045)	(0.047)	(0.030)	(0.024)	(0.030)
Formula Variables	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓
N	360	360	360	360	360

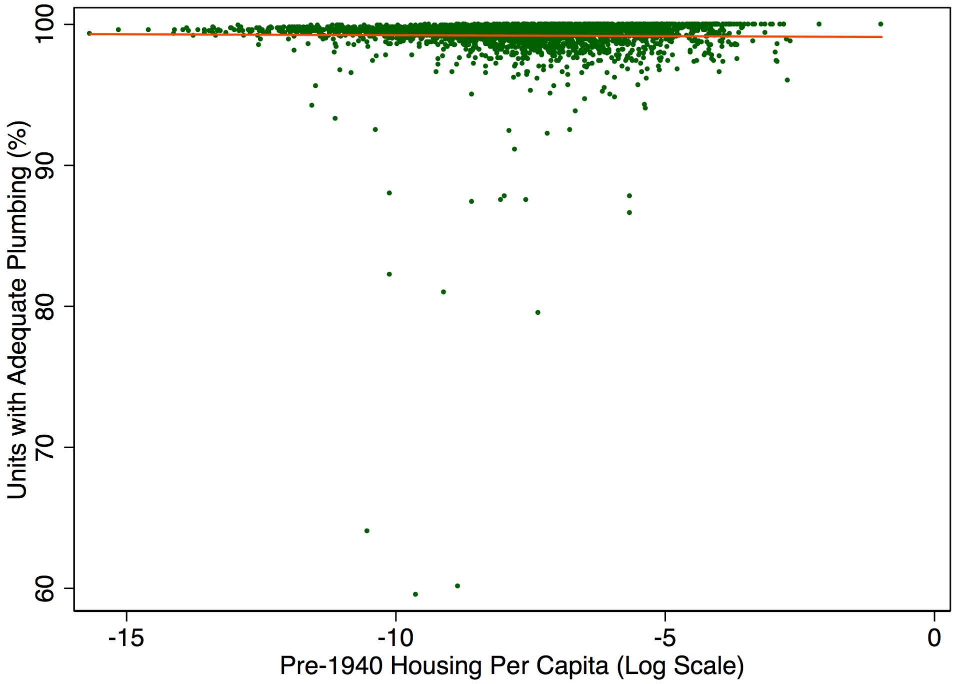
Notes: Regressions report results of IV estimates of HUD homeless assistance grant funding on per-capita capacity, per-capita unsheltered homelessness, and per-capita total homelessness. An observation is a Continuum of Care in 2011. Capacity is expressed in year-round bed equivalents (i.e. a shelter bed operating only in winter receives a value of 0.25) per capita. Someone is deemed chronically homeless (Column 2 in Panels B and C) if he or she has a disabling condition and has either been homeless for over a year or has been homeless four or more times in the past three years. Controls include the CoC program formula variables (all available in 2000 Census), as well as dummy variables for each population quintile, median household income, median one-bedroom apartment rent, the share of the population that is white, the share of births registered to unmarried parents, the percent of the population in poor health, the percent of families below half of the federal poverty line, the number of vacant housing units, and the share of renters who pay over 30% of their income in rent.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figure A1: Stability of Point In Time Counts, 2009-2011



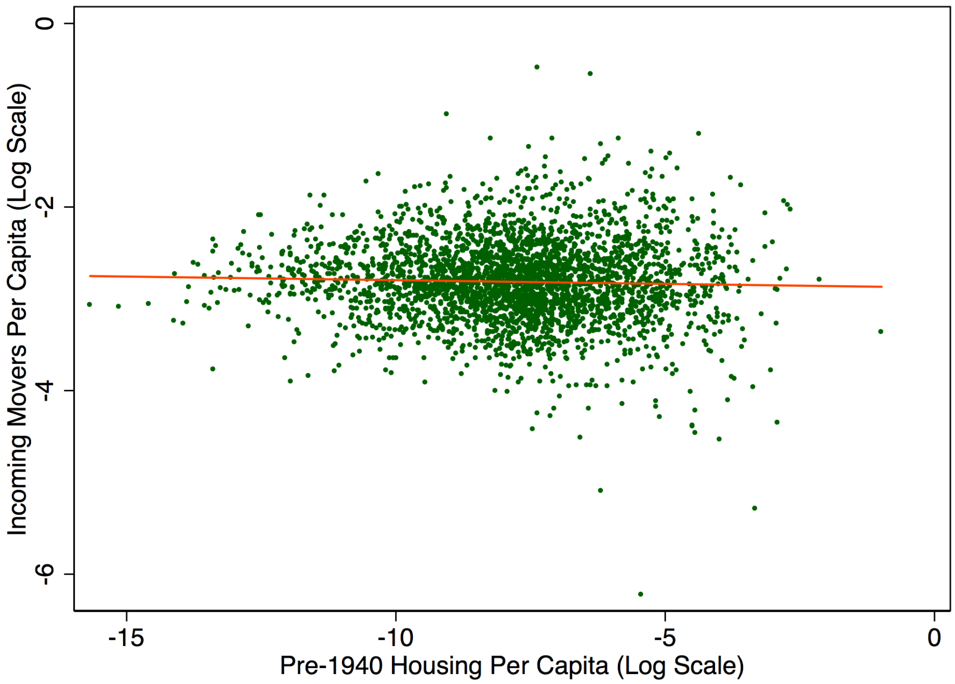
Notes: I plot total Point In Time estimates of homelessness for each Continuum of Care in 2009 and 2011. An observation is a Continuum of Care, and both axes are plotted on a log scale. The red line is simply the forty-five degree line.

Appendix Figure A2: Pre-1940 Housing & Inadequate Plumbing Prevalence, 2011



Notes: I plot the percentage of units with adequate pluming in a county against the per-capita occupied pre-1940 housing prevalence in that county (log scale). An observation is a county in 2011. Both variables are taken from the 2011 one-year American Community Survey estimates. The trendline represents the unweighted best linear prediction, and its estimated slope is statistically indistinguishable from zero (-0.013 with a standard error of 0.015).

Appendix Figure A3: Pre-1940 Housing & Incoming Migration, 2011



Notes: I plot the number of people who move to a county in 2011 (per-capita) against the per-capita occupied pre-1940 housing prevalence in that county (log scale). An observation is a county in 2011. Both variables are taken from the 2011 one-year American Community Survey estimates. The trendline represents the unweighted best linear prediction, and its estimated slope is statistically indistinguishable from zero (-0.007 with a standard error of 0.004).