Ending Homelessness: More Housing or Fewer Shelters?

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Abstract

Over the past decade, a major effort to "end homelessness" has lead to a marked expansion in permanent housing for the homeless relative to shelters. In this paper, I use community-level data over the period 2007–2014 in the United States to estimate short and long run associations between homeless populations and inventories of homeless assistance beds—in shelters and permanent supportive housing. I find that in the first year, one additional permanent housing bed is associated with 0.12 fewer homeless people on the streets and in shelters; however, this negative association is fully muted after the first year. The muting effect is driven entirely by the homeless subpopulation with relatively shorter spells of homelessness. Shelters are not associated with long-run reductions in the unsheltered homeless population, and are thus strongly and positively associated with the sheltered homeless population. Ultimately, sustained reductions in homelessness are strongly associated with eliminating shelters but not with housing the homeless. Aside from providing new evidence regarding homelessness policy, this paper is also the first to use national panel data to explain how within-community variation in homelessness relates to non-policy factors. The homelessness rate is significantly associated with median rent but weakly associated with unemployment and weather.

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1 Introduction

Homelessness has long been viewed as an intractable problem. The associated costs are substantial—homeless individuals frequently use emergency rooms, shelters and sometimes jails, while the instability associated with homelessness among families can lead to separation of families and negative educational outcomes for children (Culhane, Metraux and Hadley 2002; Gubits et al. 2015). A growing consensus has formed, however, that homelessness can be ended, and that doing so should be the primary goal of homeless assistance. The U.S. Interagency Council on Homelessness, the federal agency tasked with coordinating the federal response to homelessness, has set the goals of ending homelessness among veterans by 2015, among the chronically homeless by 2017 and among families by 2020 (United States Interagency Council on Homelessness 2015). As of 2009, there were 234 separate local and state government plans to end homelessness (National Alliance to End Homelessness 2009). One nonprofit organization embarked upon—and accomplished—its goal of encouraging communities to place over 100,000 homeless people into permanent housing in five years (Leopold and Ho 2015).[1]

The central strategy in plans to end homelessness center around quickly placing currently homeless people into permanent housing. Arguably the most important component of this strategy is an approach called Housing First, which with no preconditions places homeless individuals with mental illness and/or substance abuse challenges into permanent supportive housing (PSH).[2] PSH has no time limits and offers—but typically does not require—mental health treatment and engagement with other supportive services. In accordance with the Housing First strategy, the stock of PSH beds for the formerly homeless has increased by over 50 percent since 2007 (see Figure 1). Other, more temporary forms of assistance in

[1]Participating communities in the 100,000 Homes Campaign placed 105,580 homeless people into permanent housing (Leopold and Ho 2015). The actual effect of the campaign on the provision of housing was likely much smaller given that these communities still would have made placements in the campaign's absence.

[2]The Interagency Council on Homelessness calls Housing First "the most effective approach to ending chronic homelessness" (United States Interagency Council on Homelessness n.d.).

which people are still defined as homeless have not kept pace. The stock of transitional housing beds—which provide stays of 6 to 24 months and typically require compliance with supportive services—has fallen by 18 percent since 2007. The stock of emergency shelter beds—which provide stays lasting a few days up to several months—has increased by 7 percent in the majority of cities and states which do not provide a legal right to shelter for residents who need it. Meanwhile, the stock of emergency shelter beds has increased by 49 percent in the few cities and states which are required by "right to shelter" laws to respond to increased demand (see Figure 2). Ultimately, there has been a major shift in how assistance to the homeless is provided—instead of simply providing temporary forms of assistance (i.e., emergency shelter and transitional housing) in which people are still defined as homeless, communities are offering more permanent forms of assistance in which people are no longer defined as homeless (i.e., PSH).

Despite claims that this policy shift is an effective way to end homelessness, we have little evidence about whether it is actually doing so. In particular, there is a lack of research estimating how the different forms of homeless assistance relate to total homeless populations. This paper uses panel data from U.S. Continuums of Care (414 geographic entities which span the United States and are each composed of a city, a county, a group of counties or an entire state) between 2007 and 2014 to estimate how different forms of homeless assistance inventory are associated with counts of the homeless. I find that emergency shelter and transitional housing are strongly and positively associated with sheltered homeless counts, with no long run negative associations with unsheltered homeless counts. Meanwhile, PSH has no long-run negative association with total homeless counts, as a modest contemporaneous reduction is fully muted after one year. In other words, ending homelessness is strongly associated with eliminating shelters but not with adding housing for the homeless. The results also provide the first estimates of the relationship between key economic variables and homelessness based on variation within communities across the United States. I find that increases in housing prices (as measured by median rent) are positively associated

with homelessness rates. Unemployment rates and weather-related variables have small and insignificant associations with homelessness rates.

This paper has important limitations. Most importantly, causal impacts of homeless assistance types are not identified, a shortcoming of much of the previous literature on the determinants of homelessness as well. However, much of the shift in inventories during the study period was arguably driven by exogenous factors (e.g., public campaigns and political shifts), while other evidence suggests that inventories may not strongly respond to homeless populations.[3] Another limitation of this paper is that other forms of assistance to the homeless—such as prevention programs and short-term rental subsidies—are omitted from analysis due to lack of data availability; while such forms of assistance have traditionally been less pervasive than those considered here, their omission could bias results.[4] A final limitation is due to the imprecision of counts of homeless people sleeping on the streets. If the unsheltered homeless are undercounted, associations between homeless counts and inventory types will be biased upwards. At the same time, however, progress in ending homelessness is generally measured based on the same data used in this paper, and so the biased results are the correct results if society is concerned only with the homeless people who are "seen."[5]

The rest of the paper proceeds as follows: Section 2 reviews the related literature. Section 3 provides on overview of homeless assistance programs, as well as a framework for how housing for the homeless affects homeless populations. Section 4 describes the data and methodology. Section 5 presents results. Section 6 discusses policy implications. Section 7 concludes.

[3]This is discussed in more detail in the discussion section.

[4]The Homelessness Prevention and Rapid Re-Housing Program, as part of the American Recovery and Reinvestment Act of 2009, provided $1.5 billion to communities for homelessness prevention and rapid re-housing programs.

[5]Each year, the U.S. Department of Housing and Urban Development publishes an "Annual Homeless Assessment Report." See, for example, U.S. Department of Housing and Urban Development (2014).

2 Literature Review

Other studies which use homeless counts to assess the roles of policy and economic conditions have typically relied on either cross-sectional data or time-series data within a particular city. Cross-sectional studies generally find that housing prices, climate and apartment vacancy rates are associated with higher homeless populations (Bohanon 1991; Honig and Filer 1993; O'Flaherty 1996; Quigley, Raphael and Smolensky 2001; Byrne et al. 2013). Grimes and Chressanthis (1997) and Early and Olsen (1998) find that rent control has little or no significant role in explaining homelessness. Time-series studies based on administrative shelter data in New York City and Philadelphia find that negative macroeconomic conditions and higher rent increase the number of families in homeless shelters, while temperature is particularly important for individuals in shelters (Cragg and O'Flaherty 1999; Culhane et al. 2003; O'Flaherty and Wu 2006; O'Flaherty and Wu 2008). There is some evidence from these studies that higher shelter quality can increase the number of people in homeless shelters, and that placing families from shelters into housing reduces the number of families in shelters, although substantially less so than on a one-for-one basis. O'Flaherty and Wu (2006) find that each person placed from shelters into permanent housing reduces the sheltered homeless population by 0.36 people.

Two other studies use panel data to study the determinants of homeless populations. Quigley, Raphael and Smolensky (2001) use panel data on the number of homeless families receiving emergency housing assistance across counties in California to estimate the determinants of homelessness among this specific subpopulation, finding that higher rates of homelessness are related to higher rent and lower vacancy rates. And in the paper most related to this one, Byrne et al. (2014) use the same national, panel data to estimate the association between inventories of homeless assistance beds and the population of chronically homeless individuals (individuals homeless for a year at a time or four times within three years, and who have a disabling condition). Aside from only studying the chronically homeless, Byrne et al. (2014) differ from this paper in their reliance on time-invariant measures

of housing costs and economic indicators, their reliance on variation across communities to identify associations between chronic homelessness rates and inventory types in addition to variation within communities, and not allowing for dynamic associations between inventory types and homelessness (i.e., not simultaneously including contemporaneous and lagged inventories). They find that an additional PSH bed is associated with a 0.07 reduction in the chronically homeless population, which is similar to the 0.05 reduction I find within this subpopulation.[6] Associations between chronic homelessness and inventories of emergency shelter and transitional housing are positive across both studies; however, their estimates are larger and are statistically different from zero, perhaps due to their partial reliance on variation between communities.[7]

The contributions of this paper to the literature are twofold. First, it is one of the few papers to use panel data to estimate associations between homelessness and economic factors, and it is the only paper to rely on variation within communities across the United States. The results in this paper confirm the importance of housing prices for homeless population sizes. Second, this is the first paper to estimate the association between total homeless populations and the major forms of homeless assistance inventory. Of particular importance is evidence of a muting effect for PSH, in which the contemporaneous negative association with homelessness disappears after one year. That the muting effect is fully attributable to placing non-chronically homeless people into PSH has important implications for how assistance is targeted.

[6] Byrne et al. (2014) do not use a linear functional form to assess the relationship between inventories of beds and homeless populations. Rather, they assume that each additional bed (per 10,000 adult residents) is associated with a fixed percentage change in chronically homeless people (per 10,000 adult residents). Also, their preferred model interacts PSH beds with a linear time trend, allowing the association to change linearly over time. The 0.07 estimated reduction in chronically homeless people associated with a one bed increase in PSH is based on an example used in the paper, which compares hypothetical communities that begin the study period with the median rate of PSH beds and diverge to the 25th and 75th percentile of PSH beds in each year thereafter. Chronic homelessness rates in all years are predicted based on PSH beds and mean values of all other regressors.

[7] Byrne et al. (2014) find that one additional emergency shelter bed per 10,000 adults is associated with a 2.6 percent increase in the chronic homelessness rate, and that one additional transitional housing bed per 10,000 adults is associated with a 1.5 percent increase in the chronic homelessness rate.

3 The Homelessness System and Housing the Homeless

On a given night in January 2014, 578,424 homeless people were counted in the United States, about two-thirds of whom were sheltered (in emergency shelters and transitional housing), with the other one-third sleeping in places not meant for human habitation (U.S. Department of Housing and Urban Development 2014). The homeless are very poor, with average incomes of approximately half of the federal poverty level, and they disproportionately have an array of special needs, with 66 percent reporting problems with alcohol, drugs or mental health (Burt et al. 1999). Spell lengths of homelessness vary substantially, from a few days to years at a time (see, for example, Kuhn and Culhane (1998)). Those who have been homeless for at least a year, or have experienced at least four separate spells of homelessness in the past three years, and have a disability are defined as chronically homeless—17 percent of homeless people on a given night in 2014 met this definition (U.S. Department of Housing and Urban Development 2014).[8]

Communities have traditionally responded to homelessness with three basic forms of assistance—emergency shelter, transitional housing and permanent supportive housing (PSH). Emergency shelter is the final safety net for individuals and families with no other place to go. For individuals, shelters often provide congregate sleeping quarters that are exclusively open during the evening and nighttime hours and do not offer substantive accompanying services. For families, shelters are more likely to provide private or even apartment style living quarters that are open at all hours and offer extensive supportive services (Spellman et al. 2010). In both cases, emergency shelter is generally intended to provide short term stays lasting no longer than several months and typically for much shorter periods.

Transitional housing is used as a longer-term, service-rich residential program to help

[8] An individual is defined as disabled if he or she has any of the following conditions: (i)"a diagnosable substance abuse disorder," (ii) "a serious mental illness," (iii) "a developmental disability" or (iv) "a chronic physical illness or disability, including the co-occurrence of two or more of these conditions."

transition people into permanent housing, build self-sufficiency, and overcome mental health and substance abuse challenges. Services are generally mandatory and offered on site. Accommodations are typically apartment-style where individuals or families receive private rooms or apartments, and stays last from six months up to two years. People living in transitional housing programs are defined as homeless for purposes of counts conducted by the Department of Housing and Urban Development, which are those used in this paper.[9]

PSH is similar to transitional housing, except that there are no limits as to how long people can stay. These programs are encouraged by the federal government to target the chronically homeless and adhere to the Housing First approach, where people are accepted immediately and unconditionally, and with no obligation to engage with supportive services. People living in PSH are not defined as homeless.[10]

Funding sources for these three forms of homeless assistance include the federal, state and local governments and private donors (Burt et al. 1999; Burt et al. 2002). In many programs—particularly transitional housing and PSH—residents pay 30 percent of their total income, including public assistance, toward their rent.[11] Figure 1 shows the number of beds of each type since 2007. Notably, the national inventory of PSH beds rose from just under 190,000 in 2007 to over 300,000 in 2014. Figure 3 shows national homeless counts since 2007. Of the 11 percent decline in total homelessness since 2007, 113 percent is due to the declining street count. And while it is tempting to attribute the decline in street homelessness to the concurrent expansion of PSH, a substantial portion may be due to miscounting (Corinth 2015).

While PSH has the immediate effect of ending spells of homelessness for the people it serves, the long-run effect of an additional PSH bed on the homeless population depends on three factors: (1) how long the person who receives the housing would have otherwise

[9]See Burt (2006) and Gubits et al. (2015) for a more detailed description of transitional housing for families, and Spellman et al. (2010) regarding transitional housing for individuals.

[10]See Burt (2005) for a more detailed description of PSH and Tsemberis, Gulcur and Nakae (2004) for more description of the Housing First approach.

[11]Spellman et al. (2010) decompose costs for each form of assistance for both individuals and families.

remained homeless, (2) how quickly the person transitions from the housing unit into private housing, and (3) the extent to which PSH attracts more people into homelessness or keeps people homeless longer. If the individual placed in PSH stays there longer than he would have otherwise remained homeless, then the long run effect will be less than one in absolute value. If the individual stays in housing for a shorter amount of time than he would have otherwise remained homeless, then the long run effect could be greater than one in absolute value. Even in this case, however, the effect may be muted by incentivizing people to stay homeless longer or entering homelessness in the first place. Three simple examples illustrate how these factors determine the long run effect of PSH:

Example 1 (multiplying effect): The homeless people targeted for housing will be homeless forever unless they receive housing. If an individual is placed into housing, he will stay in it for a year, at which point he permanently moves into private housing. Assuming housing does not attract anyone into homelessness, the cumulative effect on homelessness is one person in the first year, two people in the second year, and N people in the Nth year.

Example 2 (muting effect): The homeless people targeted for housing will exit homelessness after one year if they do not receive housing. If an individual is placed into housing, he will stay there forever. Assuming housing does not attract anyone into homelessness, the cumulative effect on homelessness is one person in the first year, and zero people after the first year.

Example 3 (constant effect): The homeless people targeted for housing will transition into private housing at the same exact time regardless of whether they receive housing. Assuming housing does not attract anyone into homelessness, the cumulative effect on homelessness is one person.

These examples suggest that whether the immediate one-person reduction in homeless-

ness is amplified or muted in the long run depends on whether PSH speeds up or slows down transitions into private housing. Any incentive effect would further mute the long run effect. For a community wishing to maximize the reduction in homelessness, the best individuals to target are those who would otherwise remain homeless for a long time but also will transition relatively quickly from PSH into private housing. The chronically homeless are the best targets only if the ratio of their counterfactual homeless spells to their stays in PSH is larger than this ratio for other segments of the homeless population (assuming no incentive effects). A simple mathematical model in the appendix formally demonstrates this insight.

4 Data and Methodology

Homeless counts are conducted annually by 414 Continuums of Care (CoCs) which span the United States; each CoC is composed of a single city, a single county, a group of counties or an entire state (See Figure 5 for a map of CoC boundaries).[12] As a condition for funding from the U.S. Department of Housing and Urban Development, CoCs are required to conduct counts of their sheltered homeless populations every year and their unsheltered populations in every odd year, although many CoCs conduct both counts every year.[13] Counts are conducted by volunteers on a night of the CoC's choosing during the last two weeks in January.[14] While many CoCs take measures to avoid double-counting or missing individuals on the street, counts are inherently difficult to conduct and may thus be noisy or even biased estimates of the street population (U.S. Department of Housing and Urban Development 2008). Along with counts of the street and sheltered homeless, CoCs must also provide an inventory of all emergency shelter, transitional housing and PSH beds.

[12]The number of CoCs and their geographic boundaries occasionally change based on mergers and consolidations of existing CoCs. For purposes of data analysis, CoCs are combined in years before mergers in order to maintain geographic consistency. For cases in which CoCs add territory previously unallocated to any CoC, years prior to acquisitions for these CoCs are dropped.

[13]In 2014, a non-mandatory even year, 78 percent of CoCs conducted a count of their unsheltered homeless population (U.S. Department of Housing and Urban Development 2014).

[14]There are a relatively few number of exceptions in which CoCs conduct counts in months besides January, typically doing so in February.

Table 1 shows the distribution of CoC homeless counts and bed inventories in 2014. New York City and Los Angeles County have, by far, the largest homeless populations at 67,810 and 34,393 people respectively. Together, they contain 18 percent of the national homeless population. The CoC with the third highest homeless population, Las Vegas/Clark County, counts 9,417 homeless people. The inventory of emergency shelter beds in New York City, which is one of the few locations to guarantee residents a right to shelter, represents 24 percent of the entire national inventory of emergency shelter beds. And while New York City has enough emergency shelter and transitional housing beds for 98 percent of its homeless population, Los Angeles has only 34 percent. As a result, Los Angeles is home to 13 percent of the U.S. unsheltered population. Given the outsized effect New York City and Los Angeles County have on national homeless counts and bed inventories, robustness checks which exclude them from analysis are performed.

Unemployment rates, median rents and climate have been shown in previous research to be important predictors of homelessness, and are thus included as control variables in regressions.[15] Unemployment and housing variables are based on county-level data, and so when CoCs are composed of multiple counties, a population-weighted average is used. Also, multiple CoCs that are contained within a single county are merged for purposes of the analysis. Average count-day temperatures and indicators for the presence of snow and rain are taken from the nearest weather station to the centroid of a given CoC. Summary statistics for all variables are shown in Table 2.

In order to estimate the short and long run relationships between homelessness and the major forms of homeless assistance, I estimate the following equation

$$H_{c,s,t} = \sum_{i=0}^{1}(\alpha_{E,i}E_{c,s,t-i} + \alpha_{T,i}T_{c,s,t-i} + \alpha_{P,i}P_{c,s,t-i} + \beta_i X_{c,s,t-i}) + \delta W_{c,s,t} + \gamma_c + \eta_{s,t} + \epsilon_{c,s,t}$$

[15]The rental vacancy rate has also been shown to predict homelessness; however, a significant number of CoCs are not covered by annual data, and thus, the vacancy rate is excluded from regressions. Unemployment data come from the Bureau of Labor Statistics, median rents come from the Department of Housing and Urban Development, and weather-related variables come from the National Oceanic and Atmosphere Administration—based on the Global Summary of Day dataset.

Here, c denotes a particular CoC, s denotes a particular state and t denotes a particular year. H is the homeless count per 10,000 residents, E is the stock of emergency shelter beds per 10,000 residents, T is the stock of transitional housing beds per 10,000 residents and P is the stock of PSH beds per 10,000 residents. X is a vector of CoC, time-varying control variables including the unemployment rate and the logarithm of the median rent for a two-bedroom apartment. W is a vector of CoC-level, time-varying weather related variables including average temperature and the presence of rain and snow on the day of the count. γ_c denotes CoC fixed effects and $\eta_{s,t}$ denotes year-state effects. Identification thus relies on variation within CoCs controlling for all time-varying state-level factors. Observations are weighted by CoC population as of 2010. Following Byrne et al. (2014), I drop the Detroit, MI and New Orleans, LA CoCs due to problems with their counting methodologies.[16]

In addition to the baseline results for the full sample, I also estimate the main equation under several variations to the sample. These include dropping New York City and Los Angeles due to their outsized influence on national homeless counts and bed inventories, dropping CoCs with a legal right to shelter given the structural endogeneity between shelter beds and homeless populations, and leaving observations unweighted. I also estimate the equation on the full sample, interacting inventories of each type with right-to-shelter status.

Next, I estimate the equation for several mutually exclusive and collectively exhaustive pairs of segments of the homeless population—these include the chronically homeless versus the non-chronically homeless, the sheltered homeless versus the unsheltered homeless, and homeless individuals versus homeless families. PSH often targets the chronically homeless, the unsheltered, and individuals; we would therefore expect relatively stronger negative associations for these subsets of the homeless population. If emergency shelter and transitional housing are effectively targeting people who would otherwise remain on the streets, we would expect to find negative associations between these forms of assistance and unsheltered

[16]Unlike Byrne et al. (2014), I do not drop the Los Angeles, CA CoC in base specifications as counts were retroactively modified in the more recent data I use to resolve major problems (U.S. Department of Housing and Urban Development 2014).

homelessness.[17]

One potentially important factor that could affect estimates of associations between bed inventories and homelessness is migration. A CoC that expands its inventory may experience an inflow of homeless people seeking services or a reduced outflow of homeless people to other CoCs. In either case, the estimated association of the CoC's inventory with the CoC's homeless population will be higher (more positive) than the association of the CoC's inventory with the national homeless population. In order to test whether migration influences associations between inventory types and homelessness, I estimate an equation including the homeless assistance inventory of each type in the rest of the state, per 10,000 people in the rest of the state. This rate reflects the potential availability of inventory in other within-state CoCs. If expanding inventory drives migration, we would expect inventory in the rest of the state to be inversely related to homelessness in a given CoC. Given that rest-of-state inventories may be highly correlated with state-year effects, I replace these with pure year effects for this specification.

5 Results

Baseline regression estimates based on the full sample are shown in Table 3. Specification (1) excludes covariates aside from homeless assistance beds and includes year effects but not year-state effects, specification (2) adds in the additional covariates, and specification (3) adds in the year-state effects.

Across all three specifications, the coefficients on current emergency shelter beds and transitional housing beds are large and positive, implying that adding shelter in which users are defined as homeless is associated with a higher homeless count. The lagged coefficients for both forms of assistance share the same sign as the current year coefficients, implying that they reinforce current associations. The coefficients on PSH, meanwhile, are negative but

[17] Endogenous responses of inventory to homeless populations could of course negate such a relationship. This is discussed further in the discussion section.

small, implying that adding housing assistance in which users are not defined as homeless is associated with a lower contemporaneous homeless population. However, the lagged coefficients on PSH are positive and fully (or almost fully) mute the contemporaneous association, so that the long-run association is near zero or even slightly positive.

Based on the full specification in column (3), adding one emergency shelter bed is associated with a 0.91 long-run increase in the homeless count, and adding one transitional housing bed is associated with a 0.76 long-run increase in the homeless count (long run associations based on all specifications for all inventory types are shown in Table 9). Adding one PSH bed is associated with a 0.12 decrease in the contemporaneous homeless count, but a 0.07 aggregate increase in the count after one year. While the 0.07 long-run increase is not statistically different from zero, we can reject a reduction of larger than 0.08 at the 95 percent confidence level. In other words, a one person long-run reduction in the homeless population is associated with adding at least 12.6 PSH beds.

Other coefficients generally have the expected signs. Based on the full specification, a permanent one percentage point increase in the unemployment rate is associated with a 0.43 person increase in the homeless count per 10,000 people, or a 2.7 percent increase relative to the average homelessness rate. After one year, however, the homelessness rate is only 0.17 people higher, or a 1.1 percent increase. A permanent 10 percent increase in median rent is associated with a 0.70 person increase in the homelessness rate per 10,000 people, or a 4.4 percent increase relative to the average homelessness rate. After one year, the homelessness rate is 1.39 people higher, or an 8.75 percent increase. The long run association between the homelessness rate and the unemployment rate is not statistically different from zero, while the long run association with median rent is statistically different from zero at the 95 percent level. The coefficients on temperature and rain are statistically insignificant, while an indicator for falling snow or ice is significant and associated with a 0.67 person increase in the homelessness rate. It is unclear how extreme weather should affect homeless counts because it may force people from the streets into shelter where they are easier to count, it

may lead people into motels or other places where they will not be counted, or it may lead volunteer counters to spend less time searching for people on the streets.

Results in Table 4 test the robustness of results to several sample exclusions and leaving observations unweighted. The long run associations between homelessness and each inventory type are not substantially changed, although excluding right-to-shelter locations reduces the association with emergency shelter from 0.91 to 0.72.[18] The long run association with PSH remains positive and the muting effect remains at least marginally significant in all except the unweighted specification, in which an additional PSH bed is associated with 0.10 long run reduction in homeless people. Results based on excluding New York City produces results similar to those excluding right-to-shelter locations—given that New York City is by far the largest right-to-shelter location, this is not surprising. Excluding Los Angeles does not meaningfully change results.

Table 6 shows results for various subsets of the homeless population. Notably, emergency shelter is overwhelmingly (positively) associated with the non-chronically homeless and families, subsets of the population much less likely to be found on the streets. Consequentially, an additional emergency shelter bed is associated with just a 0.09 contemporaneous reduction in the unsheltered population, which is fully muted after one year resulting in a 0.03 person increase. Transitional housing is strongly associated with the non-chronically homeless and individuals, and is associated with a 0.12 long run increase in the unsheltered population. PSH has small, positive associations with all segments of the population except for the chronically homeless, for which an additional PSH bed is associated with 0.05 fewer chronically homeless people. Also, there is no muting effect for the chronically homeless, but a strong and significant muting effect for the non-chronically homeless. Finally, median rent is much more important for the non-chronically homeless than the chronically homeless, and is important for both the sheltered and unsheltered, and for both individuals and families.

Results in Table 7 are based on the addition of rest-of-state inventories of beds. Larger

[18] Alternatively, Table 5 shows results based on interacting right-to-shelter status with inventories of each type.

inventories of emergency shelter and transitional housing in the rest of the state are not associated with lower rates of homelessness in a particular CoC. However, there is a significant negative association with PSH beds in the rest of the state. If we consider a hypothetical state consisting of two CoCs with equal populations, an additional PSH bed in one CoC is associated with 0.21 fewer homeless people in the other CoC. This suggests that migration may play a role in the lack of a negative association between PSH and homelessness within a CoC.[19] Surprisingly, however, there is no muting effect based on rest-of-state inventories, while there is a muting effect based on own-state inventories. If anything, we would expect a larger muting effect based on rest-of-state inventories because people placed in PSH in their own CoC and who eventually exit are more likely to provide an opening for a new homeless people from the local CoC. Therefore, the "migration effect" found here may be due more to omitted time-varying state-level factors than actual reductions in homelessness associated with PSH increases in nearby CoCs.

6 Discussion

The extent to which these findings can inform policy depends in large part on the potential endogeneity of homeless assistance inventory. If CoCs respond to larger homeless populations with more inventory, the associations found here will be larger (more positive) than causal effects. For example, PSH could have a large negative effect on homeless counts, but if CoCs respond to larger homeless populations with more PSH beds, then we might not detect it. Thus, it is important to highlight how each inventory type is funded, how it is used, and why its stock changed during the study period.

Emergency shelter and transitional housing programs, first of all, are funded in large part by private donors, which may be less responsive to changes in homeless populations

[19] Table 7 shows results for the same specification for various subsets of the homeless population and suggests that the non-chronically homeless and families are the overwhelming drivers of the "migration effect."

than local governments.[20] And with the exception of the few locations with right-to-shelter laws, CoCs are not required to respond to increased demand. Between 2007 and 2014, there was a 49 percent increase in emergency shelter beds in right-to-shelter locations, and a 7 percent increase everywhere else. Furthermore, emergency shelter and transitional housing are not well-targeted to people who would otherwise be sleeping on the street. A majority of entrants into emergency shelter (82 percent) and transitional housing (89 percent) were not sleeping in unsheltered locations the night prior to entry (U.S. Department of Housing and Urban Development 2015). Unless these forms of assistance are highly effective at identifying people who would otherwise be homeless, communities may be unlikely to respond to greater homeless populations with forms of assistance which are not well-targeted to them. Ultimately, shelters may not be strongly responsive to increases in homeless populations in the majority of communities which have no legal obligation to provide it, with variation in inventories driven more heavily by exogenous factors such as local budgets or costs. And because preferred specifications include interacted state-year effects, state-wide responses to larger homeless populations do not drive the associations found in this paper.

PSH relies heavily on public and especially federal funding (Burt 2005). And while it is possible that CoCs respond to larger homeless populations with more PSH, the 2007–2014 study period was marked by a major policy shift which encouraged more than a 50 percent increase in the national PSH inventory. CoC-specific ten year plans to end homelessness and public campaigns likely drove differential expansions of PSH across CoCs, although the possibility that plans themselves or the magnitude of expansions responded to homelessness increases cannot be ruled out.[21] And again, inclusion of interacted state-year effects controls for state-wide responses to larger homeless populations.

Assuming that most of the variation in homeless assistance inventory was driven by exoge-

[20] Gubits et al. 2015 briefly discuss funding sources for emergency shelter and transitional housing.

[21] Although the timing of ten-year plans could plausibly provide a source of exogenous variation in inventory changes, plans affected full system responses to homelessness beyond PSH. So for example, plans for expanded PSH may have been made in conjunction with plans for reduced shelter beds. Thus, plans, individually, would not qualify as a valid instrument.

nous factors during the 2007–2014 study period—a plausible but not definitive assumption—the associations found here have important implications for homelessness policy. The shift toward permanent housing options in lieu of shelter for the homeless has been driven by a goal of ending homelessness. In terms of the homeless we can find, reductions are heavily attributed to reductions in shelter, but not attributed at all to expansion of housing. A goal of ending homelessness, measured on the basis of homeless counts, should thus be undertaken with serious caution. Cuts to shelter inventory may not significantly increase the number of people found on the street, but cuts could increase the number sleeping in unsheltered locations who are not found by volunteer counters—in abandoned buildings, in their cars, or in temporary accommodations the night of the annual homeless count where they can avoid potential contact with authorities. Others may resort to unsafe housed situations with abusive partners or relatives. Investment in permanent housing may lead to small short-run reductions in homelessness, but if there are no long-run effects, limited funds will be tied up in serving people who otherwise could have escaped homelessness with more temporary assistance. Evaluating success based on ending homelessness also ignores other potential outcomes such as increased employment and improved mental health attained via service-rich shelter programs. The following discussion considers implications of the results for each form of homeless assistance inventory individually.

As the final safety net for people with no place else to go, a vital role of emergency shelter is to prevent people from sleeping on the street. Based on the results in this paper, emergency shelter is strongly and positively associated with overall homeless counts, but only weakly associated with unsheltered homeless counts in the short run, and not at all in the long run. Meanwhile, it is most strongly and positively associated with the non-chronically homeless and families, segments which are least likely to end up on the street.[22] Thus, there is little evidence that the majority of the emergency shelter inventory prevents

[22] The non-chronically homeless make up 70 percent of the unsheltered population, but 92 percent of the sheltered population. Families make up 14 percent of the unsheltered population, but 48 percent of the sheltered population (U.S. Department of Housing and Urban Development 2014).

unsheltered homelessness—at least that which is measured by counts of the homeless and defined by the Department of Housing and Urban Development. Large, targeted cuts to the inventory of emergency shelter may lead to a significant decrease in homelessness without a significant increase in people found sleeping on the street. However, emergency shelters may nonetheless play vital roles in shielding vulnerable individuals and families from harmful or crowded living environments (or even unsheltered locations not found by volunteer counters), and in providing other valuable social services to families.

Transitional housing is more heavily associated with individuals than families, a demographic more likely to show up on the streets within the homeless population. However, transitional housing is similarly strongly and positively related to sheltered homelessness, and is not negatively associated with unsheltered homelessness. Therefore, cuts to transitional housing programs are unlikely to significantly increase the unsheltered homeless population. But given the mission of many transitional housing programs to help people achieve self-sufficiency and overcome substance abuse and mental health challenges, homelessness reductions may not capture their full potential value.

Permanent supportive housing has arguably represented the central strategy for ending homelessness over the past decade. However, an additional PSH bed is associated with only a 0.12 contemporaneous reduction in the homeless count, which is fully muted after one year so that there is no associated long-run reduction. There are several potential explanations for why an additional PSH bed does not decrease homelessness on a one-for-one basis. These include (i) a muting effect, (ii) biased street counts, and (iii) migration.

First, the lack of a long-run negative association between PSH and homelessness could be explained by a strong muting effect. The basic model presented earlier demonstrates that the long-run effect can be less than one if people stay in PSH for a lengthier amount of time than they would have otherwise remained homeless. Consistent with the muting effect explanation, I find that the modest negative contemporaneous association (-0.12) is fully muted after one year. Moreover, this muting effect is fully driven by the non-chronically

homeless, individuals who may be less likely to stay homeless without assistance. However, since 2007, 51 percent of new PSH beds have been targeted to the chronically homeless (see Figure 4). And nonetheless, the contemporaneous association between PSH beds and the chronically homeless is only -0.04, with a long run association of -0.05, neither of which is statistically different from zero. Even if the chronically homeless are not subject to a strong muting effect (which cannot be ruled out), it remains to be explained why their short run association with PSH is approximately ten times smaller than the rate at which new PSH beds are targeted to them.

The other potential explanation for a muting effect is that additional PSH induces people to enter homelessness or remain homeless longer. For example, people may exert less effort to exit homelessness on their own if they believe they are likely to receive PSH in the near future. Or alternatively, newly opened beds in shelters caused by placement of sheltered homeless individuals into PSH might be offered to people who would not otherwise be homeless. This would quickly and strongly mute the immediate one-person reduction in homelessness caused by the PSH placement, and is consistent with the lack of any contemporaneous association between PSH and sheltered homelessness.

Aside from a muting effect, the second potential explanation for the lack of a long-run negative association between PSH and homelessness is that street counts are highly flawed.[23] In particular, there may be a less than one probability that a given individual is enumerated by volunteer counters. In this case, both contemporaneous and long run reductions in homelessness would be biased toward zero, because any person placed from the street into PSH might not have otherwise been found. However, I find a -0.13 contemporaneous reduction in the street count for each additional PSH bed which is only fully muted after one year—this muting effect is not consistent with an explanation fully based on uninformative street counts. Still, it is possible that the chronically homeless who sleep on the streets are particularly difficult to count, and such a story could explain the extremely modest association

[23] Corinth (2015) argues that miscounting of the street homeless is a major explanation for the national reduction during this study period.

for this subpopulation.

The third potential explanation for the lack of a long-run negative association between PSH and homelessness is that migration across CoCs masks it. If expanded PSH induces homeless migration from other CoCs—or reduces migration out of the CoC—then the association between PSH within a CoC and its own homeless population will be smaller than that with the national homeless population. Indeed, I find PSH in the rest of the state is negatively associated with the homeless population within a particular CoC. However, the lack of a muting effect for rest-of-state inventory suggests that omitted state-year effects, rather than migration, may be driving this association. Moreover, the "migration" effect for the chronically homeless is small, and cannot explain the small association between PSH and the chronically homeless population.

Ultimately, the lack of an association between PSH and homeless populations is likely driven by a combination of these explanations—a muting effect driven by placement of the non-chronically homeless into PSH, the pull of otherwise not homeless people into shelters when the sheltered homeless are offered beds in PSH, flawed street counts of the homeless, and perhaps to a limited extent, migration. Of course, endogenous PSH expansion in response to higher homeless populations may play a role as well. There are several important policy implications of these findings and explanations. First, PSH must be targeted appropriately to those who are least likely to escape homelessness on their own in order to avoid full muting effects. Recent emphasis from the federal government on targeting the chronically homeless, and new coordinated entry systems are likely to improve effectiveness. Second, even when PSH is well-targeted, measuring its effectiveness based on reduced homeless counts should be undertaken with extreme caution. PSH tenants who would otherwise be sleeping on the street may have been missed by flawed street counts, and so no homelessness reduction would be measured. PSH tenants who would otherwise be sleeping in shelters may be replaced by someone who would have otherwise been housed, again resulting in no change in the homeless count. Unless intake criteria for shelters are static and

street counts are highly correlated with actual street populations, CoCs should not expect significant reductions in homelessness due to expansion of PSH.

Even if homeless counts were perfect and intake criteria were fully static, however, there is still no affirmative evidence in this paper that well-targeted PSH would substantially reduce homelessness in the long run. A full muting effect for the chronically homeless cannot be rejected at any level of statistical significance, and the small negative contemporaneous association with PSH could be explained by incentives for lengthier spells of homelessness in addition to any muting effect that occurs within the first year. Local and national plans to end homelessness should therefore be modest about how PSH will affect homeless counts as well as true homeless populations.[24]

Aside from results on homeless assistance, this paper provides new evidence on other factors associated with homelessness. As the first study to exploit within-community variation using panel data from across the United States, I confirm the importance of housing prices established in cross-sectional and time-series studies—I find that a 10 percent increase in median rent is associated with a contemporaneous 4 percent increase in homelessness, which grows to 9 percent after one year. This finding provides additional support to the theory that the cost of housing is a major determinant of homelessness. Meanwhile, associations with unemployment rates and weather are generally smaller and insignificant.

7 Conclusion

The results in this paper suggest that measuring the effectiveness of homeless services based on homeless counts should be undertaken with serious caution. Changes in homeless counts are more likely to reflect changes in the inventory of beds counted as homeless than how effective they are at assisting individuals or families. There is no evidence that emergency shelters and transitional housing programs prevent a significant number people from

[24]For example, the Supportive Housing Opportunities Planner (SHOP) Tool, produced by the U.S. Interagency Council on Homelessness, assumes a one-for-one effect of PSH for the chronically homeless on their population in the first year, which is amplified in future years.

being found on the street, although they may be extremely important in serving people who would otherwise live in harmful environments—such as with abusive partners, or potentially in locations not meant for human habitation (e.g., cars) but not encountered during street counts. Permanent supportive housing, meanwhile, is not associated with any long-run reduction in homelessness. The muting effect driven by the non-chronically homeless suggests that PSH should be better targeted to the chronically homeless, although the lack of affirmative evidence that PSH reduces even the chronically homeless population suggests that plans to end chronic homelessness using PSH should be more modest. This is also the first paper to rely on variation within communities across the United States to estimate associations between economic factors and homelessness. Housing prices are strongly associated with homelessness, confirming research based on cross-sectional and time-series studies.

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Appendix

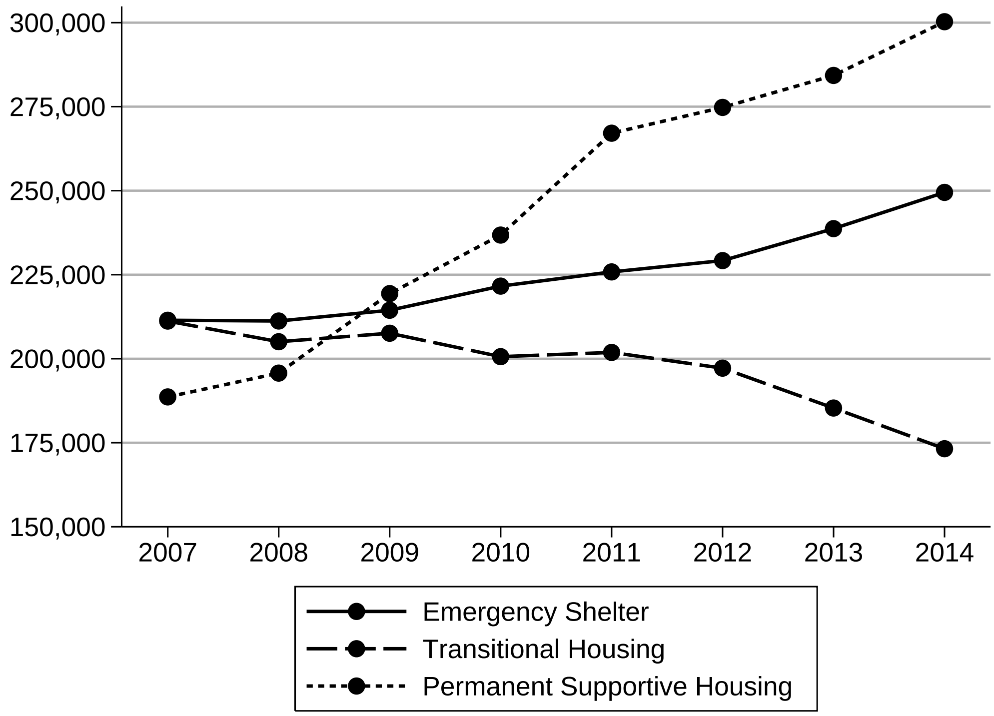

Figure 1: U.S. Inventory of Homeless Assistance Beds by Type, 2007–2014

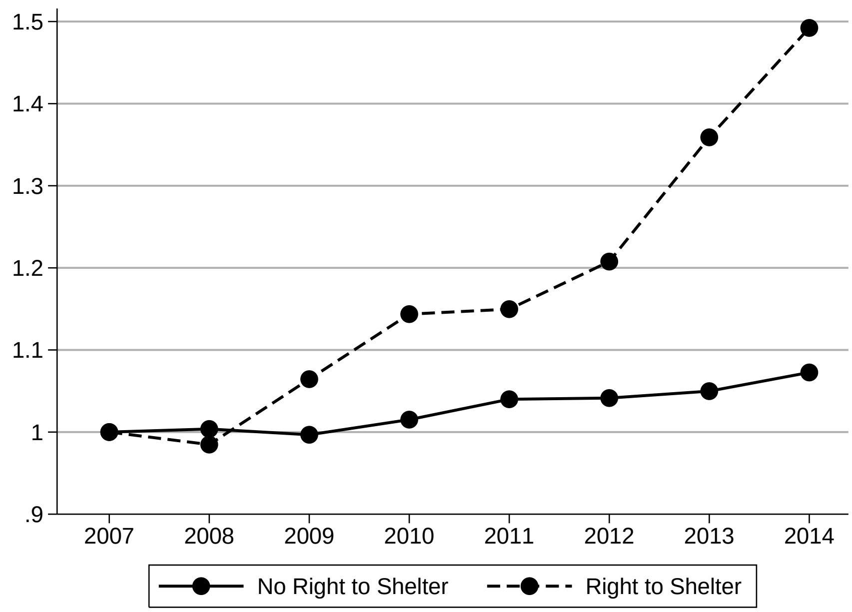

Figure 2: Relative Inventory of Emergency Shelter Beds by Right-to-Shelter Status, 2007–2014

Note: The vertical axis denotes the inventory of emergency shelter beds in a given year relative to the inventory in 2007. CoCs identified as having a right-to-shelter include New York, NY; Washington, DC; Hennepin County, MN; Columbus, OH; the state of Massachusetts; and Montgomery County, MD. Locations are identified based on Leopold (2014) and confirmed by official city and state websites listed in Corinth (2015).

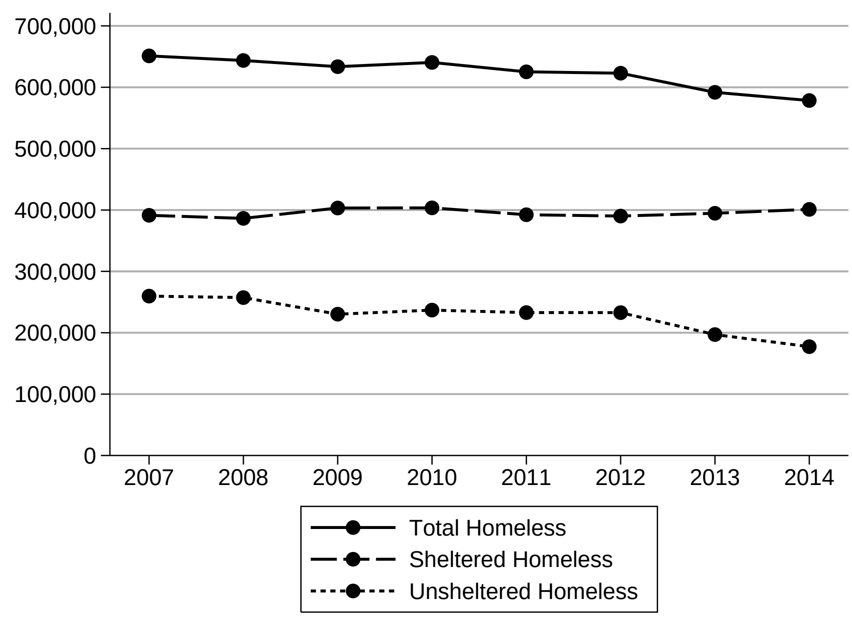

Figure 3: U.S. Homeless Point-in-Time Count, 2007–2014

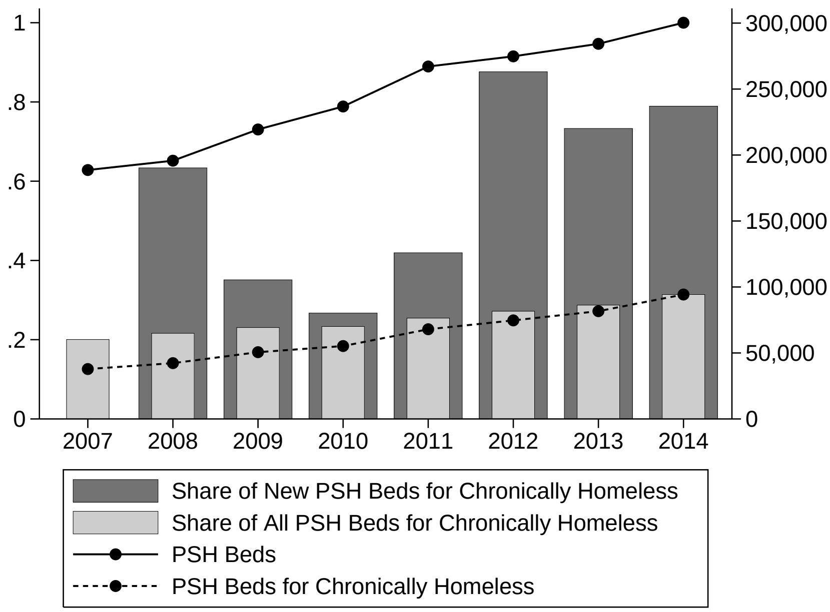

Figure 4: Inventory of PSH Beds for Chronically Homeless, 2007–2014

Source: HUD Annual Homeless Assessment Report, 2014
Note: Share of all PSH beds for chronically homeless is calculated by dividing PSH beds targeted to chronically homeless by total PSH beds. Share of new PSH beds for chronically homeless is calculated by dividing the change in PSH beds targeted to chronically homeless by the change in total PSH beds.

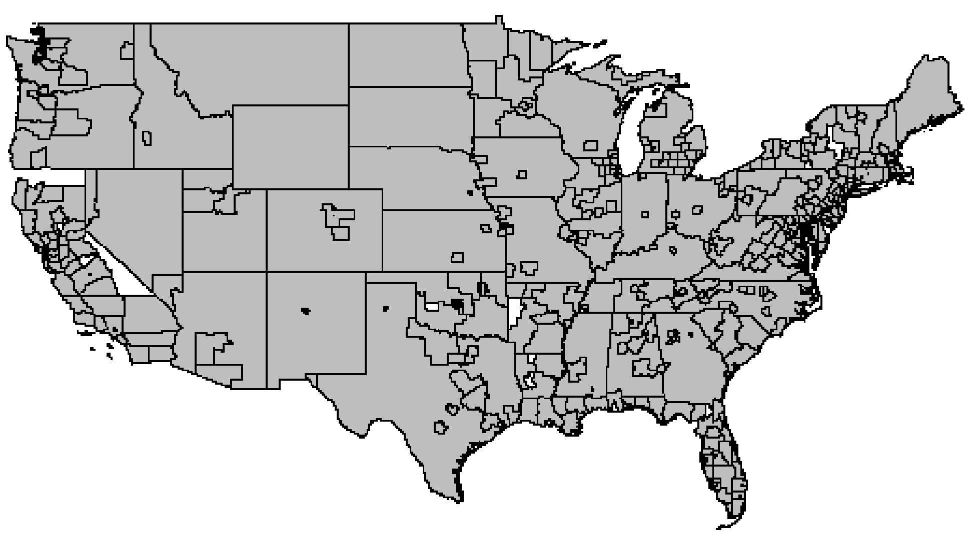

Figure 5: Continuum of Care Boundaries

Source: HUD CoC Shapefiles, 2013

Table 1: Distribution of Homeless Counts and Homeless Assistance Bed Inventories, 2014

Continuum of Care (CoC)	State	Homeless Count	Emerg. Shelter	Trans. Housing	Perm. Supp. Housing
New York City	NY	67,810	61,056	5,454	21,813
Los Angeles City & County	CA	34,393	4,798	7,023	12,846
Las Vegas/Clark County	NV	9,417	2,852	1,115	2,167
Seattle/King County	WA	8,949	2,754	3,865	4,687
Texas Balance of State (BoS)	TX	8,903	4,014	1,649	1,177
San Diego City and County	CA	8,506	524	3,948	2,914
District of Columbia	DC	7,748	5,157	2,124	6,414
Georgia Balance of State	GA	7,577	1,526	1,230	2,134
San Jose/Santa Clara City & County	CA	7,567	593	1,141	3,683
Metropolitan Denver Homeless Initiative	CO	6,621	2,492	3,159	2,007
San Francisco	CA	6,408	1,657	575	6,843
Chicago	IL	6,287	2,048	3,902	8,406
Boston	MA	5,987	4,849	1,313	6,042
Phoenix/Mesa/Maricopa County Regional	AZ	5,918	2,722	2,837	5,455
Philadelphia	PA	5,738	3,644	1,929	4,602
Santa Rosa/Petaluma/Sonoma County	CA	3,879	557	418	804
.					
.					
Mendocino County	CA	1,404	103	87	441
(75th Percentile)					
.					
.					
Albany City & County	NY	650	318	165	829
(50th Percentile)					
.					
.					
Columbus-Muscogee/Russell County	GA	312	184	42	168
(25th Percentile)					
.					
.					
Ithaca/Tompkins County	NY	47	19	26	45
Salem County	NJ	42	27	30	75
Cattaragus County	NY	18	29	17	50
Boone, Baxter, Marion, Newton Counties	AR	28	28	0	0
Garrett County	MD	13	21	9	24

Note: CoC counts and inventories are based on their official 2014 boundaries—prior to merging multiple CoCs within a given county.

Table 2: Summary Statistics, 2007–2014

Variable	Mean	Std. Dev. (overall).	Std. Dev. (within CoC)
Homeless counts per 10,000 residents			
Total	15.87	17.26	5.14
Chronically homeless	2.43	3.90	1.74
Non-chronically homeless	13.44	14.67	4.52
Sheltered	10.77	12.57	2.57
Unsheltered	5.10	9.87	4.43
Individuals	9.60	11.01	3.56
Members of families	6.27	8.49	2.94
Bed Inventories per 10,000 residents			
Emergency shelter	5.95	9.21	1.74
Transitional housing	5.23	5.07	1.57
Permanent supportive housing	6.57	8.81	2.43
Other variables			
Unemployment Rate (percent)	7.28	2.53	1.97
Median rent for 2 bedroom apartment (dollars)	983.96	298.42	70.90
Average count-day temperature (degrees Fahrenheit)	34.60	15.97	9.09
Rain on count-day (0=No, 1=Yes)	0.24	0.41	0.38
Falling snow/ice on count-day (0=No, 1=Yes)	0.26	0.43	0.34

Note: All estimates are based on the period 2007–2014, and are weighted based on 2010 CoC populations.

Table 3: Base Results

	Specification 1	Specification 2	Specification 3
Emergency shelter beds	0.791***	0.777***	0.786***
per 10,000 residents	(0.153)	(0.151)	(0.209)
Lagged one year	0.199	0.207	0.120
	(0.183)	(0.182)	(0.198)
Transitional housing beds	0.805***	0.779***	0.734***
per 10,000 residents	(0.120)	(0.112)	(0.0931)
Lagged one year	0.0421	0.0501	0.0260
	(0.0922)	(0.0983)	(0.0880)
Permanent supportive housing bed	-0.125*	-0.142*	-0.118
per 10,000 residents	(0.0710)	(0.0805)	(0.0801)
Lagged one year	0.122	0.151	0.187**
	(0.0929)	(0.0982)	(0.0787)
Unemployment rate		0.879***	0.425
		(0.296)	(0.415)
Lagged one year		-0.720***	-0.257
		(0.238)	(0.386)
Logarithm of median rent		3.298	7.383
		(3.159)	(4.744)
Lagged one year		-1.988	7.181
		(3.962)	(6.302)
Average count-day temperature		-0.0145	0.00943
		(0.0130)	(0.0225)
Rain on count-day		-0.112	-0.550
		(0.260)	(0.418)
Falling snow/ice on count-day		-0.121	0.665**
		(0.185)	(0.277)
Year*State Effects			X
Observations	2,035	2,001	1,943
Groups	385	381	374
R^2 (within)	0.240	0.261	0.364
R^2 (overall)	0.443	0.462	0.409

Dependent variable is homeless count per 10,000 residents. Observations are weighted based on 2010 CoC population estimates. Homeless counts and bed inventories are generally conducted simultaneously during the month of January. The current unemployment rate and median rent are based on values for the previous year, and lagged values are based on values for the year prior. Weather-related variables are based on readings at the nearest weather station to each CoC centroid during a particular year. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 4: Results Excluding New York City, Right-to-Shelter Communities, and Unweighted

	Excluding NYC	Exluding LA	Excluding NYC & LA	Excluding Right-to-Shelter	Unweighted
Emergency shelter beds per 10,000 residents	0.710**	0.789***	0.710**	0.677**	0.905***
	(0.294)	(0.209)	(0.295)	(0.303)	(0.340)
Lagged one year	0.0616	0.113	0.0546	0.0454	0.00534
	(0.179)	(0.198)	(0.179)	(0.181)	(0.194)
Transitional housing beds per 10,000 residents	0.783***	0.749***	0.788***	0.763***	1.060***
	(0.0890)	(0.0913)	(0.0893)	(0.0898)	(0.180)
Lagged one year	-0.0305	0.0341	-0.0180	-0.0406	0.0518
	(0.0867)	(0.0873)	(0.0876)	(0.0867)	(0.185)
Permanent supportive housing beds per 10,000 residents	-0.144*	-0.0605	-0.0919	-0.152*	-0.150*
	(0.0870)	(0.0798)	(0.0914)	(0.0883)	(0.0833)
Lagged one year	0.242***	0.126*	0.188**	0.252***	0.0522
	(0.0776)	(0.0749)	(0.0777)	(0.0772)	(0.102)
Unemployment rate	0.373	0.443	0.385	0.510	-0.780
	(0.437)	(0.416)	(0.437)	(0.469)	(0.607)
Lagged one year	-0.159	-0.340	-0.233	-0.159	0.320
	(0.403)	(0.375)	(0.390)	(0.424)	(0.556)
Logarithm of median rent	6.501	7.196	6.399	5.978	9.628
	(4.799)	(4.739)	(4.793)	(5.384)	(8.817)
Lagged one year	7.019	7.859	7.524	8.343	-7.488
	(6.379)	(6.265)	(6.321)	(7.331)	(12.10)
Average count-day temperature	-0.00228	0.0122	0.000277	-0.00234	-0.00391
	(0.0226)	(0.0227)	(0.0228)	(0.0236)	(0.0308)
Rain on count-day	-0.574	-0.571	-0.585	-0.630	-0.792
	(0.427)	(0.418)	(0.428)	(0.457)	(0.557)
Falling snow/ice on count-day	0.479*	0.679**	0.495*	0.411	0.624
	(0.271)	(0.274)	(0.270)	(0.310)	(0.393)
Year*State Effects	X	X	X	X	X
Observations	1,936	1,940	1,933	1,867	1,943
Groups	373	373	372	361	374
R^2 (within)	0.273	0.366	0.274	0.272	0.267
R^2 (overall)	0.370	0.407	0.375	0.237	0.390

These results are based on specification (3) from the baseline results, except that the first column omits the New York City CoC, the second column omits all CoCs in Los Angeles County, the third column omits New York City and Los Angeles, the fourth column omits all locations with a right-to-shelter, and the fifth column includes all observations but leaves them unweighted. CoCs identified as having a right-to-shelter include New York, NY; Washington, DC; Hennepin County, MN; Columbus, OH; the state of Massachusetts; and Montgomery County, MD. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 5: Interacting Right-to-Shelter Status with Inventories

		Interactions
Emergency shelter beds	0.663**	0.0723
per 10,000 residents	(0.303)	(0.336)
Lagged one year	0.0569	0.299
	(0.182)	(0.263)
Transitional housing beds	0.756***	0.658
per 10,000 residents	(0.0906)	(0.567)
Lagged one year	-0.0287	0.846*
	(0.0875)	(0.445)
Permanent supportive housing beds	-0.153*	0.448***
per 10,000 residents	(0.0892)	(0.169)
Lagged one year	0.250***	-0.296**
	(0.0780)	(0.145)
Unemployment rate	0.419	
	(0.417)	
Lagged one year	-0.315	
	(0.395)	
Logarithm of median rent	6.685	
	(4.780)	
Lagged one year	7.553	
	(6.391)	
Average count-day temperature	0.00548	
	(0.0229)	
Rain on count-day	-0.527	
	(0.424)	
Falling snow/ice on count-day	0.606**	
	(0.280)	
Year*State Effects	X	
Observations	1,943	
Groups	374	
R^2 (within)	0.370	
R^2 (overall)	0.390	

These results are based on specification (3) from the baseline result, except that this specification includes interactions between CoC right-to-shelter status and inventories of homeless assistance bed types. CoCs identified as having a right-to-shelter include New York, NY; Washington, DC; Hennepin County, MN; Columbus, OH; the state of Massachusetts; and Montgomery County, MD. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 6: Results by Subsets of Homeless Population

	Chronic status		Sheltered status		Family status	
	Chronic	Non-chronic	Sheltered	Unsheltered	Individuals	Families
Emergency shelter beds per 10,000 residents	0.0266	0.760***	0.880***	-0.0942	0.223***	0.563***
	(0.0449)	(0.205)	(0.181)	(0.0853)	(0.0809)	(0.186)
Lagged one year	-0.0149	0.135	-0.00691	0.127	0.133	-0.0127
	(0.0545)	(0.195)	(0.158)	(0.0983)	(0.0893)	(0.161)
Transitional housing beds per 10,000 residents	0.0893**	0.645***	0.657***	0.0775	0.468***	0.267***
	(0.0429)	(0.0888)	(0.0685)	(0.0661)	(0.0733)	(0.0679)
Lagged one year	0.0304	-0.00443	-0.0181	0.0440	0.0217	0.00421
	(0.0494)	(0.0878)	(0.0599)	(0.0728)	(0.0703)	(0.0584)
Permanent supportive housing beds per 10,000 residents	-0.0436	-0.0740	0.00834	-0.126	-0.0856	-0.0321
	(0.0309)	(0.0681)	(0.0304)	(0.0790)	(0.0558)	(0.0443)
Lagged one year	-0.00993	0.197**	0.0305	0.157**	0.0914*	0.0961
	(0.0430)	(0.0780)	(0.0367)	(0.0706)	(0.0546)	(0.0592)
Unemployment rate	0.0915	0.334	-0.00583	0.431	0.0924	0.333
	(0.142)	(0.419)	(0.189)	(0.405)	(0.273)	(0.296)
Lagged one year	0.0611	-0.318	-0.0987	-0.158	0.0882	-0.345
	(0.187)	(0.356)	(0.183)	(0.352)	(0.349)	(0.243)
Logarithm of median rent	0.819	6.564	2.565	4.818	3.398	3.985*
	(1.503)	(4.620)	(1.923)	(4.338)	(3.769)	(2.234)
Lagged one year	2.523	4.658	2.118	5.063	5.095	2.085
	(1.882)	(5.688)	(2.632)	(6.147)	(4.023)	(4.592)
Average count-day temperature	0.00108	0.00835	0.0127	-0.00330	0.00939	0.0000449
	(0.00597)	(0.0205)	(0.0103)	(0.0205)	(0.0142)	(0.0172)
Rain on count-day	-0.120	-0.430	-0.0159	-0.534	-0.523*	-0.0268
	(0.171)	(0.408)	(0.184)	(0.392)	(0.296)	(0.257)
Falling snow/ice on count-day	0.0942	0.571**	0.410**	0.256	0.370**	0.295
	(0.0727)	(0.259)	(0.179)	(0.197)	(0.164)	(0.210)
Year*State Effects	X	X	X	X	X	X
Observations	1,943	1,943	1,943	1,943	1,943	1,943
Groups	374	374	374	374	374	374
R^2 (within)	0.213	0.345	0.614	0.157	0.296	0.286
R^2 (overall)	0.0558	0.386	0.760	0.0577	0.376	0.236

These results are based on specification (3) from the baseline results, except that each pair of columns restricts analysis to mutually exclusive and collectively exhaustive subsets. The first pair of columns is restricted on the basis of whether people are chronically homeless, the second pair on the basis of whether people are sheltered or unsheltered, and the third pair on the basis of whether people are homeless as individuals or as members of families. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 7: Results Including Rest-of-State Inventory

	Own State	Rest-of-State
Emergency shelter beds	0.744***	0.118
per 10,000 residents	(0.167)	(0.111)
Lagged one year	0.222	-0.0415
	(0.194)	(0.147)
Transitional housing beds	0.789***	0.0461
per 10,000 residents	(0.107)	(0.0745)
Lagged one year	0.0587	0.0820
	(0.0975)	(0.0909)
Permanent supportive housing beds	-0.159*	-0.201**
per 10,000 residents	(0.0829)	(0.0808)
Lagged one year	0.143	0.00828
	(0.110)	(0.0941)
Unemployment rate	0.890***	
	(0.309)	
Lagged one year	-0.658***	
	(0.251)	
Logarithm of median rent	3.827	
	(3.145)	
Lagged one year	-2.195	
	(4.163)	
Average count-day temperature	-0.00523	
	(0.0130)	
Rain on count-day	-0.113	
	(0.269)	
Falling snow/ice on count-day	-0.0329	
	(0.177)	
Observations	1,953	
Groups	374	
R^2 (within)	0.267	
R^2 (overall)	0.429	

These results are based on specification (2) from the baseline results (which omits state-year effects), except that this specification includes rest-of-state inventories of homeless assistance bed types. Rest-of-state inventory rates are calculated by summing all beds of a given type in the state except for the CoC in question, dividing by the population in the rest of the state, and multiplying by 10,000. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 8: Results by Subset of Homeless, Including Rest-of-State Inventory

	Chronic status		Sheltered status		Family status	
	Chronic	Non-chronic	Sheltered	Unsheltered	Individuals	Families
Own-state inventory						
Emergency shelter beds per 10,000 residents	-0.00144	0.745***	0.871***	-0.128*	0.200***	0.544***
	(0.0417)	(0.166)	(0.133)	(0.0768)	(0.0687)	(0.142)
Lagged one year	-0.00170	0.224	0.0278	0.194*	0.187**	0.0350
	(0.0481)	(0.187)	(0.134)	(0.115)	(0.0946)	(0.155)
Transitional housing beds per 10,000 residents	0.119**	0.670***	0.692***	0.0969*	0.516***	0.273***
	(0.0494)	(0.0877)	(0.0769)	(0.0556)	(0.108)	(0.0713)
Lagged one year	0.0214	0.0373	-0.00111	0.0599	-0.000137	0.0589
	(0.0436)	(0.0895)	(0.0594)	(0.0732)	(0.0692)	(0.0726)
Permanent supportive housing beds per 10,000 residents	-0.0672**	-0.0916	-0.0189	-0.140*	-0.126***	-0.0332
	(0.0267)	(0.0712)	(0.0287)	(0.0749)	(0.0470)	(0.0501)
Lagged one year	-0.0247	0.167	0.0113	0.131*	0.0668*	0.0759
	(0.0309)	(0.103)	(0.0554)	(0.0725)	(0.0345)	(0.0920)
Rest-of-state inventory						
Emergency shelter beds per 10,000 residents	0.0243	0.0939	0.0285	0.0898	0.112	0.00672
	(0.0277)	(0.103)	(0.0763)	(0.100)	(0.0879)	(0.0636)
Lagged one year	-0.0345	-0.00703	0.0172	-0.0587	-0.104	0.0621
	(0.0436)	(0.137)	(0.0906)	(0.136)	(0.123)	(0.0786)
Transitional housing beds per 10,000 residents	-0.0154	0.0616	-0.0601	0.106	-0.0684	0.115**
	(0.0280)	(0.0715)	(0.0502)	(0.0728)	(0.0589)	(0.0530)
Lagged one year	0.0513*	0.0307	0.0390	0.0430	0.0581	0.0239
	(0.0274)	(0.0741)	(0.0364)	(0.0893)	(0.0591)	(0.0671)
Permanent supportive housing beds per 10,000 residents	-0.0329	-0.168**	-0.105***	-0.0959	-0.0535	-0.148***
	(0.0352)	(0.0712)	(0.0377)	(0.0767)	(0.0618)	(0.0511)
Lagged one year	-0.00999	0.0183	0.0148	-0.00649	0.0603	-0.0520
	(0.0555)	(0.0807)	(0.0418)	(0.0956)	(0.0820)	(0.0591)
Year*State Effects	X	X	X	X	X	X
Observations	1,953	1,953	1,953	1,953	1,953	1,953
Groups	374	374	374	374	374	374
R^2 (within)	0.105	0.252	0.541	0.0570	0.177	0.189
R^2 (overall)	0.0123	0.398	0.758	0.0928	0.372	0.239

These results are based on specification (3) from the baseline results, except that each pair of columns restricts analysis to mutually exclusive and collectively exhaustive subsets, and rest-of-state inventory rates are included as additional regressors. The first pair of columns is restricted on the basis of whether people are chronically homeless, the second pair on the basis of whether people are sheltered or unsheltered, and the third pair on the basis of whether people are homeless as individuals or as members of families. Data are based on the period 2007–2014. Robust standard errors are shown in parenthesis. * indicates significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level.

Table 9: Estimates of Total Association between Inventory Types and Homeless Counts

Specification	Description	Emergency Shelter	Transitional Housing	Permanent Supportive Housing
Baseline Results				
(1)	Excludes unemployment, rent and temperature	**.989** (.061)	**.847** (.115)	**-.003** (.074)
(2)	Includes above, excludes year*state effects	**.984** (.059)	**.830** (.111)	**.009** (.073)
(3)	Includes above	**.907** (.174)	**.760** (.098)	**.070** (.078)
Selected Samples and Weighting				
(3)	Excludes New York City	**.771** (.174)	**.753** (.098)	**.099** (.078)
(3)	Excludes Los Angeles	**.902** (.073)	**.783** (.095)	**.066** (.077)
(3)	Excludes New York City and Los Angeles	**.765** (.175)	**.770** (.098)	**.096** (.079)
(3)	Excludes right-to-shelter locations	**.723** (.177)	**.723** (.091)	**.100** (.076)
(3)	Unweighted	**.911** (.207)	**1.112** (.282)	**-.097** (.127)
Interact with Right-to-Shelter Status				
(3)	No right-to-shelter	**.720** (.176)	**.727** (.091)	**.096** (.077)
	Right-to-shelter	**1.091** (.087)	**2.231** (.865)	**.248** (.182)
Subset Analysis				
(3)	Chronically homeless	**.012** (.024)	**.120** (.046)	**-.054** (.041)
(3)	Non-chronically homeless	**.895** (.076)	**.641** (.085)	**.123** (.077)
(3)	Sheltered	**.873** (.053)	**.639** (.066)	**.039** (.046)
(3)	Unsheltered	**.033** (.049)	**.122** (.076)	**.031** (.074)
(3)	Individuals	**.356** (.051)	**.489** (.080)	**.006** (.054)
(3)	Families	**.550** (.058)	**.271** (.070)	**.064** (.056)
Include Rest-of-State Inventory				
(2)	Includes rest-of-state inventory	**.965** (.060)	**.847** (.106)	**-.016** (.087)

Estimates are the sum of current and lagged estimates on the association between each form of assistance and homeless counts. Standard errors are shown in parenthesis. Estimates corresponding to all results in previous tables (with the exception of Table 8) are shown.

A Simple Model of Housing the Homeless

The immediate effect of adding a PSH bed is straightforward; if homeless people can be effectively targeted, then putting the homeless individual into a PSH bed will reduce homelessness by one person. The long-run effect, however, can be larger or smaller (in absolute value) for a couple reasons. First, if being placed in PSH changes the rate at which an individual transitions into private housing, the long-run effect on homelessness will change as well. If PSH increases the transition rate, then the long-run effect will be greater than one, but if PSH decreases the transition rate, then the long-run effect will be less than one. For example, if PSH only housed people who had no chance of ever transitioning to private housing on their own, then the long term effect would be bounded below by one, since homelessness is forever decreased by that one person. The speed at which PSH transitions people into private housing would determine how much larger than one this long-run effect is, since more people are taken out of homelessness each time the PSH bed opens up. Second, PSH may affect people not receiving it. PSH is intended to draw exclusively from the homeless population, and thus, a homeless individual who may have transitioned into private housing may be induced into staying homeless longer in hopes of obtaining a PSH bed. Additionally, more people may enter homelessness in the first place to obtain future access to PSH.

For purposes of the model, suppose there are three possible states—private housing, homelessness, and PSH. Movement between all three states is allowed with two exceptions—people cannot transition directly from private housing into PSH (since PSH draws only from the homeless population), and people cannot transition directly from PSH into homelessness (since PSH has no time limit). Newly opened PSH beds are allocated randomly to the pool of homeless people. For notation, let H_t denote the stock of homeless individuals, and let P_t denote the stock of PSH beds. Also, let r_H denote the rate at which individuals transition from homelessness into private housing, and r_P the rate at which people transition from PSH into private housing. Timing commences as follows:

- Period t begins
- PSH beds are added to or removed from inventory
- Current PSH users transition into private housing with probability r_P
- Homeless people are randomly selected for PSH openings
- Remaining homeless people transition into private housing with probability r_H
- People in private housing transition into homelessness
- Count of H_t is conducted
- Period t ends

Given this timing convention, the number of homeless people at time t is given by

$$H_t = N_t + (1 - r_H)(H_{t-1} - \Delta P_t - r_P P_{t-1}) \tag{1}$$

where N_t denotes the number of new homeless individuals. The number of new homeless individuals each period is allowed to depend on the stock of PSH, and is given by the function

$$N_t = \bar{N} + \alpha r_P P_t \tag{2}$$

where α captures the responsiveness of new homelessness to beds which will open up in the next period due to current PSH users transitioning into private housing. It is assumed that newly homeless people are not eligible for PSH immediately, and so the proportion of PSH which is newly constructed is irrelevant. Also, the change in the stock of PSH beds in the next period is assumed to have expectation zero.

The transition rate from homelessness into private housing also depends on the availability of PSH, as people may be induced to remain homeless longer in order to gain admission

to PSH. I assume the transition rate r_H is a linear function of the odds of receiving PSH.[25]

$$r_H = \bar{r}_H + \beta \frac{\Delta P_t + r_P P_{t-1}}{H_{t-1} - \Delta P_t - r_P P_{t-1}} \tag{3}$$

In this case, β captures the responsiveness of an individual's probability of exiting homelessness to the odds of obtaining of newly available PSH beds—both those which are newly constructed and those which have opened up due to previous users exiting into private housing.

Substituting the expressions for N_t and r_H into the expression for the homeless population, we get

$$H_t = \bar{N} + \alpha r_P P_t + (1 - \bar{r}_H)(H_{t-1} - \Delta P_t - r_P P_{t-1}) - \beta(\Delta P_t + r_P P_{t-1}) \tag{4}$$

Taking the derivative with respect to P_t, we see that the short-run effect of a one bed increase in PSH inventory is given by

$$\frac{dH_t}{dP_t} = \alpha r_P - 1 + \bar{r}_H - \beta \tag{5}$$

If incentive effects are zero ($\alpha = \beta = 0$), then the short-run effect is still less than one in absolute value since the placed individual may have exited homelessness on his own before the end of the period. Nonzero incentive effects decrease the short-run effect even further. We can also examine the longer term effects of a permanent increase in PSH inventory from a steady state equation for the number of homeless.

$$H = \bar{N} + \alpha r_P P + (1 - \bar{r}_H)(H - r_P P) - \beta r_P P \tag{6}$$

[25] The transition rate from homelessness into private housing is assumed to be linear in the odds of receiving PSH, and not the probability, for mathematical convenience. It is unclear which functional form assumption is more realistic, although both should be similar given that newly available PSH beds are generally small relative to the homeless population.

The marginal effect of a one bed increase in PSH inventory at time T on homelessness at time $T+t$ is given by

$$\frac{dH_{T+t}}{dP_T} = r_P(\alpha - \beta - 1)\sum_{t=0}^{T-1}(1-\bar{r}_H)^t + (r_P(\alpha-1) - \beta + \bar{r}_H - 1)(1-\bar{r}_H)^T + r_P \tag{7}$$

As $t \to \infty$, we obtain

$$\lim_{t\to\infty}\frac{dH_{T+t}}{dP_T} = \frac{r_P(\alpha-\beta-1)}{\bar{r}_H} + r_P \tag{8}$$

This long-run effect can be decomposed into three separate effects.

$$\lim_{t\to\infty}\frac{dH_{T+t}}{dP_T} = -\frac{r_P}{\bar{r}_H} + (\alpha-\beta)\frac{r_p}{\bar{r}_H} + \bar{r}_H\frac{r_P}{\bar{r}_H} \tag{9}$$

The "magnification effect," $-\frac{r_P}{\bar{r}_H}$, is due to the relative effectiveness (or ineffectiveness) of PSH in transitioning people into private housing. If $r_P = 0$, then an individual placed in PSH in the first period remains there forever, and so as long as he had a nonzero probability of transitioning to private housing out of homelessness, this first effect is zero. If $r_P < \bar{r}_H$, the magnification effect is less than one since PSH is slower than homelessness in transitioning people into private housing. And if $r_P > \bar{r}_H$, the magnification effect is greater than one since PSH is faster.

The "incentive effect," $(\alpha-\beta)\frac{r_P}{\bar{r}_H}$, scales down the total long-run effect of PSH by inducing more homelessness. If more people in private housing enter homelessness when there is more PSH inventory, then $\alpha > 0$. And if currently homeless people extend their spell of homelessness in response to more available PSH beds, then $\beta < 0$.

The "mistargeting effect," $\bar{r}_H\frac{r_P}{\bar{r}_H}$, scales down the long run effect of PSH due to improper targeting of homeless people to serve. The larger is $\bar{r}_H$, the larger is the probability that a given homeless person selected for PSH would have entered private housing directly from homelessness before the homeless count was taken.

We can see that the long-run effect can thus be larger or smaller than the immediate effect from placing a homeless person into PSH. If the magnification effect is less than one—that is, if PSH slows transitions into private housing—then the long-run effect will necessarily be less than one. If the magnification effect is greater than one, then the long-run effect may or may not be larger than one, and will depend on the size of the incentive and mistargeting effects.