THE IMPACT OF EMERGENCY SHELTER, TRANSITIONAL HOUSING, AND PERMANENT SUPPORTIVE SHELTER ON UNSHELTERED HOMELESS POPULATIONS IN THE UNITED STATES

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Glen Waddell

Unsheltered homeless in the United States commonly identify as chronically homeless per the Department of Housing and Urban Development (HUD) definition. This means they suffer from a disabling condition and have either been homeless for at least a year or have experienced at least four episodes of homelessness in the past three years. Understanding their relationship to public and private support systems from an aggregate perspective is imperative in determining proper channels for aid. This population also typically exhibits transient characteristics. Identifying patterns of movement in this population would also aid future research and funding decisions. To investigate the effect of shelter beds on unsheltered homeless rates and potential migration, I analyze panel data provided by HUD from 2007 to 2017. I develop an econometric model to firstly identify a relationship between increases in emergency shelter, transitional housing and permanent supportive housing beds on unsheltered homeless counts. I then add neighboring CoC and region variables in the attempt to measure a substitution effect of unsheltered homeless between CoCs and states. I initially find suggestive evidence that increases in shelter beds effect unsheltered homeless rates at the 0.01 significance level. However, upon adding controls for potential omitted variable bias and reverse causality, I discover that these suggested patterns were incorrectly specified. I find no systematic evidence of a relationship or migration on a regional or national level.

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Introduction

The movement of homeless individuals in the United States is not a new phenomenon. In the 1870s, facilitated by industrialization and the national rail system, the U.S. experienced its first national crisis around homelessness. Young, able-bodied men made up the majority of homeless at this time as they rode the rails in search of work. The tramp counterculture of this period shifted with the increased employment opportunities brought by WWII and on average the homeless population grew older and more dependent on social services (National Academies of Sciences, Engineering, and Medicine, 2018). Throughout this transition, homeless shelters developed to provide food, a place to sleep, and a voice of hope to push men back into the workforce.

Today, the demographic nature of homelessness has dramatically changed with younger men, women, and families now seeking additional aid. Homeless individuals typically no longer ride the rails in search of work, rather they frequent local shelter, jail, and social service systems to find support and housing (National Academies of Sciences, Engineering, and Medicine, 2018). And yet, these systems still witness population fluctuations with individual movement. A 2017 study conducted by Portland State University interviewed homeless individuals throughout the city querying their origins and patterns of movement. Though this was a small study, they discovered that 6.3 percent of the homeless population in the four-county Portland area moved with the goal of accessing Portland's additional homeless resources (Taponga et., al, 2018).

From an individual perspective, we know the homeless move about the United States because we see makeshift shelters come and go along freeway onramps, municipal byways, and wooded parks. And yet, we know very little of what happens to these individuals when these tents are removed. To say that homelessness is a serious economic and social problem is an understatement. High costs associated with this population due to increased use of public goods puts an additional burden on many communities. Homeless individuals frequent emergency rooms and jails. Homeless families experience extreme instability that can lead to familial separation and negative educational opportunities (Culhane et al. 2002; Gubits et al. 2015). The cost of homelessness on individuals, families and communities is consequential and detrimental. Homelessness also disproportionately affects racial and ethnic minority groups who already face greater challenges (Taponga et al. 2018).

The high cost of homelessness merits the need to better understand and provide aid to one of the most vulnerable populations in our nation. Expanding research on homelessness helps policy makers determine the effectiveness of their investments in aid. It also allows communities to create accurate goals and targets for decreasing homeless rates and identifying the proper number and type of shelter unit to provide. Temporary and supportive shelter is a major focus of homeless prevention efforts and understanding the impact of different shelter systems is essential for both aiding current homeless populations and for developing policy.

In 2007, The Department of Housing and Urban Development (HUD) took on this challenge to determine the effectiveness of their funding. They required each Continuum of Care (CoC) region across the US that received funding and allocated resources to the homeless to report an annual count of homeless individuals and available services. The Point-In-Time (PIT) count provides data on the number of homeless individuals, differentiating between individuals in families, in sheltered versus unsheltered locations, in chronically homeless situations and in additional categories (Henry, 2017). The Housing Inventory Count (HIC) shares the number of shelter beds in each CoC. It divides available shelter into five types. HUD has compiled this data and analyzes it each year for Congress.

This study references HUD's aggregate panel data from 2007 to 2017. I use their Point-in-Time (PIT) counts of unsheltered homeless individuals in each CoC as my explanatory variable. I first present estimates of unsheltered homeless response to three types of additional shelter beds: emergency shelter (ES), transitional housing (TH), and permanent supportive shelter (PSH). These shelter units are recorded as point in time counts in the Housing Inventory Count (HIC). I then consider the impact of two neighboring region variables to measure movement among unsheltered homeless populations between CoCs and states in my model. The first neighboring variable measures unsheltered counts in neighboring CoC's within a state and the second measures unsheltered counts in neighboring states within each of the nine census regions.

I initially find a strong negative relationship between increases in emergency shelter stock and unsheltered homeless counts and a positive relationship for transitional housing and permanent supportive housing stock. However, upon the addition of numerous controls where I control for timing in my model and potential migration, I discover no systematic evidence of a relationship. A substitution effect for all three shelter types within each region and state is not evident due to the statistical insignificance of my results. These results are not conclusive that additional shelter beds have no effect on unsheltered homeless in certain CoCs or that migration is not occurring, rather they conclude that on average there is no strong inference from a national or even regional level. With little research on the one available source of aggregate data on this subject, my research takes a small step to answer the question of how and where unsheltered populations move within the United States. It highlights the potential for changes in funding strategies but most importantly emphasizes the need for additional research and more precise data on this population.

Background

There are two primary theories for the proliferation of homelessness in America, one far more complex than the other. The complex explanation lies in governmental housing policies. Many families and individuals experiencing short periods of homelessness find themselves in situations where they simply no longer can afford their rent or find affordable housing. Low income at poverty rate levels often forces households to choose between food, clothing, transportation and housing. Individuals who find themselves in this situation are considered transitionally homeless, meaning they have experienced homelessness for less than one year.

The recession in the 1980s brought an inadequate supply of affordable housing and budget cuts to HUD and other social service agencies (Jones, 2015). Since then, rents in metro areas have increased as wages remain stagnant (Katz, 2006). As a result, we see more transitionally homeless families and women seeking aid in the shelter system. Researchers John Quigley and Steven Raphael provided evidence of a causal relationship between this inadequate supply of affordable housing and increases in homeless populations. They reviewed rents and estimated that a ten percent increase in rent leads to a 13.6 percent increase in the rate of homelessness (Quigley et al. 2001). Their study of the effects of housing prices, vacancies, and rent-to-income ratios on homeless rates revealed the importance of housing prices and availability in keeping homeless incidence rates low. Figure 1 depicts this relationship and highlights the strong positive correlation that exists between median gross rent and homeless rates (Taponga et., al, 2018). This research demonstrates that policy changes to address a lack of affordable housing in the United States can potentially have a positive effect on homeless rates.

The other story of homelessness appears in the far more complicated population of chronic homeless individuals, those who have been homeless on and off for decades. The chronically homeless often suffer from a disabling condition and have either been homeless for at least a year or have experienced at least four episodes of homelessness in the past three years (Henry, 2017). The modern era of homelessness which began in the 1980s witnessed an increase in chronic homelessness caused by the gentrification of inner cities, deinstitutionalization of the mentally ill, increased narcotic use and the co-occurrence with HIV/AIDS (National Academies of Sciences, Engineering, and Medicine, 2018). For these reasons, the face of homelessness changed, leading to younger, more impoverished individuals who typically had a higher burden of medical, mental health and substance use disorders (National Academies of Sciences, Engineering, and Medicine, 2018). This chronically homeless population necessitates additional support because they are more likely to be high needs high cost individuals who interact far more with health and social services.

Thanks to the efforts of many local actors to combat chronic homelessness, communities have seen an emergence of housing first models in conjunction with more supportive services. This movement manifests in transitional housing and permanent supportive housing models. On a federal level, the first legislation enacted to explicitly address this issue was the 1977 Stewart B. McKinney Homeless Assistance Act (PL 100-77) which defined homelessness, created a Health Care for the Homeless (HCH) primary care funding stream and a U.S. interagency Council on Homelessness (USICH) to independently coordinate programs across government agencies (National Academies of Sciences, Engineering, and Medicine, 2018). In 2002, USICH pushed for states and CoCs to create 10-year plan to end chronic homelessness. This goal was continued under the Obama administration in 2010 as they developed a federal strategy with four main goals to prevent and end homelessness (National Academies of Sciences, Engineering, and Medicine, 2018).

With these initiatives, chronic homelessness has decreased by 27 percent since 2007 (Henry, 2017). Despite this decrease, the chronic homeless population remain vulnerable as they make up the majority of unsheltered populations. This is evident in the 2017 PIT count where 7 out 10 unsheltered homeless identified as chronically homeless (Henry, 2017). Even though it has decreased, the share of chronically homeless that were unsheltered was higher in 2017 than in 2007. California, with one of the highest homeless rates, demonstrates this as 87.6 percent of their chronically homeless population was unsheltered in 2017 (Henry, 2017). The large share of chronic homeless within unsheltered populations motivates my research decision to use unsheltered homeless as my dependent variable. In doing so, I can better understand how increases in various available shelter types affect a population that utilizes public funds more frequently. I explore changes in unsheltered chronic homeless from 2007 to 2017 in Figure 2. Here, it can be noted that despite overall decreases in unsheltered and sheltered chronic homelessness, the unsheltered population accounts for 78 percent of the increase in total chronic homelessness between 2016 and 2017.

On a national level, overall homeless rates have fallen by 14 percent between 2007 and 2017 (Henry, 2017). During this time, unsheltered populations declined by 25 percent while those in emergency shelters or transitional housing declined by 8 percent (Henry, 2017). This decrease could be explained by increased funding towards more supportive housing services like PSH which would then capture more unsheltered and emergency shelter homeless populations. Permanent supportive housing stock has increased since 2007 each year thanks to some communities investing in increased housing for the homeless. Many cities such as Portland de-emphasized emergency shelter systems in the early 2000s with the goal of focusing on safe and permanent housing alternatives. Inventory of PSH stock grew by 165,164 beds in total since 2007 which is an increase of 88 percent (Henry, 2017). Such an increase would help ease or even remove the burden of homelessness for individuals that are relatively transitional while supporting more chronically homeless individuals with additional services.

Despite these efforts, homelessness remains a serious issue. On a single night in 2017, for every 10,000 people in the nation, 17 were suffering from homelessness accounting for a total of 553,742 people (Henry, 2017). The majority of these homeless are centralized in five states: California, New York, Florida, Texas and Washington. In Figure 3, I divide the total unsheltered population from 2007-2017 into each of the nine census regions. It demonstrates that since 2007 the Pacific region and the South Atlantic region contain more unsheltered homeless than any other region in the United States. This prompts my decision to model homelessness in the Pacific region, particularly along the West Coast.

Regarding total homeless populations, New York City and California's LA CoC contain the two highest counts of homeless individuals. This makes sense as NYC and LA are the two largest cities in the United States. In 2017, the NYC CoC measured 76,501 homeless persons while LA found 55,188 individuals. However, like many other regions in the United States, these two major cities differ in their proportion of sheltered versus unsheltered homeless. Thanks to the landmark 1979 lawsuit *Callahan v. Carey,* NYC legally guarantees homeless residents meeting certain welfare or need standards a mandated right to shelter (Callahan v. Carey, 1979). During the 2017 PIT count, NYC only lacked 364 available beds to house its total homeless population. LA CoC lacked 39,963 beds. This discrepancy helps explain why 95 percent of the homeless population in NYC was sheltered whereas only 25 percent of homeless in LA CoC were sheltered that same night (Henry, 2017). This is suggestive of a correlation between available beds and unsheltered homeless rates.

The relationship between available beds and unsheltered homeless can be extrapolated to examine the entire United States. It is important to note that an increase of unsheltered homeless in LA can also be explained by the correlation between warm weather and unsheltered populations. In California, Oregon, Nevada and Hawaii half of the state’s homeless populations are unsheltered. This can be viewed in contrast to colder Iowa and Nebraska who both had fewer than 5 percent of people living without shelter (Henry, 2017). Despite a correlation between climate and unsheltered homeless, recent events over the past couple decades, such as tight housing markets and the Great Recession, have kept people in emergency shelters or on the streets because of fewer funds and supplies of PSH options (O’Flaherty, 2018). It would therefore be suggestive that increasing available shelter beds has an important influence on homeless rates, particularly unsheltered homeless rates, and implies that developing a stronger understanding of this relationship is essential.

Literature

Until recently, economic literature on homelessness was seldom published due to a lack of credible aggregate data. However, more and more economists are developing methods to answer fundamental questions regarding the prevalence of homelessness and the effects of policies. One such method, that I employ as well uses bed inventory information as the main independent variable. Historically, many economists have looked at the use of funding information as the main independent variable. The approach of bed inventory information cuts directly to the variables of interest.

Byrne et al. were one of the first to follow this approach using the same national panel data that I used in this study. They conducted a longitudinal analysis at a community level with six years of data across a set of 372 CoC communities (Byrne et al. 2014). In this analysis, they estimated the association between PSH beds and the amount of chronically homeless people. While conducting research, they removed CoCs in Guam, Puerto Rico, and U.S. Virgin Islands as well as Detroit and New Orleans. These later CoCs were removed due to problems in counting methodology. They removed Los Angeles as well for a robustness check. They also map CoC's to measure CoC-level independent variables using county-level data. They were forced to drop additional CoCs and merge others due to unavailable data and irregular geographic composition. I followed their lead in dropping regions with documented counting issues, but I retained the others as I used fixed effects to control for variation across CoCs. Their choice of controls came in the form of numerous county level variables taken from the U.S. Census Bureau's American Community Survey (ACS) every five years. Although an interesting first approach in modeling the relationship between homeless individuals and shelter beds, the researchers allowed for variation across and within CoCs to identify associations using these controls.

In 2017, Corinth furthered Byrne et al.'s study using the same data with additional controls to identify the effect of additional PSH beds on homeless rates. He used data from 2007-2014, and accounted for state-year fixed effects, CoC fixed effects, and additional time varying CoC controls (Corinth, 2014). These controls include explanatory variables for the unemployment rate, log of the median rent, temperature, rain, falling snow and ice. His data for permanent supportive housing beds came from earmarked awards by HUD. He discovered that an additional 100 PSH beds reduced PIT homelessness by 10 (Corinth, 2014). He found larger effects for the unsheltered than sheltered. He rejected a one-for-one reduction in homeless population size with an additional PSH beds, sharing that only 0.3 per 10,000 of the decline in homelessness since 2007 was due to more PSH beds (Corinth, 2014). His results were not statistically significant at the one or five percent level. There were numerous other reasons for a decrease in homeless rates such as growth in veteran initiatives, more accurate street counts, changes in police interaction with homeless or increased efforts to rehouse homeless under the Homelessness Prevention and Recovery Act of 2009 (Corinth, 2014). Another important finding by Corinth was that additional emergency shelter beds and transitional housing beds were associated with a large and positive increase in homeless counts (Corinth, 2014). This essentially means that adding shelter where people are defined as homeless increases homelessness. These results provide helpful background that I will further in my research.

In 2017, Portland State University also discussed the movement of homeless peoples into the Portland area for homeless resources. Their analysis of the 2017 PIT count for Portland-Gresham-Multnomah County CoC surveyed unsheltered homeless on their locational choices. They found that two thirds of the people were from or had lived in the region for at least two years (Portland State University, 2017). They discovered that 6.3 percent of the total homeless population were homeless when they moved to Portland to access resources (Portland State University, 2017). Although the PSU researchers tracked only a small fraction of the overall homeless population, their study hints at the concept that visible and unsheltered homeless may migrate to the region.

Corinth also attempted to to identify migration of homeless populations in his 2014 study. He discovered that potential movement of homeless populations between

CoCs would influence the association between PSH beds and homeless rates. In particular, he shared that the estimated association of a CoC's PSH inventory and its homeless populations compared to an association between the CoC's PSH inventory and national homeless population rates would be higher (Corinth, 2014). He developed an equation to measure PSH inventory in the rest of the state. He used CoC level controls and pure year effects. Additionally, he looked at a lagged right-hand side version of the model. His results are suggestive with movement but not affirmative due to potential omitted variable bias. In the long run, an additional PSH bed is associated with 0.36 fewer homeless people in the rest of the state (Corinth, 2014).

My research furthers this theory by narrowing my variables of interest. Rather than developing my own equation to determine bed inventory in the rest of the state, I develop my variable in R and use it to identify a substitution effect between local beds and rest of state beds. I narrow my definition of homelessness to unsheltered homeless and look at the association for each type of shelter bed. I further address movement between CoCs and regions.

Empirics

In this section, I transition from a descriptive discussion of homelessness in the United States to address the problem with direct empirical observation. Generally, I seek to determine the effect that three types of shelter (ES, TH, and PSH) have on unsheltered populations. I use this initial specification to model potential movement of this population between CoCs and regions. These models and my ensuing analysis of them using the statistical language R construct my mode of evaluation.

Data

In this study, I take advantage of the Department of Housing and Urban Development's (HUD) report of available resources and homeless counts. Congress requires the compilation of this Annual Homeless Assessment Report (AHAR) each year. Since 2007, Congress utilizes the report to count and track homeless populations. This information helps them allocate funding to Continuums of Care (CoC) across the country which use these funds to combat local homelessness. The data in these reports can be broken into two main components: Point-in-Time counts (PIC) and Housing Inventory Counts (HIC) which are both conducted in Continuums of Care (CoC). CoCs are composed of a single city, county, group of counties or entire states (Turnham 2004). There are 414 CoCs in the United States. They provide funding and support to local nonprofits for the rehousing of homeless individuals and families. CoCs are required to report both homeless rates and shelter stock each year to Congress.

To determine the number of homeless in a given CoC, typically volunteers perform counts on a given night during the last two weeks of each January (Turnham 2004). Homeless individuals are classified into different categories such as unsheltered, sheltered, individuals, and chronically homeless. These counts are needed annually for sheltered populations and every two years for unsheltered populations. However, most CoCs conduct this count annually (Corinth, 2014).

CoCs also report Housing Inventory Counts (HIC) which measure the inventory of provided beds and units dedicated to serve homeless persons within each CoC. They are measured as point in time counts as well. There are five categories of beds or units: 1. Emergency Shelter, 2. Transitional Housing, 3. Rapid Re-housing, 4. Safe Haven and 5. Permanent Supportive Housing. I use emergency shelter (ES), transitional housing (TH), and permanent supportive housing (PSH) beds in my analysis because they are consistent throughout the 10-year period (2007-2017). They are discussed in more detail in the conceptual model section.

Characteristics & Concerns:

Despite the accumulation of aggregate data on this subject since 2007, the nature of the data is complex. Homelessness is difficult to measure because people cycle in and out of shelters quite rapidly (O'Flaherty, 2018). This complexity is evident in the lack of aggregate and reliable data in the past. In order to work with this dataset, it is important that I address potential areas of imprecision and measurement error that stem from quantifying this population.

The major concern comes from imprecision in counting the population. The methodology for conducting PIT and HIC counts has become more consistent between CoCs since 2007 but it is important to note that it realistically varies. Although HUD produced a guidebook for counting unsheltered populations before the data collection began in 2004, there have been no aggregate studies on whether these methods were strictly followed (Turnham 2004).

One example of where counting methods may diverge between CoCs is with the use of volunteers. By using volunteers or even contracting the responsibility to other organizations, the diligence, understanding and lack of bias in producing homeless counts are questionable (O'Flaherty, 2018). Volunteers are unable to enter private property, which restricts them from counting people that seek shelter in parking garages or stairwells (Turnham 2004). They face additional constraints counting in crowded or dangerous areas. In 2005, NYC introduced plants, volunteers acting as homeless individuals, in an effort to improve their counting methodology. They found that more than half the plants not staying in shelters were missed during the PIT count that year (Hopper et. al, 2008). This leads to certain areas within a CoC containing better estimates of unsheltered homeless persons and is therefore a source of potential measurement error in the data that could bias results. An additional problem with varying methods of conducting counts is that some CoCs measured unsheltered homeless every year while others measured every two years.

Ideally, I would include explanatory variables that present information on how each CoC conducts their counts; however this information does not yet exist. Instead, I remove the CoCs of Detroit and New Orleans due to imprecision in their reports. I chose to do this based on two previous studies that worked with similar data (Byrne et al. 2014, Corinth, 2017). Thanks to their research, I also removed the CoCs of Guam, Puerto Rico, and the Virgin Islands due to their isolated locations and possible lack of influence on movement. I follow this same logic in my methodology when I eliminate Alaska and Hawaii to form the "west" variable in my heterogeneous analysis.

Despite this effort, the imprecise nature of this data could lead to potential issues in analysis. Economist Brendan O'Flaherty recently published "Homeless Research: A Guide for Economists (and Friends)" in which he addresses issues such as heteroscedasticity and correlations between errors and policies of interests that arise when this data is used as a dependent variable. He argues that in order to combat additional measurement error, methodology reports must be collected and used to control for such errors (O'Flaherty, 2018). I use CoC fixed effects to help control for some of the variation in counting across CoCs, but additional research into the strength of the data is necessary for future studies.

Conceptual model

I use Ordinary Least Squares regressions to identify a relationship between my dependent variable and a multitude of independent variables using observations from PIT and HIC counts provided by HUD. In general, regressions are used to statistically explain changes in the dependent variables that occur due to changes in the independent variables (Dougherty, 2011). I can model actual relationships given only observed sample characteristics provided by HUD's dataset. I model a version of reality to explain the association between unsheltered homeless counts and variation in shelter beds.

An ideal model of this relationship would randomly assign variation in the number of homeless beds, implying endogeneity. As a proxy, I develop a model with additional controls and econometric methods in an attempt to satisfy this assumption. I address the potential of omitted variable bias, measurement error, and reverse causality in developing my model and interpreting my results. In doing so, I argue that variation in shelter beds is exogenous to homelessness itself, meaning it is not caused by homelessness.

My baseline specification looks at the influence of emergency shelter, transitional housing, and permanent supportive housing beds on unsheltered homeless rates. This baseline model is based on two previous studies that used bed inventory counts as independent variables (Byrne et al. 2014, Corinth, 2017). I model this relationship using the regression below:

$$Total\_unsheltered_{it} = \beta_o + \beta_1 ES_{it} + \beta_2 TH_{it} + \beta_3 PSH_{it} + \varepsilon_{it}$$

It is plausible that unobservable variables may be correlated with the three shelter types. One could imagine that unemployment rates, income, weather, and other demographic differences influence variation in shelter beds and unsheltered homeless counts. These would all potentially bias my results if I fail to control for them in the model. This bias is called omitted variable bias and occurs when a variable correlated with both the dependent and one or more of the independent variables are left out of the model (Rethemeyer, 2003). This is demonstrated in Figure 5 where a prediction is trying to be made for Y thanks to some X_1. Here, another variable X_2 interferes because it effects both X_1 and Y but is not controlled for in the model. I will use fixed effects to account for variables that do not change with time. A limitation remains because I cannot incorporate all influential models that do vary with time. Unfortunately, due to the scope of this paper and a lack of readily available resources, I am unable to obtain additional datasets on a national level. I attempt to address these specifically with the inclusion of my migration variables but this does not cover all possible omitted variables which is important to remember when interpreting results. For this reason, I cannot argue that my identification strategy for a causal effect is conclusive.

My supplemental specifications add the additional controls of CoC fixed effects and trend, trend squared and region trend variables. I utilize logarithmic variations of my baseline variables and lag my explanatory variables to address reverse causality. Further, I include shelter explanatory variables that measure counts of each shelter type in the rest of the state and region to address possible movement of individuals. The addition of these variables now allows for a substitution effect between one CoC and its neighboring CoCs or region to be captured. A possible substitution effect between a shelter type in different CoCs or regions and the local CoC hints at movement of unsheltered homeless populations. I formally express this model below:

$$
\begin{aligned}
&Total\_unsheltered_{it} \\
&= \beta_o + \beta_1 ES_{it-1} + \beta_2 TH_{it-1} + \beta_3 PSH_{it-1} \\
&+ \beta_4 RoS\_ES_{it-1} + \beta_5 RoS\_TH_{it-1} + \beta_6 RoS\_PSH_{it-1} + \beta_7 RoC9\_ES_{it-1} \\
&+ \beta_8 RoC9\_TH_{it-1} + \beta_9 RoC9\_PSH_{it-1} + \beta_{10} trend_{it} + \beta_{11} trend_{it}^2 \\
&+ \beta_{12} trend\_region_{it} + \mu_i + \varepsilon_{it}
\end{aligned}
$$

My dependent variable measures the total number of unsheltered homeless people on a certain year in a given CoC. I chose this variable for three reasons. Firstly, unsheltered populations were identified in previous research to be more affected by changes in bed inventory counts (Corinth, 2014). Secondly, this population is typically more transient and would therefore reveal potential patterns of migration. Thirdly, unsheltered individuals are more likely to be chronically homeless and therefore frequently utilize expensive social systems. Using this population as my dependent variable provides additional research on a group of homeless that are both costly and risky for communities.

I log both my dependent and independent variables to supply a more convenient mechanism of interpretation. My point estimates should be interpreted as elasticities. Using a logarithmic form also helps control for model misspecification because it picks up non-linearity in the data. In my model, my explanatory variables consist of the three shelter types, neighboring CoC and regional counts for those three shelter types. I also include trend variables and CoC fixed effects as well as contemporaneous versions of the three shelter types. These are discussed in detail as follows.

In the baseline model, the explanatory variables of emergency shelter, transitional housing and permanent supportive housing refer to the three most consistent forms of shelter beds as defined by HUD. Emergency housing (ES) is a short-term solution offering support for a few days to several months. Transitional housing (TH) aids people for 6-24 months and requires compliance with supportive services. These supportive services vary but may include mandatory sobriety and counseling (Turnham 2004).

Finally, permanent supportive housing (PSH) pairs long term subsidized housing with ongoing supportive services (Bryne et al. 2014). PSH come in the form of either project-based apartment buildings or units in the private market rented for 30 percent of a tenant's income. This fraction of a tenant's income comes from the definition of affordable housing (Turnham 2004). Typically, a homeless individual in PSH gains more autonomy over their placement which allows for more stability to effectively address additional problems. This approach has gained popularity because of its high 80 percent retention rate in two-year housing (Tsemberis & Eisenberg, 2000. Additionally, PSH is more cost effective because it offsets the use of healthcare, criminal justice, emergency shelter and other public services frequented by chronic homeless populations.

My supplemental specifications include additional explanatory variables and controls. To address the movement of unsheltered homeless populations, I add variables that measure the amount of shelter beds (ES, TH and PSH) in neighboring states and regions. RoS measures the number of beds for a certain shelter type in all the neighboring CoCs. It is defined as all the other CoC's shelter beds within a state minus the local or i[th] CoC. RoC9 does the same except it looks at neighboring regional beds. Region is defined by the nine census regions. A substitution effect between a certain bed type and its neighboring bed type would suggest movement of an unsheltered individual.

I control for trends in years to help absorb the differences in variables that occur across time. These trend variables serve as a proxy for any additional unobservable variables that are strongly correlated with time (Gatewood). They help capture aggregate time series trends that appear in the panel data. The model, without controlling for these trends, would be influenced in a manner that is not casual. Omitted variables could potentially bias the results if they are not controlled for. The trends pick up and control for changes in unobservable factors specific to individual years that influence variation in shelter beds. I include a trend variable as well as a squared trend to deal with the possibility that the data is non-linear. Additionally, I add a region trend variable which is an interaction term between my trend variable and my C9 census region variables. I cannot control for all differential trends in my model, leaving a potential for bias in my results.

Additionally, I control for CoC fixed effects to account for any CoC characteristic that does not change with time. This is called time-invariant unobserved heterogeneity and follows the same logic as time fixed effects explored above. Including CoC fixed effects helps control for omitted variable bias. With them, I look at the relationship between beds and unsheltered homeless counts within each CoC and not across CoCs. These trends can also help absorb the difference in weather and similar factors that differ across regions. For example, it would be unwise to compare homelessness in sunny California to Iowa in the winter because unsheltered counts would vary due to climate. Instead, I look at the relationship only within California and only within Iowa and control for differing effects that weather could cause with the CoC fixed effects. It would be helpful to include additional controls to handle year-to-year changes in these types of variables but these do not yet exist on a national level (Corinth 2014).

Results

In Table I, I begin with my most baseline model looking at the influence of the three shelter beds on unsheltered homeless rates. For ease of interpretation, the coefficient estimates are levels in this initial model. In my ensuing models, my estimates should be interpreted as log-log elasticities. The shape of the data is one plus the log. This means one can interpret the coefficient estimates as percent changes. A positive coefficient on our explanatory variables signifies an increase in unsheltered homeless where a negative coefficient highlights a decrease.

Column one is the model in simplest form which examines the influence of emergency shelter beds, transitional housing beds, and permanent supportive housing beds on unsheltered homeless counts. A relationship is evident between all three shelter types and unsheltered homeless counts at the 0.01 significance level. This suggests that increasing shelter bed in a CoC directly impacts the number of unsheltered homeless within that CoC. It appears like one additional emergency shelter bed in a CoC leads to a decrease of 0.222 unsheltered homeless. This estimate is understandable as unsheltered and chronically homeless individuals typically frequent emergency shelter systems more often. Unsheltered and chronically homeless tend to suffer a disabling condition such as a mental illness or addiction that prevents them from seeking longer term support (Henry, 2015). Unsheltered populations are also typically more transient and may prefer shorter term locations in which to reside. For these reasons, it seems logical that increasing emergency shelter beds would decrease unsheltered homeless counts.

Contrary to the effect of increased emergency shelter beds, increases in transitional housing and permanent supportive housing stock both lead to increases in the unsheltered homeless population. An increase of a TH bed increases unsheltered homeless rates in a CoC by 1.108 persons while an increase of a PSH bed increases unsheltered homeless by only 0.380 persons. It may appear surprising that additional shelter resources actually increase unsheltered homeless rates. However, it is understandable because adding more long term supportive shelter space could signify increased funding and efforts to combat homelessness. This effort would lead to better outreach and detection of unsheltered populations which are typically difficult to capture. It also demonstrates the importance of long term supportive housing solutions. Unsheltered homeless may gather in a CoC that would now contain more long term solutions knowing that there are real long term options available. The results of this baseline specification suggest that funding shelter beds merits real attention because of their influence on unsheltered populations.

Despite this initial suggestive evidence, it is plausible that this baseline model omits important variables that are correlated with my dependent and one or more of my independent variables. For this reason, I include additional controls in column two. I add CoC fixed effects. I enter a trend, trend squared, and region trend to help with differences between CoCs over time. I finally use logarithmic versions of both my independent and dependent variables. This supplies a more convenient mechanism for interpretation. It is more realistic to assume that macroeconomic shocks or changes in shelter beds lead to percentage change effects on homelessness rather than constant level effects. It also helps control for potential model misspecification.

With the inclusion of these controls in column two, I see significant changes to my point estimates. The sign on my logged ES beds variable becomes positive as well as statistically insignificant. The point estimate for my logged PSH beds variable is also now statistically insignificant. I still see that a one percent increase in transitional housing stock does have a positive impact on unsheltered homeless counts at 0.01 significance level. These changes demonstrate the importance of careful interpretation when developing a model. It would be illogical to think that additional factors such as weather, income, and unemployment have no effect on unsheltered homeless rates or the number of shelter beds available in a CoC. Without controlling for these in my model, my estimates, although statistically significant in column one, would be biased.

In column three, I address and attempt to correct another potential limitation in my model. There is a possibility for reverse causality running between unsheltered homeless and increases in shelter beds. It may appear that increases in shelter beds occur because of increases in homeless populations within that CoC. I use lagged time effects to look only at the beds that were implemented the previous year before the homeless count. In essence, I look at how a change in shelter beds last year predicts homelessness today. This helps identify the timing and controls for reverse causality.

This may appear an extreme fix, but due to the imprecise nature of the data, it is important to include. I add controls for the logged contemporaneous effects as well.

I demonstrate that a one percent increase in emergency shelter beds leads to a 0.051 percent change in unsheltered homeless. A one percent increase in transitional housing beds leads to a 0.035 percent change in unsheltered populations and finally a one percent increase in PSH beds leads to a 0.037 decrease in unsheltered populations. These estimates are not statistically significant at any level and demonstrate no consistent relationship. This may be because there is no observable relationship between the two or because I did not capture the correct lag. It may be that shelters are anticipating homelessness two years in advance and not just one.

Finally, in column four, I attempt to control for additional omitted variables regarding the movement of homeless persons. Although I add controls to deal with omitted variables that may bias my results in column two, I cannot control for everything because some correlated and relevant omitted variables may also be correlated with time. I try to address this by adding a variety of trend lines but it is not possible to control for all types of trends. In column four, I evaluate the effect of neighboring shelter beds from both a state and regional perspective to address the possibility that unsheltered homeless may be moving between CoCs. The movement of unsheltered homeless becomes an issue econometrically in my model if movement occurs within a state or region and is correlated with the number of beds in a certain CoC. The possibility of a substitution effect occurring and possibly biasing my point estimates motivates my inclusion of these variables.

With this inclusion, I see little change in my point estimates for ES, TH and PSH beds. They are once again statistically insignificant. The neighboring state and region variables present no clear patterns of a substitution effect for any type of shelter bed. They are also statistically insignificant and demonstrate little effect on the number of unsheltered homeless within a CoC. These results are not suggestive of movement among homeless populations on average across all CoCs. It is important to note that these results do not definitively demonstrate that migration does not occur. They simply present a picture from a national perspective that on average a clear trend of migration is not apparent. This may stem from the nature of the data which is gathered only annually. It may capture only large scale movement and not more seasonal patterns of migration that occur. It is plausible that many unsheltered individuals remain in a certain CoC waiting for additional housing to become available. More frequently gathered data is necessary to determine a true pattern of movement.

It appears initially that a clear pattern is evident between increases in shelter beds and unsheltered homeless rates. However, it is important to consistently ask the correct questions to form a realistic and accurate model. Accounting for additional controls to avoid omitted variable bias and lagging my explanatory variables to control for reverse causality, reveals that these suggested patterns were incorrectly specified. My final specification demonstrates no systematic evidence of a relationship. As with migration, this is not to say that additional shelter beds have no effect on unsheltered homeless in certain CoCs rather on average there is no strong inference. It may be that certain regions or states demonstrate a relationship but on a national level this effect is canceled out. As a result, my estimates do not present a justification for pouring resources into shelter beds to decrease unsheltered homeless rates.

Heterogeneous Model

In Table II and III, I form two heterogenetic models by examining the data in a region-specific manner to determine if evidence of a relationship exists on a smaller scale. I subsect the data into different regions maintaining the model with RoS and RoC9 variables formed in column four of Table I.

In Table II, I run four regressions for the census regions of East North Central, Mountain, Pacific, and West Coast. I include the latter two in order to differentiate between any influence of movement along the I-5 corridor in California, Oregon and Washington and any adverse effects that Hawaii and Alaska might play from a census region perspective. There is little effect between Pacific and the West Coast regions when looking at the influence of the three shelter types on unsheltered rates. However, it becomes important to differentiate regarding the rest of state and region variables due to the isolated nature of Hawaii and Alaska.

I strive to gather a general picture of unsheltered homelessness and its relationship to available shelter beds through these three regions. In the East North Central region, generally viewed as the Midwest, increases in ES, TH and PSH beds all slightly decrease unsheltered homelessness. There is no evidence of a substitution effect both within and between states in the Midwest. These results are statistically insignificant and demonstrate no evidence of a relationship within this region. This could be explained by the extreme climate of that region and the relatively fewer unsheltered homeless.

The Mountain region runs contrary to East North Central despite a similar climate with increases in ES, TH and PSH beds all slightly increasing unsheltered homeless. There is no significant evidence of substitution across shelter types once again stemming from statistically insignificant estimates. On the West Coast, increases in ES, TH and PSH beds generally mirror national data with little systematic evidence of a relationship to unsheltered homeless counts. Thus, constraining my model to specific regions does not demonstrate that regionally certain CoCs may see an influence between changing the number of shelter beds on unsheltered homeless rates.

In Table III, I expand my regions to include Middle Atlantic, South Atlantic, and East North Central. As I previously find, the West Coast provides little evidence of a relationship between shelter beds and unsheltered homeless counts. I include it in this table to compare to the East coast. The coasts promote ease of transport, especially the East coast, thanks to more geographically close large cities. I sought to compare the two coasts to address the influence of climate and transformational ease on movement. The census region of Middle Atlantic, despite containing states that are not explicitly coastal, is utilized to form the eastern coast.

Looking towards the East Coast, there is slight evidence of movement for PSH beds within states in New England but little evidence of other movement. This is consistent with the colder climate during January and that more homeless in that region are sheltered. However, constraining the model to census regions on the East coast also fails to demonstrate systematic evidence of a relationship due to statistically insignificant results. Ultimately, analyzing the East Coast only exemplifies the need for better data and more research as no clear patterns arise and the standard errors are too large to argue for precise effects.

Conclusion

In this paper, I take advantage of panel data provided by HUD dating back to 2007 that counts homeless rates and available shelter beds annually. I develop a model to firstly identify a relationship between increases in emergency shelter, transitional housing, permanent supportive housing beds and unsheltered homeless counts. I then add neighboring CoC and region variables in the attempt to measure a substitution effect of unsheltered homeless between CoCs and states. I initially find suggestive evidence that increases in shelter beds effect unsheltered homeless rates at the 0.01 significance level. However, upon adding controls for potential omitted variable bias and reverse causality, I discover that these suggested patterns were incorrectly specified. My final specification demonstrates no systematic evidence of a relationship or of migration between CoC's and regions. My results demonstrate that on a national and regional level no statically significant inference is evident.

From a national level, my estimates do not present a justification for pouring resources into shelter beds to decrease unsheltered homeless rates. It is plausible that certain states or CoCs demonstrate a stronger relationship. They could see reductions in unsheltered homeless by increasing shelter beds but on a national level this effect is canceled out. This may stem from a lack of access to reliable aggregate data and additional data sources such as demographics of the unsheltered population. This limitation allows for possible measurement error or omitted variable bias to occur. Despite these limitations, my model suggests that increasing shelter beds neither helps or harms unsheltered homeless counts form a regional perspective. It begs the question for further research into other factors that may affect this population.

One possibility is that unsheltered homeless may frequently utilize shelters but only for short periods of time. They would thus fail to present consistent patterns on average over time because the PIT is only once year in January. Additionally, this count occurs during the winter, a time when many unsheltered homeless seek shelter at warming centers or other seasonal shelter locations. This would suggest fewer unsheltered homeless found on the street. Perhaps if the PIT counts were conducted in the summer, more unsheltered homeless would be identified possibly changing the relationship with shelter beds. In the end, my research consensus the call of economists who research homelessness, that more frequent and reliable data is needed.

I highlight the importance of this type of aggregate research and demonstrate the imperative need for additional research and far more reliable data on this population. It is important to understand not only where unsheltered homeless are concentrated but also to determine if they move about. In doing so, researchers may be able to capture additional homeless individuals in the data which in turn would help shift funding to populations in greater need. This genre of research will help future policy makers in funding allocations both locally and regionally because they can be more informed on a population that is typically difficult to interact with. The first step for future researchers is to establish more precise data or better methodology to interpret the reliability of the data.

Figures

Figure 1. Regions with High Median Rents Have High Rates of Homelessness

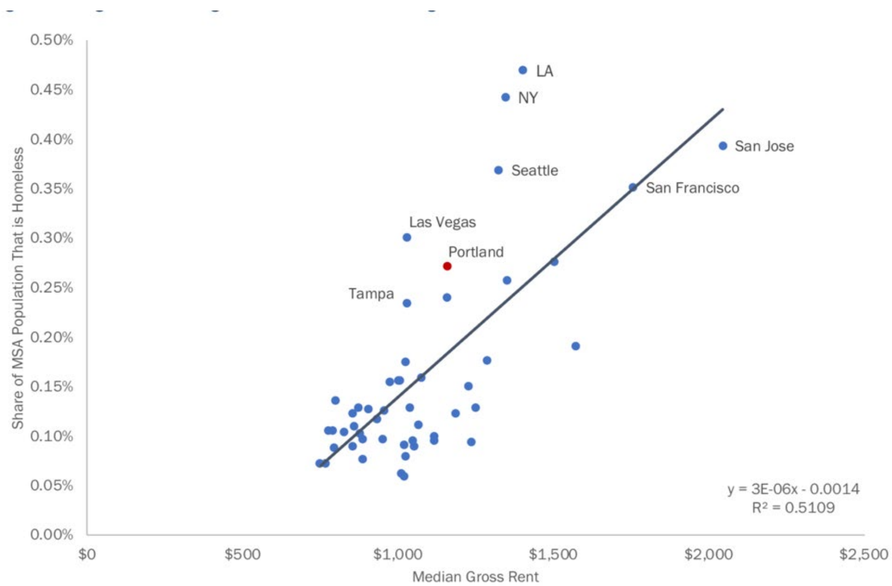

Figure 1. Reprinted from Homelessness in the Portland Area: A Review of Trends, Causes, and the Outlook Ahead, by ECONorthwest, Oct 10th 2018. Data HUD 2017 PIT counts and U.S. Census Bureau 2016 American Community Survey data, Top Metropolitan Statistical Area.

Figure 2. Total Chronically Homeless by Shelter Status, PIT Counts 2007-2017

	Change 2016-2017 (N)	Change 2016-2017 (%)	Change 2007-2017 (N)	Change 2007-2017 (%)
Total Chronically Homeless	9,476	12.2%	-32,851	-27.4%
Sheltered	2,033	8.3%	-15,139	-36.2%
Unsheltered	7,433	14.1%	-17,712	-22.7%

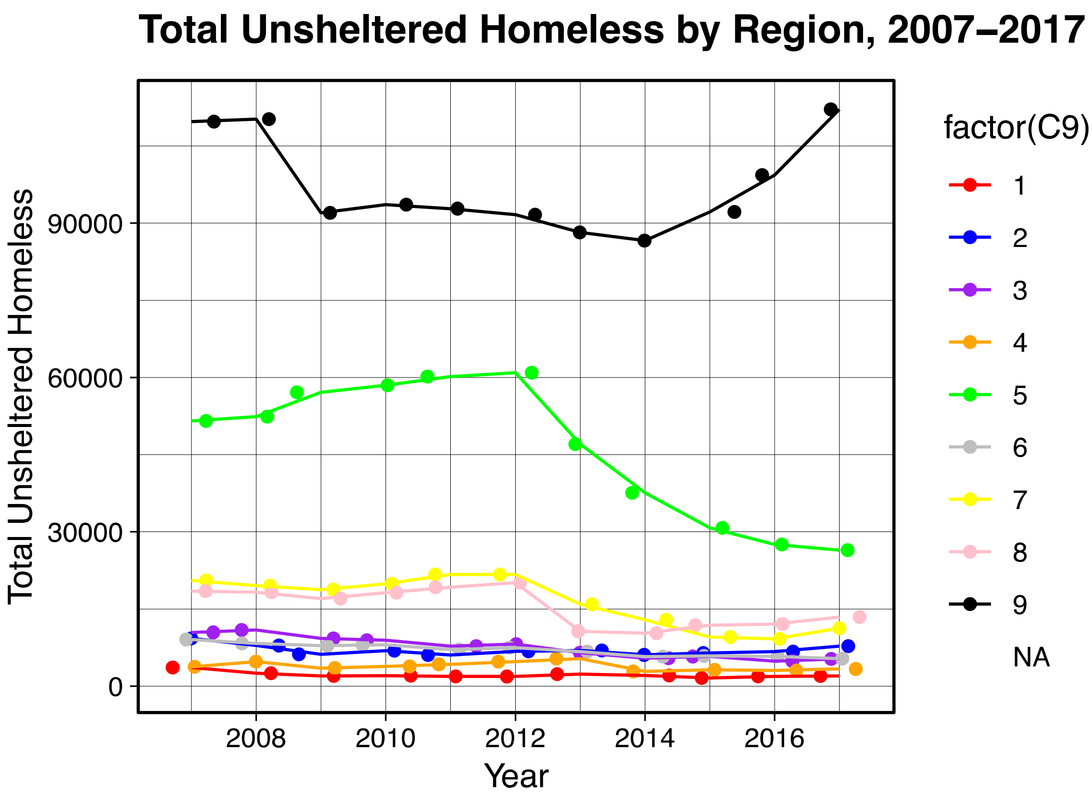

Figure 3. Total Unsheltered by Nine Census Regions, 2007-2017.

Data from HUD PIT and HIC counts. The nine census regions are as followed: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, Mountain, Pacific.

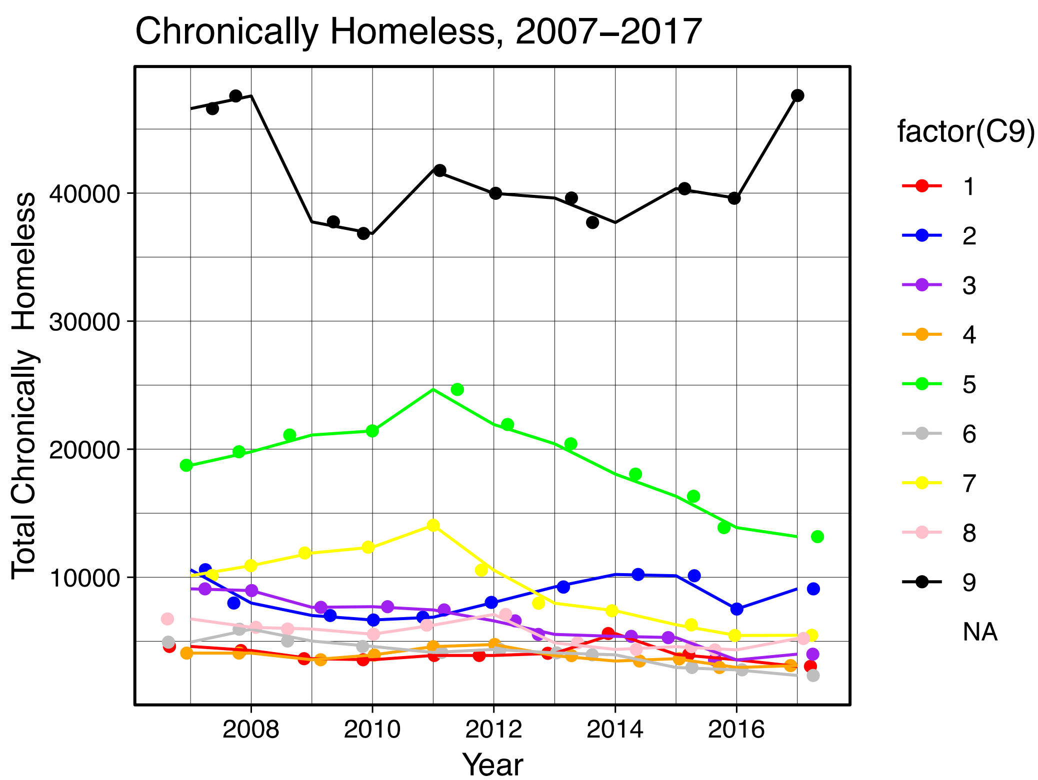

Figure 4. Total Chronically Homeless by Nine Census Regions, 2007-2017.

Data from HUD PIT and HIC counts. The nine census regions are as followed: New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, Mountain, Pacific.

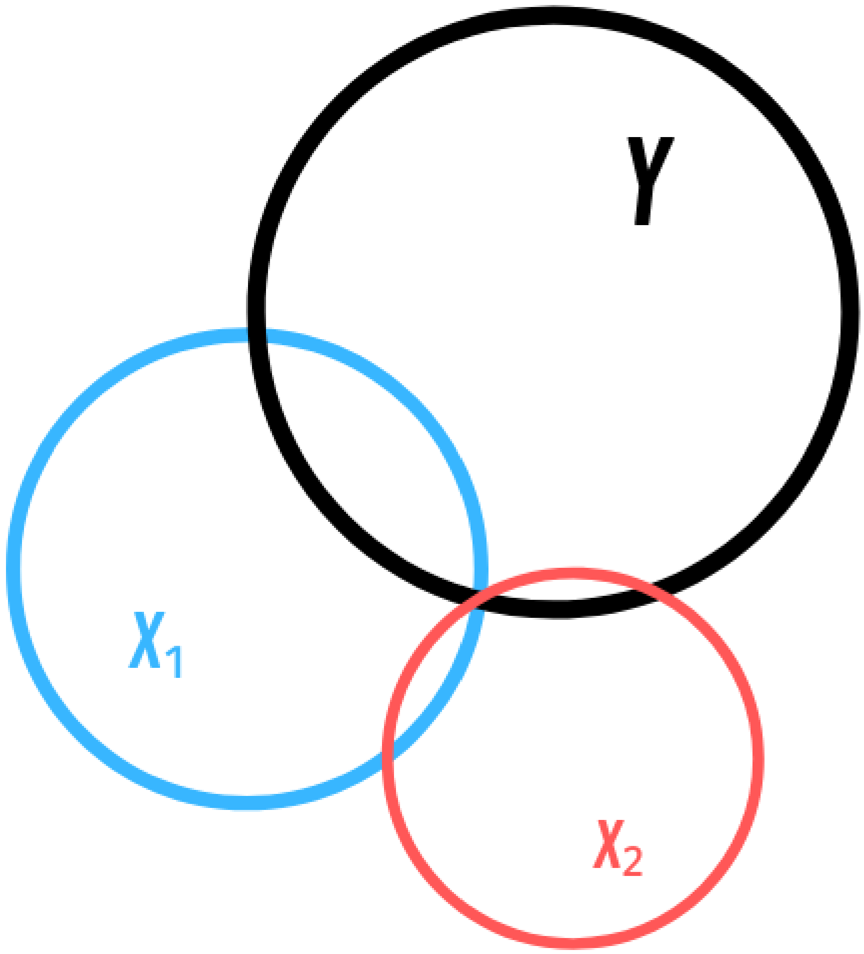

Figure 5. Omitted Variable Bias Graphic.

Table I. Effects of Shelter Types on Unsheltered Homeless

	Dependent variable:			
	Total Unsheltered	Log Total Unsheltered		
	(1)	(2)	(3)	(4)
ES beds	-0.222*** (0.012)			
TH beds	1.108*** (0.041)			
PSH beds	0.380*** (0.026)			
Log ES beds		0.038 (0.063)	-0.011 (0.066)	-0.014 (0.066)
Log TH beds		0.104*** (0.034)	0.067* (0.035)	0.063* (0.035)
Log PSH beds		0.013 (0.049)	0.070 (0.057)	0.071 (0.056)
Lag (Log ES beds)			0.051 (0.055)	0.049 (0.055)
Lag (Log TH beds)			0.035 (0.031)	0.037 (0.031)
Lag (Log PSH beds)			-0.037 (0.026)	-0.035 (0.027)
Lag (Log ES Rest of State)				0.100 (0.163)
Lag (Log TH Rest of State)				0.038 (0.125)
Lag (Log PSH Rest of State)				-0.053 (0.140)
Lag (Log ES Rest of C9)				0.081 (0.327)
Lag (Log TH Rest of C9)				-0.117 (0.293)
Lag (Log PSH Rest of C9)				-0.099 (0.252)
Constant	-90.909*** (22.942)			
CoC Fixed effects?	No	Yes	Yes	Yes
Trend, Trend Squared, Region Trend?	No	Yes	Yes	Yes
Contemporaneous Effects?	No	Yes	Yes	Yes
Observations	4,257	4,613	4,141	4,141
R^2	0.420	0.916	0.922	0.922
Adjusted R^2	0.420	0.907	0.912	0.912
Residual Std. Error	1,291.811 (df = 4253)	0.659 (df = 4137)	0.631 (df = 3677)	0.631 (df = 3671)

*p**p***p<0.01

Notes to Table I. Standard errors are in parentheses. Data is from the Department of Housing and Urban Development PIT and HIC counts between 2007 and 2017. ES stands for emergency shelter. TH is for transitional housing and PSH means permanent supportive housing. All explanatory variables are in logarithmic form lagged one year. Logarithmic versions of variables are in the form one plus the variable. Contemporaneous effects include a logarithmic measure of ES, TH, PSH that is not lagged.

Table II. Effects of Shelter Types on Unsheltered Homeless by Regions

	Dependent variable:			
	Log Total Unsheltered			
	New England	Mountain	Pacific	WA/OR/CA
	(1)	(2)	(3)	(4)
Lag (Log ES beds)	0.112 (0.101)	0.124 (0.321)	0.184** (0.084)	0.185** (0.087)
Lag (Log TH beds)	-0.009 (0.073)	0.307 (0.227)	0.075 (0.098)	0.074 (0.098)
Lag (Log PSH beds)	0.182 (0.130)	0.156 (0.224)	-0.057 (0.051)	-0.057 (0.051)
Lag (Log ES Rest of State)	0.157 (0.284)	0.120 (0.206)	-0.123 (0.297)	-0.299 (0.462)
Lag (Log TH Rest of State)	-0.211 (0.290)	0.197 (0.183)	0.008 (0.297)	-0.169 (0.421)
Lag (Log PSH Rest of State)	-0.530 (0.435)	-0.535 (0.422)	0.067 (0.244)	0.199 (0.397)
Lag (Log ES Rest of C9)	0.082 (1.594)	-2.536*** (0.904)	1.069* (0.621)	1.290* (0.761)
Lag (Log TH Rest of C9)	-1.583 (0.963)	1.114 (0.679)	-0.579 (0.821)	-0.385 (0.873)
Lag (Log PSH Rest of C9)	2.708 (2.095)	1.174 (1.493)	-0.059 (0.325)	-0.183 (0.484)
CoC Fixed effects?	Yes	Yes	Yes	Yes
Trend, Trend Squared, Region Trend?	Yes	Yes	Yes	Yes
Contemporaneous Effects?	Yes	Yes	Yes	Yes
Observations	335	160	598	558
R^2	0.951	0.894	0.953	0.939
Adjusted R^2	0.941	0.870	0.946	0.930
Residual Std. Error	0.473 (df = 279)	0.484 (df = 130)	0.414 (df = 519)	0.424 (df = 483)

*p**p***p<0.01

Notes to Table II. Standard errors are in parentheses. Data is from the Department of Housing and Urban Development PIT and HIC counts between 2007 and 2017. All explanatory variables are in logarithmic form lagged one year. The dependent variable Total Unsheltered is also in logarithmic form. Logarithmic versions of variables are in the form one plus the variable. All regressions include trend, trend squared, region trend variables, CoC fixed effects and contemporaneous effects. Contemporaneous effects include a logarithmic measure of ES, TH, PSH that is not lagged.

Table III. Effects of Shelter Types on Unsheltered Homeless, Coastal Regions

	Dependent variable:			
	Log Total Unsheltered			
	Middle Atlantic	South Atlantic	East North Central	WA/OR/CA
	(1)	(2)	(3)	(4)
Lag (Log ES beds)	0.089 (0.126)	-0.178* (0.103)	-0.050 (0.276)	0.185** (0.087)
Lag (Log TH beds)	0.071 (0.062)	0.070 (0.072)	-0.024 (0.185)	0.074 (0.098)
Lag (Log PSH beds)	-0.048 (0.070)	0.041 (0.059)	-0.063 (0.055)	-0.057 (0.051)
Lag (Log ES Rest of State)	0.309 (0.864)	-0.666 (0.505)	0.264 (0.930)	-0.299 (0.462)
Lag (Log TH Rest of State)	0.326 (0.610)	0.278 (0.229)	0.106 (0.406)	-0.169 (0.421)
Lag (Log PSH Rest of State)	-0.205 (0.346)	-0.119 (0.262)	0.444* (0.263)	0.199 (0.397)
Lag (Log ES Rest of C9)	-2.267*** (0.830)	2.514* (1.310)	1.908 (2.423)	1.290* (0.761)
Lag (Log TH Rest of C9)	0.604 (1.014)	2.539*** (0.924)	1.961 (1.847)	-0.385 (0.873)
Lag (Log PSH Rest of C9)	0.926 (0.600)	-0.932 (0.629)	1.110* (0.619)	-0.183 (0.484)
CoC Fixed effects?	Yes	Yes	Yes	Yes
Trend, Trend Squared, Region Trend?	Yes	Yes	Yes	Yes
Contemporaneous Effects?	Yes	Yes	Yes	Yes
Observations	642	923	563	558
R^2	0.863	0.922	0.810	0.939
Adjusted R^2	0.843	0.911	0.782	0.930
Residual Std. Error	0.711 (df = 558)	0.560 (df = 810)	0.768 (df = 491)	0.424 (df = 483)

*p**p***p<0.01

Notes to Table III. Standard errors are in parentheses. Data is from the Department of Housing and Urban Development PIT and HIC counts between 2007 and 2017. All explanatory variables are in logarithmic form lagged one year. The dependent variable Total Unsheltered is also in logarithmic form. Logarithmic versions of variables are in the form one plus the variable. All regressions include trend, trend squared, region trend variables, CoC fixed effects and contemporaneous effects. Contemporaneous effects include a logarithmic measure of ES, TH, PSH that is not lagged.

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