How Society Reacts to Changes in the Homeless Population?

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Abstract:

This paper investigates how fluctuations in the homeless population impact the number of homeless shelter beds available in the future. I analyze how the public response differs between two distinct homeless populations; the sheltered and the unsheltered homeless. The data used in this study comes from the United States Department of Housing and Urban Development (HUD) point-in-time (PIT) count that started in 2007. I ran linear fixed effects regressions to determine the impact of fluctuations in the homeless population on shelter bed provisions the next year. The independent variables of interest are measures of homelessness – total homeless, unsheltered homeless, and sheltered homeless – and are lagged by one year. The conclusion of these regressions is that society increases beds on account of more need in the sheltered homeless population rather than the unsheltered population.

Introduction:

Homelessness has spread throughout the world in both developed and developing countries. The United Nations has not attempted to count the total number of homeless in the world since 2005 when it was estimated at 100 million people.[1] Reliable and affordable housing is an important factor in an individual's ability to succeed. Access to housing has proven to reduce stress, resulting in a positive impact on an individual's health. One example of how housing can have this result is through improved nutrition, allowing an individual to allocate more time and resources towards purchasing nutrient dense food options.[2]

Homelessness is an issue that has existed in the United States since the 1870s (National Academy of Sciences, 2018). The problem has grown exponentially in the past forty to fifty

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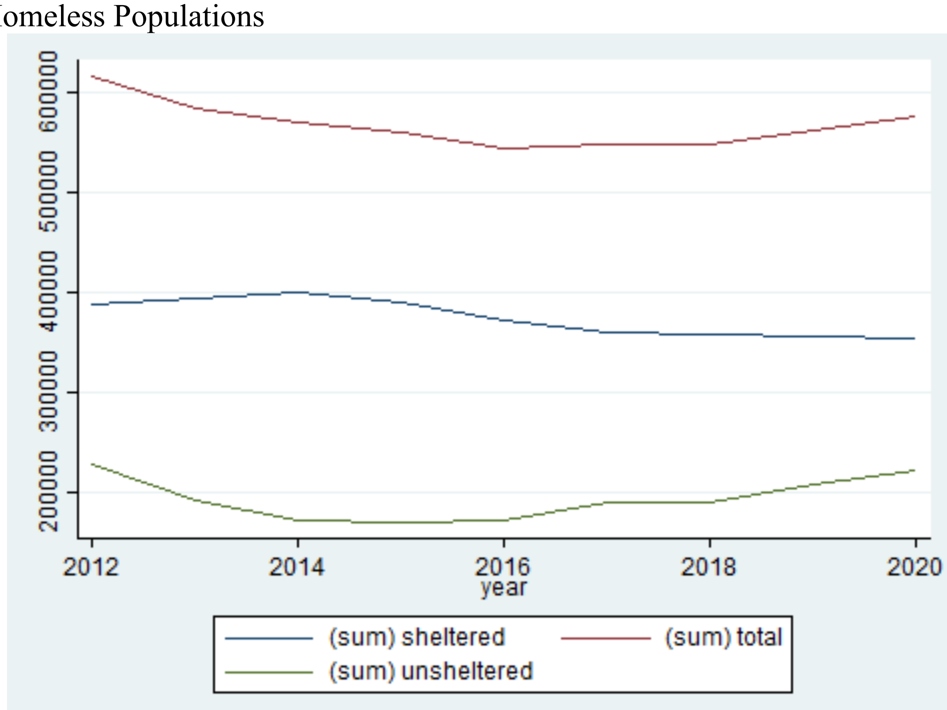
[1]https://homelessworldcup.org/homelessness-statistics/
[2]https://www.tn.gov/content/dam/tn/health/documents/healthy-places/healthy-homes/CHP_Positive_Health_Affordable_Housing_2007.pdf

years, with a spike in the early to mid 1980s. Graph 1 shows how the total homeless, unsheltered homeless, and sheltered homeless populations have changed since 2012. There is a spike trending upward in the unsheltered population from 2014 until 2020. In 2014 the unsheltered homeless population for the entire United States was 171,080 and grew to 222,061 in 2020. This is a 29.7% increase over these years. Oppositely, the sheltered homeless population decreased from 398,867 in 2014 to 353,592 in 2020. This is a 11.4% decrease between these years. There is an increase in the number of total homeless which is reflected in the graph, indicating an overall increase in homeless starting in 2016. The total homeless population was 544,394 and became 575,653 in 2020. This is a 5.7% increase over these years. This information is crucial to understanding which population is changing and whether society is addressing the correct group in their response. While these fluctuations are different between the groups, the increase in the unsheltered homeless population overshadows the decrease in sheltered homeless, ultimately resulting in an overall increase in the total homeless population.

Graph 1: Homeless Populations



The total homeless population has remained relatively consistent over this time period but shown an overall increase, Graph 1 indicates that fluctuations in the unsheltered homeless population are larger and therefore more impactful. There has been a slight decrease in both homeless populations since 2012 but they have remained relatively consistent since then (HUD, 2022). Complementing this growth in homelessness, the corresponding literature has similarly increased (Giano *et al*., 2019). Data have also become readily available. HUD started the PIT count in 2007 which has supported new literature on homelessness. The HUD PIT count is assisted by the Continuum of Care Organization (CoC) which collect data consistently to analyze homelessness. These include the number of sheltered homeless, unsheltered homeless, family homeless, and individual homeless; the sum of all categories is total homeless. An individual experiencing homelessness can fit into two categories, either unsheltered or sheltered and either individual or family. They are then counted towards the total homeless population (Hanratty, 2017).

For individuals experiencing homelessness, there are many correlating negative impacts on their health. There is evidence that homelessness and housing vulnerability are associated with diminished mental and physical health (Gaderman *et al.*, 2013). Other evidence suggests that there are increased rates of illness found in those experiencing homelessness as well as poor living conditions when housed (Sanchez, 2010). States and cities also greatly benefit from a decrease in homelessness. For example, Shelfosky (2020) finds negative effects of homelessness in cities with large populations, including physical damage on physical areas and psychological issues for those experiencing homelessness. One suggestion for the distribution of federal grants is to account for local needs when giving grants to various organizations, like the CoC Organization (Lee, 2021).

Homeless shelters are one type of aid towards homelessness. This is one of the most popular responses to homelessness as variations of shelters exist throughout the world. In the United States, some shelters are funded by the federal government, some are funded by state governments, and others are privately funded.[3]

This paper investigates how fluctuations in the homeless population impacts the number of homeless shelter beds in the future. The estimates are a numeric measure of the public's response to changes in the homeless population. I also analyze how this public response differs across two distinct homeless populations; the sheltered and unsheltered homeless. Specifically, the null hypothesis is that society does not change the number of shelter beds when there is an increase in the homeless population. This is tested against an alternative hypothesis where society changes the number of beds when the homeless population fluctuates. After controlling for housing prices, population, the unemployment rate, and political preferences at a state level, I estimate that an additional one hundred total homeless correlates to an increase in 25 beds the following year, indicating that 25% of need is met. Separating this number into the two distinctions between the types of homeless, I find that in response to the sheltered population 55% of the need for beds is addressed the following year. While the response to unsheltered population is much smaller around 5%, this means that society does not use the change in the unsheltered homeless population as an important factor in whether there should be a change in the number of shelter beds that are available.

Literature Review:

In the academic literature there are many studies investigating the predictors of homelessness, particularly in the last decade as more data have become available. For example,

[3] https://www.profitableventure.com/homeless-shelter-government-grant-loan/

the academic literature has studied substance use, mental illness, unemployment, and poverty as potential predictors. While these potential causes have long been studied, recent articles have provided more depth (Giano *et al*., 2019).

Many factors have been studied for a correlation and causal effect on patterns of homelessness. For example, one factor that has been studied extensively and shown to have a significant impact on homelessness is local median rent in a given community (Hanratty, 2017 & O'Flaherty *et al.*, 2004). As rent rises in an area, it becomes increasingly difficult for an individual to generate sufficient income to live there. Both papers also found inconsistent and insignificant relationships between homelessness populations, poverty rates, and unemployment rates (Hanratty, 2017 & O'Flaherty *et al.*, 2004). This lack of a statistical relationship is interesting because it makes intuitive sense that more homeless correlates to higher poverty and unemployment rates. However, these rates are dependent on data from the U.S. Census, which likely does not account for people experiencing homelessness. Another issue is the definition of unemployment. The economic definition of unemployment requires that an individual be actively seeking work, which some homeless are not. There have also been studies on the influence of the minimum wage on the level of homelessness. Yamagishi (2021) estimates that a ten percent increase in minimum wage in Japan resulted in a 2.5 to 4.5 percent increase in median rent. The theory behind increasing the minimum wage is positive for many social issues, however, this evidence shows that an increase in wage results in higher rates of unemployment. Generally, an increase in unemployment results in increasing numbers of homeless which suggests that raising the minimum wage alone would not be a positive intervention to reduce homelessness.

Upstream solutions to homelessness are necessary to decrease the sheltered and unsheltered homeless populations. The literature has shifted focus to solutions that seek to provide access to housing rather than access to jobs. The Homeless Emergency Assistance and Rapid Transition of Housing Act (HEARTH) was implemented in 2009. This is an aspect of the United States' framework of housing policy which includes McKinney-Vento Act and Homeless Persons' Survival Act (Beard, 2013). These are among the most important acts of federal legislation addressing homelessness because many shelters in cities across the country are funded by HEARTH and McKinney-Vento. This also focuses on ensuring that children who are experiencing homelessness are able to receive an equal education relative to other children in the area.[4] The existence of federal programs to support solutions to homelessness is important because similar issues are often allocated to State governments.

There have been many proposed solutions to discourage homelessness by cities and companies. One tactic is called hostile architecture. This can take many forms and be incorporated into common objects, such as spikes on sidewalks, curved benches, armrests, and small dividers on ledges. These are all attempts to make areas for sitting, laying down or loitering difficult and uncomfortable (Hu, 2019).

Another approach to decrease the amount of homeless in an area is called "bussing out," where cities, shelters, hospitals, and other programs buy bus tickets to other cities and give them to people experiencing homelessness. In some extreme cases like New York City, plane tickets have even been provided. Many of these programs come with a caveat stipulating that the individual will not return to that city for a certain amount of months, or sometimes ever. Accounts of these programs show varying degrees of success in providing people with a better place to live. Many end up homeless once again in a different city (Gee, *et al.*, 2017).

[4] https://www.clcm.org/mckinneyvento

In the early stages of intervention, focus was placed on providing services for people who are experiencing homelessness. While necessary, this work does not address root causes or enable society to decrease the number of homeless. The McKinney-Vento Homeless Assistance Act was first implemented in 2000 by President Bill Clinton; this came after the 1987 Stewart B. McKinney Homeless Assistance Act under President Ronald Reagan. This act is a strong example of a policy directed at aiding people with an existing problem. Society would benefit from a policy aimed to better support people and end the vicious cycle of homelessness, while this focuses on helping people who are already homeless (Giano *et al.*, 2019). Many homeless shelters in the country are still funded under this federal policy and the implementation of a federal policy addressing upstream solutions to homelessness would be impactful.

Homelessness prevention is a more recent response to the problem (Mackie, 2014 & National Academy of Sciences, 2018). This shift in focus occurred for three main reasons: the efficiency of addressing the problem early on, the benefits for a society with fewer homeless, and the benefits to the individual that avoids experiencing homelessness (Mackie, 2014). With this shift , it is important to focus on prevention as it can eliminate the existence or experience of homelessness.

Multiple studies have analyzed the use of homeless shelters in Canada (Jadidzadeh and Kneebone, 2018 & Rabinovitch *et al.*, 2016). The first study focuses on the patterns and intensity of homeless shelters in Toronto. The authors find that only about one third of the beds being used in all shelters were for homeless looking for emergency relief. The other two thirds were used by occasional and frequent users or chronic homeless (Jadidzadeh and Kneebone, 2018). The second study shows that more than half of the shelter bed nights were used by episodic and long-stay clusters and the rest by the temporary users (Rabinovitch *et al.*, 2016). Both sets of data indicate that the majority of shelter beds are used by homeless that remain homeless and do not help to reduce the total number of people that are experiencing homelessness.

One article looked at two hypotheses that had been virtually unstudied in relation to homelessness: the degree of entrepreneurial activity and the amount of labor market freedom in an area. The findings show that areas with an increased degree of entrepreneurial activity and increased labor market freedom have fewer total homeless (Cebula and Saunoris, 2021). These are examples of possible upstream solutions that attempt to stop homelessness before it begins.

Schechter (2021) looks at how the number of shelters in an area impacts the existence of an independent variable. This study finds that having at least one shelter in a community significantly reduces the rate of partner homicide. For counties that have at least one shelter, either homeless shelter, youth shelter or domestic violence shelter, this means one less partner homicide per 100,00 citizens every three to four years. This study used a difference-in-differences methodology to determine the variation in counties with no shelters, one shelter, or more than one shelter.

Empirical Model:

The main source of data for this analysis comes from the United States Department of Housing and Urban Development (HUD)'s Point-in-Time count in collaboration with the Continuum of Care Organization (CoC) for the years of 2012 through 2019. These data include the number of homeless, broken down into sheltered and unsheltered homeless. These two numbers are collected differently. The sheltered homeless are found through members of the CoC Organization calling individual shelters to record the number of people that are staying in that shelter on a given night. The unsheltered homeless number is determined through counts made by groups going out into different areas. This unsheltered homeless number represents the number of homeless that are not using a homeless shelter on that given day. The homeless population data are most commonly used as independent variables in regressions because the ultimate goal is to see how changes in these numbers cause society to react through a change in the number of shelter beds.

The sheltered individuals or families must fit HUD's definition for 24 CFR 578.3 of the Homeless Definition Final Rule: "An individual or family living in a supervised publicly or privately operated shelter designated to provide temporary living arrangement (including congregate shelters, transitional housing, and hotels and motels paid for by charitable organizations or by federal, state, or local government programs for low-income individuals)." Row 3 of Table 1 outlines the summary statistics of the sheltered homeless population. The unsheltered homeless count is somewhat subjective and may be influenced by state-level differences in rules and regulations surrounding the legality of unsheltered homeless. The unsheltered individual or family must fit HUD's definition at 24 CFR 578.3 of the Homeless Definition Final Rule: "An individual or family with a primary nighttime residence that is a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings, including a car, park, abandoned building, bus or train station, airport, or camping ground." Row 2 of Table 1 illustrates the summary statistics of the unsheltered homeless population.

To address the time-invariant differences across states, I use panel data to improve the validity of the results. I also control for macroeconomic shocks that impact all states with controls for the year of the data. The data list each shelter in each state for each year, which I collapse into aggregates. The types of shelters used in this analysis are Emergency Shelters (ES), Safe Havens (SH), and Transitional Housing (TH) shelters. Emergency Shelters are defined as "any facility, the primary purpose of which is to provide a temporary shelter for the homeless in general or for specific populations of the homeless and which does not require occupants to sign leases or occupancy agreements." (HUD, 2012). Safe Havens are defined as "a form of supportive housing that serves hard-to-reach homeless persons with severe mental illness who come primarily from the streets and have been unable or unwilling to participate in housing supportive services." (HUD, 2012). Safe Havens are no longer supported under HEARTH. While HUD does not fund any new Safe Havens, it continues to fund those existing prior to 2009. For these reasons there are relatively few Safe Havens in the data set but this category is still important to include. Transitional Housing shelters are limited to agreements and leases that do not exceed 24 months. The number of beds in these shelters, which is the dependent variable in this analysis, is aggregated in each state-year combination.

The goal of the estimation is to examine factors that influence the provision of beds in homeless shelters. Specifically, I analyze how a change in the number of homeless impacts the provisions of beds the following year. This marginal effect represents a numeric estimate of society's response to homelessness through the provision of beds. I use a variety of other explanatory variables to isolate the impact of changes in the number of homeless on the future provision of beds. For example, the unemployment rate for each state and year is included in this regression, these data come from the United States Bureau of Labor Statistics. The summary statistics of the unemployment rates can be seen in Row 6 of Table 1. I also include data on state population each year which comes from the United States Census. These annual measures are considered estimates, but are believed to be reliable accounts of population fluctuations. This variable allows controls for the large differences in population across states such as Californoia and Vermont. Row 7 of Table 1 describes summary statistics of the state populations. I also use Housing Price Index (HPI) data for each state and year which controls for differences in costs of living across states and time. The summary statistics for HPI are shown in Row 5 of Table 1. Finally, I include a measure of political affiliation in each state and year. Without an obvious annual measure, I use the percentage of Democratic voters in the previous presidential election. These data points are from the 2012 and 2016 presidential elections. While not every citizen votes, this percentage may capture political differences in solutions to homelessness. These data comes from the Federal Election Committee. Row 4 of Table 1 illustrates the summary statistics of the political affiliation variable.

Table 1: Summary Statistics of Variables

Variable	Mean (Std. Dev.)	Minimum	Maximum
Row 1 Total Homeless (# of people)	11,127.85 (21,294.53)	541	161,548
Row 2 Unsheltered Homeless (# of people)	3,787.64 (12,341.54)	10	113,660
Row 3 Sheltered Homeless (# of people)	7,340.21 (12,549.34)	423	88,044
Row 4 Democrat (% voted democrat in most recent election)	46.64% (12.13)	21.88%	90.91%
Row 5 HPI (Idex Score)	544.32 (198.09)	283.88	1,482.97
Row 6 Unemployment Rate (% of unemployed)	5.39% (1.89)	2.1%	13.5%
Row 7 Population (# of people)	6,314,126 (7,138,281)	576,305	3.95e+07

To assess society's reaction to homelessness, I use multiple linear regressions each with fixed effects for all states. The dependent variable is the number of beds, which provides a better fit of the data than the number of shelters. The two regression models are only different through the independent variables that count the number of homeless; the first regression uses the total number of homeless as an independent variable. In the second regression, the total is replaced with two controls: the number of unsheltered homeless and sheltered homeless. The differences in results between these regressions is important to understanding how the different populations impact states' response to homelessness. The independent variables that measure the level of homelessness – total homeless, unsheltered homeless, and sheltered homeless – are lagged by one year. Lagging these variables accounts for the time delay of society's response to changes in the homeless population. This method also mitigates concerns about dual causality between the number of homeless and the provision of beds. The other independent variables in the regression model account for various indicators that could explain a change in homelessness or homeless shelter beds. These include a proxy for political affiliation, Housing Price Index as a proxy for affordability in a state, the unemployment rate in a specific state in the given year, and a population estimate.

In order to isolate the effect of homeless on the provision of beds, I include a variety of other independent variables. In addition to state-level fixed effects, there are dummy variables, labeled as $year_t$ below, for each year for patterns across the country but specific to a particular year.

For state s and year t, the equation of the first regression is:

$$Beds_{s,t} = \beta_0 + \beta_1 TotalHomeless_{s,t-1} + \beta_2 Democrat_{s,t} + \beta_3 HPI_{s,t} + \beta_4 UnemploymentRate_{s,t} + \beta_5 Population_{s,t} + \sum_t \delta_t year_t + \lambda_s + \varepsilon_{s,t}$$

For state s and year t, the equation of the second regression is:

$$Beds_{s,t} = \beta_0 + \beta_1 UnshelteredHomeless_{s,t-1} + \beta_1 ShelteredHomeless_{s,t-1} + \beta_3 Democrat_{s,t} + \beta_4 HPI_{s,t} + \beta_5 UnemploymentRate_{s,t} + \beta_6 Population_{s,t} + \sum_t \delta_t year_t + \lambda_s + \varepsilon_{s,t}$$

Results:

These two regressions use different independent variables of interest. In the first regression Total Homeless in the previous year is the input variable that impacts the Beds dependent variable. The results in the first column of Table 2 are from the first regression. In this column the most notable estimate is the impact of Total Homeless, 0.241, which is statistically significant at ten percent. This indicates that with an increase of one hundred new homeless, there is an increase of 24 beds the following year. This estimated marginal effect is economically significant because it represents that only 24% of need is met. The unemployment estimate is significant in this regression at the ten percent level. The other estimate in this regression that is significant is population, with a very small negative coefficient. The marginal effect of population on this number indicates that an increase in population results in a slight decrease in the number of beds that are available. For this regression the r squared value is 0.995 calculated using a standard linear regression in Stata. This value is a strong indicator that the regression includes nearly all variables that could explain a change in the number of shelter beds the next year. The F test statistic at the bottom of Table 2 is a joint significance test of the state-level fixed effects. With such a small p-value, the null hypothesis is rejected which suggests the fixed effects have explanatory power.

The outputs from the second regression are reflected in Column 2 of Table 2. There is no output for total homeless because it is replaced with unsheltered and sheltered homeless populations. The coefficient on unsheltered homeless in this regression is 0.064 with a p-value of 0.001 which makes it clearly statistically significant. This means that for every 100 new unsheltered homeless in a state, the total beds in that state would increase by 6 by the next year. The coefficient associated with sheltered homeless is 0.549 with a p-value that is less than 0.001 which is statistically significant. This means that an increase in sheltered homeless by 100 would cause an increase of 55 new shelter beds the next year.

The difference between 6 and 55 is vast and implies that the response is linked more to the sheltered homeless population than to the unsheltered. The r squared value for this regression is 0.996 which is similar to the first regression and emphasizes the explanatory power of the variables in this regression. When looking at Graph 1 in the introduction, it is obvious that the unsheltered homeless population is increasing, so if the majority of the influence on society's decisions comes from the sheltered homeless, it may not be addressing the right problem. While running correlation matrices on all of the variables, only one relationship was notable, this was with a value of 0.995 between sheltered homeless and shelter beds. This high correlation is confirmed by the regression which indicates that as the sheltered population moves, the number of beds moves similarly.

Separating the total number of homeless into sheltered and unsheltered homeless populations improves the fit of these variables, making each significant at the five percent level. This shift also improves the fit of the other estimates, in the first regression only the unemployment rate and population are significant. In the second regression, not only do the unemployment rate and population variables become more significant, Democrat becomes significant at the ten percent level and HPI also becomes significant at the five percent level.

Table 2: Regression Results
* indicates significance at the 10% level
** indicates significance at the 5% level

Total Beds	**Column 1** Regression 1	**Column 2** Regression 2
Total Homeless$_{t-1}$	0.241* (p value = 0.070)	–
Unsheltered Homeless$_{t-1}$	–	0.064** (p value = 0.001)
Sheltered Homeless$_{t-1}$	–	0.549** (p value < 0.001)
Democrat	-28.453 (p value = 0.126)	-21.437* (p value = 0.095)
HPI	2.021 (p value = 0.306)	4.532** (p value = 0.001)
Unemployment Rate	277.69* (p value = 0.051)	288.424** (p value = 0.004)
Population	-0.002** (p value = 0.011)	-0.002** (p value < 0.001)
R^2 Value	0.995	0.996
F Test for fixed effects	198.00** (p value < 0.001)	4.28** (p value < 0.001)

The regression model satisfies the OLS assumptions of the Gauss-Markov theorem. The first assumption is that the conditional distribution of the residual, given all the independent variables, has a mean of zero. This is accounted for because all the variables are independent of each other. The second assumption is that all the variables are independently and identically distributed, meaning that they are random variables. The third assumption is that large outliers are unlikely, accounting for population in the regression and comparing all the states over multiple years allows for an unlikely chance that there are any large outliers. The time frame of 2012 to 2019 is also a good series of times where there were no significant yearly outliers that would indicate a significant reason for a fluctuation in the homeless population. I can also assume that these regressions account for homoskedasticity by including the robust standard errors function in the fixed effects regression. The fourth assumption is no perfect multicollinearity, and none of these variables are perfect functions of one another. With an r squared value so close to one, there is not much room for omitted variables. There is still a chance of omitted variable bias within these regression models as there are choices that the homeless population makes that cannot be included in the model. Such as, there are decision making ideas that cannot be measured that could change the variables. Another example of an omitted variable is the climate on a given day which may increase the number of sheltered homeless as opposed to unsheltered homeless but would likely not have a large impact on the total number of beds the next year.

Conclusion:

In conclusion, society responds to homelessness through adding or taking away shelter beds the next year. The availability of shelters and shelter beds are functions of a state's population, HPI, political affiliation, unemployment rate, and most importantly, the different homeless populations. In this analysis I reject the null hypothesis indicating that a change in the total homeless population results in a significant change in the number of shelter beds available the following year. This is also true for a change in the unsheltered and sheltered homeless populations. A notable outcome of this model is the difference in levels of impact between the unsheltered and sheltered population. If there are equal increases of 1,000 unsheltered homeless and 1,000 sheltered homeless in a specific state, there would be an additional 549 shelter beds in response to the increase in sheltered homeless and only 64 new beds in response to the increase in unsheltered homeless. There is a significant distinction between these two numbers in response to the same level of increase for each variable. This means that society increases beds on account of more need in the sheltered homeless population than the unsheltered population. This response is understandable and in some ways expected but ignores the increases in the unsheltered homeless population.

A strength of this analysis is the panel data that addresses all fifty United States and Washington D.C. over multiple years, because of the size of this data, external validity would have to be on an international level. The only way for this to work externally is if there are similar variables like unemployment rate and HPI that can be found within the new country. This analysis could be extended to answer a potential endogeneity question. Two approaches that could be possible are a vector autoregression or an independent variable regressions. The lagged effects of total beds being in the next year is the way this analysis accounts for the implicit endogeneity issue. Overall, society uses the sheltered homeless population as a strong factor in changing the number of beds available the following year and meets approximately 24% of the need for a change in the total homeless population.

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