Local Economic Conditions' Effect on Homelessness and the Impact of Available Beds

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Abstract

This article estimates the effect of bed availability from the previous year on homelessness, building on top of the model proposed by Dr. Hanratty. Our model estimates that the percent of vacant rental properties in the community, percent of properties in the community which are rental properties, the local median rent, the local Unemployment rate, and the available beds from a year prior each have a statistically significant impact on the homeless rate, where all of the impacts are positive except for the percent of local properties which are rentals, which has a negative impact on homelessness rates. When controlling for community fixed effects, we saw the same variable having a statistically significant positive impact on the homeless rate with the expectation of rent share, which saw a statistically significant negative impact on the homeless rate. We saw an increase in available beds did not lead to a decrease in the unsheltered homeless population. Rather, it elevated the overall homeless rate and was not associated with an immediate or permanent reduction in homelessness.

Keywords: Homeless; labor market; income; low-income housing; public policy

JEL Codes: J40, I32, R38

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1 Introduction

This paper is an investigation of the effect of bed availability from the previous year on the current homelessness rate, building upon the model proposed by Dr. Hanratty. To achieve this, we utilize extended data derived from the U.S. Department of Housing and Urban Development's (HUD's) annual point-in-time counts of homelessness, which provides a comprehensive view of homelessness in the United States. Our objective is to discern the effects of bed availability on the homelessness rate, with a particular focus on understanding their impact on the overall homeless rate, family homeless rate, individual homeless rate, sheltered homeless rate, and unsheltered homeless rate in the United States.

One of the challenges frequently faced by researchers on the subject of homelessness is the method of measuring the homeless population. In this paper, we employ HUD data, which defines the homeless population as comprised of temporarily sheltered homeless individuals – those residing in shelters, transitional housing, or hotels/motels – and unsheltered homeless individuals who do not have access to a location intended for regular sleeping, such as cars, parks, or abandoned structures[5]. It is important to acknowledge that this data might exhibit sampling bias, as it can be more difficult to identify individuals in unsheltered locations[5]. As a result, the HUD data may potentially underestimate the extent of homelessness in areas with limited shelter availability, as individuals in these communities may remain unsheltered and unaccounted for[5]. In addition to this, any policies or variables that can be used to better quantify the unsheltered homeless into the sheltered category will most likely see an increase in total homeless, which could represent a decrease in the uncounted unsheltered homeless.

To unravel the complexities of the homelessness issue, this paper draws upon data from multiple sources to analyze the impact of economic conditions and the number of available beds on homelessness rates. Our primary data source is constructed from HUD's point-in-time counts of homelessness spanning from 2007 to 2019, and housing inventory from the same time frame. Additionally, we utilize American Community Survey (ACS) data for demographics, and Bureau of Labor Statistics (BLS) data for labor market outcome information.

Utilizing Dr. Hanratty's Ordinary Least Squares (OLS) model as a foundational framework, we attempt to replicate her results and subsequently extend our analysis. We intend to incorporate the lagged effect of available beds impact on factors laid out by Dr. Hanratty's OLS model and the future policy suggestion. We seek to find a reasonable and empirical approach to the homeless solution.

2 Literature Review

We begin by discussing a pivotal paper in the sphere of homelessness research in economics. Elliot and Krivo (1991) outline four structural factors which are widely believed to be determinants of homelessness: lack of low-cost housing, high poverty rates, poor economic conditions, and lack of community mental health facilities. In analyzing data from the 1980 Census of Population and Housing and U.S. Department of Housing and Urban Development's 1984 study of homelessness, they discovered that per-capita spending on mental health resources and the availability of low-cost housing were the only two of the four 'determinants' which held a statistically significant relationship with homelessness. Although poverty rate and unemployment did not hold a statistically significant relationship with homelessness, the percentage of jobs which were unskilled did show statistical significance. Thus, policy implications flowed naturally from Elliot and Krivo's (1991) conclusion: to combat homelessness, governments should invest in mental health resources and in constructing affordable housing.

Similarly, Byrne, et. al. (2014) sought to analyze the impact of one specific possible determinant of homelessness: namely, local investment into permanent supportive housing, which is broadly defined as subsidized housing paired with supportive services. They develop a dataset by combining data from the U.S. Census Bureau, the U.S. Historical Climatology Network, the U.S. Housing and Urban Development, and the American Community Survey

(ACS) to gather housing, economic, climate, demographic, and community safety-net data together. Using a Poisson regression model, Byrne, et. al. (2014) conclude that communities that invest more resources into Permanent Supportive Housing (PSH) show greater reductions in homelessness over time. Thus, their findings are in line with the results of Elliot and Krivo (1991), in that both papers suggest affordable housing as a means of reducing the incidence of homelessness.

In contrast, Early (1999) provides a bit of a warning towards the implementation of the policy suggestions brought forth by previous works. Through a theoretical framework starting with fairly standard microeconomic utility functions and probability theory, Early (1999) derives a probability of becoming homeless, which he compares to a combined dataset from the Urban Institute survey and the American Housing Survey from 1985 to 1988, to garner data for both the homeless and the housed. Early (1999) concludes theoretically, and shows empirically, that with greater availability of shelter beds, the probability of an individual becoming homeless increases. Thus, Early (1999) warns that the means of applying the policy suggestions of affordable housing is incredibly important, since public provision of beds in homeless shelters can be more detrimental than helpful to society.

Next, Foote (2016) provides an analysis of Panel Study of Income Dynamics (PSID) data to show the relationship between negative house price shocks and migration. By analyzing how leveraged homeowners are through the loan-to-value ratio, Foote (2016) notes that negative housing price shocks prevent heavily leveraged homeowners from migrating. This understanding is crucial to the analysis of homelessness, since one key driver of homelessness, even if temporary, could be amount of leverage into a home during an economic downturn.

Finally, the study we seek to replicate, Hanratty (2017), determines how local economic conditions impact homelessness. Hanratty (2017) recognizes that many studies on the impacts of homelessness rely upon cross-sectional models, and may be susceptible to biased results if they fail to control for area-level characteristics which are correlated with homelessness and economic conditions. So, using a combined U.S. Housing and Urban Development point-in-time count of homelessness from 2007-2014, ACS data for area-level economic and demographic characteristics, US Census Bureau and Bureau of Labor Statistics (BLS) data for unemployment and local area poverty rate, Hanratty (2017) analyzes the impact of housing market conditions -median rent and vacancy rate- and labor market conditions- unemployment rate and poverty rate- on the rate of homelessness using a multivariate OLS regression with area and year fixed effects. They conclude that policy targeting a lower homelessness rate should look towards communities with high poverty rates and rent.

3 Data

Table 1: Summary Statistics

Statistic	Dataset	Mean	St. Dev.
Population	Census	754,241	1,067,158
Median Rent (2014)	ACS	928.057	211.629
% of Rental Households which are Vacant	ACS	5.439	3.704
% of Households which are Rentals	ACS	28.423	8.555
Unemployment Rate from ACS	ACS	7.815	2.690
Unemployment Rate from BLS	BLS	6.898	2.784
% of Population within 100% of Poverty Threshold	ACS	15.638	5.646
% of Population who are Black	ACS	12.661	12.259
% of Population who are Hispanic	ACS	9.089	9.694
% of Population who are Babyboomers (born 1946 and 1964)	ACS	27.086	2.639
% of Population Living Alone	ACS	18.312	5.089
% of Population in Single Parent Household	ACS	10.444	2.285
% of Population who are Veterans	ACS	8.242	2.512
% of People in Poverty Receiving SSI	ACS	13.835	4.237
Total Homeless per 10k Population	PIT	19.647	20.378
Homeless in Families per 10k Population	PIT	12.041	13.984
Individual Homeless per 10k Population	PIT	7.606	9.272
Sheltered Homeless per 10k Population	PIT	13.468	12.731
Unsheltered Homeless per 10k Population	PIT	6.179	13.757
Sheltered Chronically Homeless per 10k Population	PIT	0.053	0.160
Permanent Supportive Housing per 10k Population	HIC	16.163	170.237
Family Permanent Supportive Housing per 10k Population	HIC	6.628	70.615

The HUD Point-in-Time (PIT) count is a count of people experiencing homelessness within each Continuum of Care (CoC.) The counts for homeless individuals are taken one day per year, and data for unsheltered homeless can be reported by CoC's every other year, as those are estimates of homeless individuals in the local area, but outside of the shelter, causing difficulties for measurement. The sheltered and unsheltered homeless counts are further disaggregated by family homeless and individual homeless, as well as by various demographic characteristics. Similarly, the Housing Inventory Count (HIC) is a count of beds at each continuum of care, disaggregated by family housing, individual housing, and chronically homeless housing. Furthermore, the beds can be categorized into five program types: Transitional Housing (TH), Emergency Shelter (ES), Rapid Re-housing (RRH), Safe Haven (SH), and Permanent Supportive Housing (PSH).

The American Community Survey is a rich dataset with individual-level and household-level data. Each observation has a state and county federal information processing code, which can be aggregated to form the Federal Information Processing Standard (FIPS) code. Also, the Bureau of Labor Statistics (BLS) offers Local Area Unemployment Statistics (LAUS) data by year. For each year-level dataset, there are observations for each county, uniquely identified by FIPS code. The LAUS data reports the average unemployment rate in each county for that calendar year. Median Rent is adjusted to 2014 dollars using CPI-W, in accordance with Hanratty (2017). In addition, poverty rate reports the percentage of individuals within the local area who are within 100 percent of the poverty threshold. Finally, the regression uses the percentage of people in poverty, according to the previous definition, who are receiving SSI.

The dataset for this project was created by linking the HUD PIT and HIC data by CoC number: a unique identifier given to each continuum of care. Then, using a crosswalk designed by Byrne, et. al. (2016), the CoC's could be linked to different FIPS codes. These FIPS codes are unique local-area identifiers for counties, which are included in the BLS LAUS and within the ACS data. Thus, the linked dataset from the two HUD datasets could be further linked to local-area aggregated, weighted averages from the ACS: weights were either ACS household weight or ACS person weight, depending upon if the variable would be observed by houses, like the variable VACANT, or if the variable would be observed by individuals, like the demographic variables for race and age. Furthermore, that combined dataset could be similarly linked to the BLS LAUS data by FIPS codes to gather local-area unemployment and poverty statistics.

4 Empirical Methods

$$Homeless\ Rate_{jt} = \beta_1 H_{jt} + \beta_2 E_{jt} + \beta_3 D_{jt} + \beta_4 S_{jt} + \beta_5 L_{j(t-n)} + \delta_j + \gamma_t + \varepsilon_{jt'} \quad (1)$$

Our primary model is based off of Hanratty's (2017) OLS model, where the dependent variable is the rate of homeless people per 10,000 population in a given community j and given year t.

Our first independent variable is H_{jt} measuring the housing market conditions in community j in year t: the variables that makeup housing market conditions are vacant rate, rent share, and median rent in our regression[5]. Next, we have E_{jt} which is the labor market condition in community j in year t, represented by the unemployment rate and poverty rate[5] given by the American Community Survey.

D_{jt} is a control for demographic characteristics in a given community j and year t, which measures the percentage of the given community that is Black, Hispanic, veteran, single parent, and/or living alone[5]. S_{jt} is the indicator of the availability of income-tested transfer and supportive services in given community j in year t but in our regression only accounts for percentage of the people within 100% of the poverty threshold who take Supplemental Security Income[5].

δ_j and γ_t are represent community and year fixed effects, respectively. Therefore, the variable δ_j is the unmeasured community j characteristics that are potentially correlated with area homeless rates.

4.1 The Lagged Available Total Bed Effect

Our paper extends upon Hanratty's (2017) model by adding the lagged number of available total beds per 10,000 population of the community j in the year $(t-n)$. We are using the availability of beds n-years ago, at time period $(t-n)$, as we are expecting the previously available number of beds to impact individual expectations of bed availability at time period t, thus affecting homeless rates. This follows by assuming individuals follow a utility-function model for choosing to become homeless, as described by Early (1999). If so, then the probability that one would be able to find a publicly-funded shelter would hinge upon available data on the number of available beds for homeless individuals. Therefore we might expect, if some people are indeed choosing to become homeless, a positive correlation between amount of available beds in any year, and homelessness rates the next year.

5 Results

This section will discuss the result of our model, but before that, we will summarise Dr. Hanratty's model. Dr. Hanratty's model suggests that a single percentage point increase in the rental market share will increase the total homeless rate by 0.8 individuals per 10,000 population, a $100 increase in the median rent would increase the total homeless rate by 2 individuals per 10,000 population, a percentage point increase in the poverty rate would increase the total homeless rate by 0.6 individuals per 10,000 population. Dr. Hanratty's model showed that the Vacancy rate and the Unemployment rate are not statically significant in regard to their effect on the total homeless rate. As a disclosure, we were not able to replicate her result due to our data not matching hers 100% and our given time constraints. However, although we were close to her result in this attempted replication, we found fewer observations than Dr. Hanratty's paper due to missingness from some areas or continuums of care in the dataset mapping process.

5.1 The Lagged Available Total Bed Effect Result

Table 2: Lagged Beds Effect Result Without Community Effects

	Dependent variable:					
	Total Homeless		Family Homeless	Individual Homeless	Sheltered Homeless	Unsheltered Homeless
	(1)	(2)	(3)	(4)	(5)	(6)
Vacant Rate	0.077	0.226***	0.277***	−0.051	−0.065***	0.291***
	(0.083)	(0.054)	(0.041)	(0.032)	(0.025)	(0.047)
Rent Share	1.365***	0.284***	0.116***	0.167***	0.118***	0.166***
	(0.045)	(0.035)	(0.027)	(0.021)	(0.016)	(0.031)
Median Rent	0.023***	0.010***	0.002**	0.008***	0.005***	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)
Unemployment Rate	1.406***	0.955***	0.701***	0.253***	0.150***	0.805***
	(0.178)	(0.116)	(0.088)	(0.069)	(0.053)	(0.101)
Poverty Rate	0.298**	−0.048	−0.252***	0.204***	−0.117***	0.069
	(0.119)	(0.078)	(0.060)	(0.047)	(0.036)	(0.068)
Lag Available Beds		0.925***	0.441***	0.484***	0.879***	0.045***
		(0.016)	(0.012)	(0.009)	(0.007)	(0.014)
Observations	2,877	2,661	2,661	2,661	2,661	2,661
Log Likelihood	−11,835.720	−9,723.838	−8,993.822	−8,340.623	−7,638.124	−9,360.309
Akaike Inf. Crit.	23,719.440	19,495.680	18,035.640	16,729.250	15,324.250	18,768.620
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 3: Lagged Beds Effect Result With Community Effects

	Dependent variable:					
	Total Homeless		Family Homeless	Individual Homeless	Sheltered Homeless	Unsheltered Homeless
	(1)	(2)	(3)	(4)	(5)	(6)
Vacant Rate	0.269***	0.227***	0.164***	0.062	−0.001	0.228***
	(0.085)	(0.073)	(0.046)	(0.039)	(0.034)	(0.061)
Rent Share	−0.799***	−0.432***	−0.321***	−0.111**	−0.218***	−0.213***
	(0.109)	(0.096)	(0.061)	(0.052)	(0.045)	(0.081)
Median Rent	0.026***	0.012***	0.009***	0.003**	0.005***	0.007***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
Unemployment Rate	0.509***	0.295**	0.189**	0.106	0.014	0.281**
	(0.156)	(0.132)	(0.084)	(0.071)	(0.062)	(0.111)
Poverty Rate	0.094	0.072	0.043	0.029	0.008	0.064
	(0.141)	(0.121)	(0.077)	(0.065)	(0.057)	(0.102)
Lag Available Beds		0.723***	0.317***	0.406***	0.706***	0.017
		(0.033)	(0.021)	(0.018)	(0.016)	(0.028)
Observations	2,877	2,661	2,661	2,661	2,661	2,661
Log Likelihood	−9,993.667	−8,673.321	−7,468.528	−7,027.747	−6,678.735	−8,205.583
Akaike Inf. Crit.	20,529.330	17,888.640	15,479.060	14,597.500	13,899.470	16,953.170
Note:						*p<0.1; **p<0.05; ***p<0.01

Our model is extended upon Dr. Hanratty's by extending the data to 2019 before the start of Coronavirus Disease 2019 (COVID-19) and adding the lagged available beds into the regression. We found that data after 2019 was rather unreliable and therefore was omitted from our extension, as data collection was more difficult during the extended period of social distancing and other temporary COVID-19 policies, affecting the data. Table 2 presents the lagged beds effect result without the community effect factored into the regression. When we add the lagged effect as presented in model(2) we see that the addition of the new variable overall lowered the average effect of all variables compared to model(1). We also saw that the poverty rate was no longer statistically significant in its effect on the total homeless rate.

As shown in Table 2 model(2), it is estimated that a percentage point increase in the vacant rate will increase the total homeless rate by 0.226 individuals per 10,000 population, a percentage point increase in rent market share will increase the total homeless rate by 0.284 individuals per 10,000 population, a $100 increase in median rent will see the total homeless rate increase by 1 individuals per 10,000 population, a percentage point increase in the unemployment rate will see the total homeless rate increase by 0.995 individuals per 10,000 population, and lastly through the lagged bed effect we see that an increase in a single bed per 10,000 population will increase the homeless rate by 0.925 individuals per 10,000 population. We found that the poverty rate is not statistically significant to our total homeless rate when accounting for lagged available beds.

Table 3 controls for the unmeasurable variation between communities across our data by factoring each community by the CoC number. We saw that with the community effect estimate in the model(2) for rent share and poverty rate flipped signs. In both Tables 2 and 3, we see that the lagged available bed effect is similar between the total homeless and the sheltered homeless and that across all dependent variables, the unsheltered homeless model(6) has the lowest effect across the 5 models.

Presented in Table 3 model(2) we can estimate that a percentage point increase in the vacant rate will increase the total homeless rate by 0.227 individuals per 10,000 population, for percentage point increase in rent market share will decrease the total homeless rate by 0.432 individuals per 10,000 population, for a $100 increase in median rent will see the total homeless rate increase by 1.2 individuals per 10,000 population, a percentage point increase in the unemployment rate will see the total homeless rate increase by 0.295 individuals per 10,000 population, and lastly lagged bed effect see that an increase in a single bed per 10,000 population will increase the homeless rate by 0.723 individuals per 10,000 population.

5.2 Testing Different Lagged Variables

Table 4: Testing Different Lagged Variables With Community Effects

	Dependent variable:					
	Total Homeless			Unsheltered Homeless		
	(1)	(2)	(3)	(4)	(5)	(6)
Vacant Rate	0.227***	0.177***	0.131*	0.228***	0.196***	0.148***
	(0.073)	(0.062)	(0.068)	(0.061)	(0.049)	(0.053)
Rent Share	−0.432***	−0.514***	−0.486***	−0.213***	−0.193***	−0.184**
	(0.096)	(0.083)	(0.093)	(0.081)	(0.066)	(0.072)
Median Rent	0.012***	0.015***	0.016***	0.007***	0.007***	0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployment Rate	0.295**	0.294***	0.411***	0.281**	0.267***	0.343***
	(0.132)	(0.109)	(0.119)	(0.111)	(0.086)	(0.092)
Poverty Rate	0.072	0.198*	0.186*	0.064	0.179**	0.209**
	(0.121)	(0.104)	(0.111)	(0.102)	(0.082)	(0.086)
Lag Available Beds	0.723***			0.017		
	(0.033)			(0.028)		
Lag Available Beds t-2		0.574***			−0.032	
		(0.028)			(0.022)	
Lag Available Beds t-3			0.475***			−0.054**
			(0.032)			(0.025)
Observations	2,661	2,445	2,228	2,661	2,445	2,228
Log Likelihood	−8,673.321	−7,391.332	−6,721.234	−8,205.583	−6,815.645	−6,162.794
Akaike Inf. Crit.	17,888.640	15,322.670	13,980.470	16,953.170	14,171.290	12,863.590
Note:						*p<0.1; **p<0.05; ***p<0.01

In this section, we test various periods on our lagged available bed effect variable. According to articles by the National Alliance to End Homelessness Permanent, Permanent Supportive Housing (PSH) has a one-year housing retention rate of 98 percent and Rapid Re-Housing (RRH) saw individuals exit homelessness in an average of 2 months and remained housed a year after at between 75 percent to 91 percent[8]. Although this does not categorize all the available bed types, it gives a good indication of the period in which the homeless will stay in the housing and the effect it may have in lagged effect. We suspect that the lagged effect may not account for the duration in which the effect becomes quantified in the drop in homelessness.

In the model in which the community fixed effects aren't accounted for, i.e. Table 2, we did not see any statistically significant changes in the variable effects up to (t-5). But in the model where we controlled for community fixed effects, as seen in Table 4, we saw that at (t-2), the unsheltered homelessness lagged available beds variable started to switch signs and a one bed per 10,000 population increase in lagged available beds 2 years prior decreased the unsheltered homelessness population by 0.032 individuals per 10,000 population. And starting at (t-3), we see that the effect becomes statically significant, and a single bed decreases unsheltered homelessness by an estimated 0.054 individuals per 10,000 population. Although not included in the table, models estimating lag available beds remain similar from (t-3) to (t-5). We also see that the effect of lag available beds on total homelessness decreases as the lag approaches 3 years. This is in line with economic intuition, as individuals are going to weight recent data more heavily than data from further in the past when forming expectations.

5.3 Brief Summary on Policy RD Result

Initially, our paper aimed to find the effect of the Housing First policy in California in the regression discontinuity in time method but our approach was found to be erroneous. The Housing First policy was enacted in the State of California in 2016, its goals were to build rapid housing and increase the bed availability for the homeless. The first concern that arose was the use of regression discontinuity in time where the year data collected was not continuous, but rather abstract. Therefore our regression discontinuity did not have enough data points in the pre-cut-off and post-cutoff to make a conclusion on the effect of the policy. The Second concern arose from the lagged effect of the policy, where the policy's real effect can not be determined by a cutoff date. We would see a spike in the homeless rate 1-2 years after 2016 which was the planned cutoff, this may be due to the effect of the policy inadvertently better accounting for the unsheltered homeless as sheltered homeless and increasing the total homeless rate. We were also concerned that the policy enactment would incentivize homeless from surrounding states to migrate to California and that we not be able to quantify the effect. Generally, the large cities in California such as San Francisco and San Jose saw trends in which the policy increased the total homeless rate rather than reduced it. We find our initial model with a disproportionate amount of variables to be able to make a strong causal relation in the post and pre-cutoff period.

6 Discussions

In terms of what our result means, we found that lag in available beds was statically significant in increasing the homeless rate across all models both without and with community effects, except in the unsheltered homeless with community effects. We found that the addition of lag available beds in the model decreased the average effect of other factors except in total homeless without community effect. The vacant rate in Table 2 saw an increase when adding lag available beds, but the effect of the poverty rate became statistically insignificant and flipped signs. The increase in available beds means that there is more room to have a better quantification of the homeless rate in a given population. As mentioned before there is difficulty in how HUD calculates and quantifies the unsheltered homeless. When an Unsheltered homeless individual is sheltered through an available bed, that individual is still counted towards the total homeless and will not increase nor decrease the rate. But if that individual was not accounted for by the HUD as an unsheltered homeless this will increase the sheltered homeless rate along with the total homeless rate. We see this clearly in Tables 2 and 3 with how the Lag available beds variable in the sheltered homeless model(5) is very close to the total homeless model(2). The difference between the total homeless and sheltered homeless rates lag available beds effect is represented by the unsheltered lag available beds. When accounted for community effect, the unsheltered homeless lag available beds variable is no longer statistically significant, and in both tables, the sign remains positive indicating that there is an increase homeless rate.

The lag in available beds in theory should be decreasing the unsheltered population, but clearly, when lagged by only a year it does not show such effect. We started to suspect that the duration for which an individual stays in the homeless housing may be longer than a year and the effect starts showing post (t-1). What we found is that when community effects are accounted for the available beds start to affect the overall homelessness and unsheltered homeless in the way we theorized at (t-2) and start to become statically significant at (t-3). What this suggests is that there is an effect in increasing available beds on reducing homelessness but may be countered by the temporary increase in year 1 as we are better able to quantify. It is also possible that the available bed has a staggered effect on the homelessness rate as the duration may vary on the individuals and therefore start to show significance at a later period.

Our model fails to adjust for the drug use rates and mental illness rates. These factors may be directly affecting the homeless rate, especially chronic homelessness. There are some suggestions on the effects of these variables on long-term homelessness but are harder to calculate.

7 Conclusion

In conclusion, our research was on the impacts of bed availability from the previous year on the current homelessness rates in the United States on the homeless rate. Drawing on our data from the U.S. Department of Housing and Urban Development (HUD) and extending Dr. Hanratty's Ordinary Least Squares (OLS) model, we hope to find effective policy suggestions.

Our findings indicated that the lagged effect of available beds per 10,000 population from the previous year had a notable impact on the homelessness rate. Contrary to initial expectations, an increase in available beds did not lead to a decrease in the unsheltered homeless population. Rather, an increase in available beds was associated with an increase in the overall homeless rate and did not have an immediate or permanent reduction in homelessness. However, when we looked at different time-length lags, we saw that at lags of 2 and 3 years there was a decrease in unsheltered homelessness when accounted for the community effect, with a lag of 3 years being statically significant.

It is important to acknowledge the limitations of our study given our time constraint. The lack of data beyond 2019, caused by the COVID-19 pandemic, created challenges in producing unbiased results. Additionally, our model did not account for variables such as drug use rates and mental illness, which very likely play significant roles in long-term homelessness.

In the exploration of the Housing First policy in California, our initial empirical approach faced challenges due to a lack of data when using regression discontinuity in time and potential migration effects.

We hope our research contributes to the ongoing discourse on homelessness, as we dissect the lagged effects of available beds and highlight the need for multifaceted strategies in public policies regarding the homeless.

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