Homelessness And Inequality in The United States

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1. Introduction

1.1 Motivation

Homelessness is a serious and persistent issue in many parts of the United States. Being surrounded by the homeless happens daily for people living in New York City, which causes panic due to their actions of wandering around and sleeping everywhere, including the subway station and the street. According to HUD[1] 582,462 people were experiencing homelessness in the United States and its territories in 2022, about 0.18% of the nation's population. Among major states, California and New York have the largest homeless population of 171,521 and 74,178, respectively, accounting for 43% of the homeless; Washington and Texas collectively account for 9% of the total homeless population in America. Homelessness has been termed as an epidemic in the US, with thousands of individuals, including families and veterans, experiencing homelessness (National Alliance to End Homelessness, 2022). Even though the number of people experiencing homelessness is lower today than a decade ago, this remains a serious problem due to the unsafe and untidy conditions caused by them. The United States has implemented various programs and initiatives to address homelessness, but the problem persists due to its complexity and the multiple factors that contribute to it. Although recent studies have been investigating the causes, including extreme poverty, low job skills, high unemployment, high rates of personal social adjustment problems (e.g., mental disorders, alcoholism, crime), low levels of social support, and a high standard of living Crisis that may lead to homelessness, its presence remains a mystery.

1.2 Problem Statement

The main goal of this paper is to examine the causes of this homelessness epidemic in the US. There are various factors, such as income inequality, substance abuse, housing costs, increased domestic violence, mental health, and disabilities, among other factors, that have driven thousands of people to be homeless in the US. For instance, the increase in income disparities in some communities in the US has contributed significantly to an increase in homelessness (Cleveland, 2020). The housing market often rates housing prices based on those who earn more, leaving those who earn less out of the housing market (Cleveland, 2020). We want to learn whether these variables have an impact on homelessness and how they impact homelessness. Thus, if these significant

[1] *2023 US Department of Housing and Urban Development: 2022 AHAR: Part 1 - PIT Estimates of Homelessness in the U.S.*

impacts exist, our study aims to find them and determine factors that can be implemented to improve the homelessness situation.

2. Literature Review

To develop a theory to explain homelessness, our paper builds on previous theoretical works. Marjorie Honig and Randall K. Filer (1993), using cross-sectional data in 1984, found that higher rents were associated with higher rates of homelessness. While growth in private-sector employment showed a strong negative relationship to homelessness, the overall unemployment rate did not have observable impacts on homelessness. As for government expenditure, only program-specific benefits (AFDC and SSI) had a significant impact on homelessness, as opposed to overall expenditures on public welfare. Elliott, M., & Krivo, L. J. (1991) found that the availability of low-income housing and mental health care were the strongest predictors of homelessness rates, while poverty and unemployment rates were not. Cebula and Saunoris (2021) used state-level macroeconomic data to investigate the factors that contribute to the homeless problem in the United States. Following the vector autoregressive (VAR) method, they can examine between homeless rate, labor market freedom, and entrepreneurship. Their findings show that greater labor market freedom and more entrepreneurial activities are associated with lower rates of homelessness. On the contrary, changes in labor market freedom and entrepreneurship do not have a significant effect on the homeless effect.

Most research has applied primarily cross-sectional data to identify factors contributing to homelessness. While able to provide a detailed profile of geographic and demographic characteristics, this method has produced a static representation of a dynamic problem. This data pattern isn't well suited to assess the social processes that increase individuals' vulnerability to homelessness and evaluate the effect of a policy aiming at the homelessness problem.

In this paper, we employ a more granular panel analysis at the state level dating from 2009. Our model argues that homelessness is a consequence of a combination of housing prices, income inequality, unemployment rate, and policy factors. More precisely, we assume that homelessness results from an imbalance between the cost of available housing and individual income. Such an imbalance is more likely to occur in unequal income distribution areas, where an adverse economic shock (depicted by the unemployment rate) is more likely to tip a lot of households below the homelessness threshold.

3. Data

3.1 Source and variables

We chose to use panel data from the US states from 2009 to 2020 to comprehensively analyze the factors that influence homelessness over time. By excluding data from the time of the great recession, which caused significant but unusual influences on the economy and society, we can focus on more typical economic conditions. We can examine how the factors influencing homelessness have changed over time and identify trends that might not be visible in a cross-sectional analysis by analyzing panel data.

The data in this paper are from different sources. The homeless rate is derived based on the point-in-time count of homeless people and population. As Meyer et al. (2021) have explained, the HUD provides the number of sheltered and unsheltered homeless individuals on one evening in January as the measure of homeless people in each CoC point. The state level of homeless people is the summation of each CoC point. Thus, based on the annual population of each state, we derive the homeless percentage, which represents the number of homeless as a percentage of the total population. In other words, it measures the relative size of the homeless population within the context of the state's overall population. This variable can be used as an indicator of the extent to which homelessness is a social issue in a particular state. The data on homeless residents can be traced back to as early as 1999. However, due to the limitation of GINI inequality, we only use data from 2009 to 2020 in the analysis.

Income inequality and other control variables, including the unemployment rate and social assistance spending in government expenditure, are from the US Census Bureau. We use the Housing Price Index (HPI) as the indicator for measuring housing costs, and the data for the Housing Price Index (HPI) is sourced from the Federal Housing Finance Agency (FHFA). As explained from the website of the Census Bureau, income inequality (GINI coefficient) is calculated based on the American Community Survey, which is annual household survey data including social, economic, housing, and demographic observations. Thus, we can calculate the regional GINI coefficient based on household income within each state. Other control variables include the unemployment rate, which measures local labor market conditions. The last two variables are the social assistance spending in government expenditure per capita and housing cost. Total assistance and subsidies is a variable provided by the US Census Bureau that represents the total amount of financial assistance and subsidies received by households in a given geographic area. This includes any government assistance programs such as food stamps, housing subsidies, and welfare payments, as well as any other forms of financial assistance received by households. The Housing Price Index (HPI) is a measure of the change in home prices over time and is based on data from home sales transactions. The state HPI values can provide useful information about changes in the price of homes overtime at the state level.

3.2 Summary Statistics

The data summary can be shown in Table 2. As shown in the table, the average homeless rate in the last two decades is about 0.16% in the United States. The GINI coefficient ranges from 0.41 to 0.52, with an average of 0.46. The variance is 0.00, suggesting that there is a relatively low variation in the GINI coefficient across the US. The negative skewness and kurtosis suggest that the distribution is slightly left-skewed and platykurtic, which means that the distribution has fewer extreme values than a normal distribution.

As for housing cost, the mean is 519.24, the variance is 28176.63, the skewness is 1.42, and the kurtosis is 2.49. This suggests that housing costs in the US vary widely, with an average cost of 519.24 units of currency. The positive skewness and kurtosis indicate that the distribution is right-skewed and leptokurtic, with a few areas experiencing extremely high housing costs. The variance between the unemployment rate and the social assistance percentage is quite high.

To avoid the multicollinearity problem, we have reported the pair-wise correlation of explanatory variables in Table 3. It shows that the correlation ranges from -0.16 to 0.54, which is not a big concern in this case. As we know, only when the absolute value of correlation is larger than 0.7 can it give rise to the multicollinearity problem.

We can see from the table that the state of California had the highest number of homeless individuals over the past 12 years. The states with the lowest numbers are Wyoming, North Dakota, and Delaware. In addition to the states mentioned, the chart also reveals that several other states had high levels of homelessness over the past 12 years, including New York, Texas, Florida, Massachusetts, and Oregon. On the other hand, states such as Vermont and West Virginia also had relatively low numbers of homeless individuals during this period. These findings suggest that homelessness is a complex issue that varies widely across different regions of the United States.

We can also see from the table that the states of Michigan, Nevada, the District of Columbia, Alaska, and Mississippi had the highest unemployment rates, while North Dakota, New Hampshire, Hawaii, Vermont, and Nebraska had the lowest unemployment rates over the past 12 years. These findings suggest that the labor market conditions in Nevada and Alaska may have been challenging during this period, while Vermont and North Dakota had relatively strong job markets.

3.3 Unit Root Test

Before building the models and inputting our data, we must ensure that our data are stationary to avoid spurious regressions. Therefore, we used the Maddala-Wu (MadWu) test, a unit root test for panel data that incorporates the individual-specific fixed effects into the test statistic to account for the cross-sectional dependence in the data. It is designed to address the issue of spurious regression that arises when the traditional unit root tests are applied to panel data without accounting for individual heterogeneity. It is based on the null hypothesis that all the panels contain unit roots against the alternative that at least one panel is stationary. The test statistic is a modified version of the standard Dickey-Fuller test statistic, and it follows a chi-squared distribution under the null hypothesis. A statistic is then computed using the t-statistics associated with the lagged variable. The results are reported in Table 4 in the Appendix, indicating that the null is rejected in all cases, suggesting that the variables do not contain a unit root.

4. Methodology

4. 1 Model Description

Based on our short and wide panel, we first run a pooled OLS model. By pooling the data, we assume that there is no heterogeneity-the same relationship holds for all the data. Therefore, in this model, a common constant term holds both cross-sectionally and over time. However, the "no heterogeneity" assumption may not hold in panel data, so we compute the clustered standard errors for the pooled OLS estimator and compare them with the conventional ones.

Both fixed effects and random effects models can be used in panel data structures to capture heterogeneity. First, we construct a fixed effects model. The equation below includes both state-fixed effects (*Fi*) and time-specific effects (*Tt*). State-fixed effects account for state-specific heterogeneity that is fixed over time (e.g., state-specific government policies, climate, culture, and so forth), while time-specific effects account for shocks that impact all states simultaneously (e.g., changes in federal government policies and macroeconomic environment).

$$Homeless.Percentage_t = \beta_1 Inequality_{it} + \beta_2 Unemployment.rate_{it} + \beta_3 Inequality_{it} * Unemployment.rate_{it} + \beta_4 Gov.assist.per.capita_{it} + \beta_5 Housing.cost_{it} + F_i + T_t + \varepsilon_{it}$$

Then, we build a random effects model. The error term ω_{it} measures the random deviation of each intercept term from the “global” intercept term α.

$$Homeless.Percentage_t = \alpha + \beta_1 Inequality_{it} + \beta_2 Unemployment.rate_{it} + \beta_3 Inequality_{it} * Unemployment.rate_{it} + \beta_4 Gov.assist.per.capita_{it} + \beta_5 Housing.cost_{it} + \omega_{it}$$

The random effects model is valid only when the composite error term is uncorrelated with all of the explanatory variables. If this condition is satisfied, the coefficient estimates given by both models are unbiased. However, since there are fewer parameters to be estimated in the random effects model, the RE model could give a more efficient estimation. We conduct the Hausman test to select a better model to fit our data.

Endogeneity can be a severe problem. This may arise from both omitted variables and simultaneous equations systems. So, we decided to introduce the panel vector auto-regression (VAR) framework and include two-way fixed effects to better analyze the association of potential factors on homelessness. The GMM estimation of the panel VAR model estimates a panel vector autoregressive model with fixed effects. It is a combination of a single equation dynamic panel model (DPM) and a vector autoregressive model (VAR). Starting from the first difference moment conditions, it formalizes the ideas to reduce the number of moment conditions by linear transformations of the instrument matrix and defines the one- and two-step GMM estimator. Then, it sets up the system moment conditions as defined in Blundell and Bond (1998) and presents the extended GMM estimator. In addition, specification tests and classical structural analysis for PVAR are conducted. Finally, it implements the first difference and the forward orthogonal transformation to remove the fixed effects.

The main benefit of panel Vector Autoregression (panel VAR) is its ability to analyze the dynamic relationships between multiple variables over time and across different cross-sectional units (e.g., individuals, firms, or countries) and address the endogeneity problem by using lagged values of the variables as instruments, which provide more accurate and efficient estimates.

Based on previous research and our own theoretical understanding of the issue, these variables are considered potential factors that may influence homelessness. By including these variables in our model, we can examine the unique effects of our independent variables of interest while accounting for the influence of other factors that may also affect homelessness.

$$Y_{it} = \alpha + \beta\ Y_{it-1} + F_i + T_t + \varepsilon_{it}$$

Where i denotes state, and t denotes year, Y_{it} denotes the endogenous variables in this model which are HomelessPercentage, Income Inequality, Unemployment rate, Inequality*Unemployment, Government assistance per capita, and housing cost, F_i denotes the state fixed effect and T_t denotes the year fixed effect.

$$Homeless.Percentage_t = \alpha_1 + \beta_{11} Homeless.Percentage_{t-1} + \beta_{12} Inequality_{t-1} + \beta_{13} Unemployment.rate_{t-1} + \beta_{14} Unemployment.rate_{t-1} * Inequality_{t-1} + \beta_{15} Gov.assist.per.capita_{t-1} + \beta_{16} Housing.cost_{t-1} + F_1 + T_{1t} + \varepsilon_{1t}$$

$$Unemployment.rate_t = \alpha_2 + \beta_{21} HomelessnessPercentage_{t-1} + \beta_{22} Inequality_{t-1} + \beta_{23} Unemployment.rate_{t-1} + \beta_{24} Unemployment.rate_{t-1} * Inequality_{t-1} + \beta_{25} Gov.assist.per.capita_{t-1} + \beta_{26} Housing.cost_{t-1} + F_2 + T_{2t} + \varepsilon_{2t}$$

$$Inequality_t = \alpha_3 + \beta_{31} Homeless.Percentage_{t-1} + \beta_{32} Inequality_{t-1} + \beta_{33} Unemployment.rate_{t-1} + \beta_{34} Unemployment.rate_{t-1} * Inequality_{t-1} + \beta_{35} Gov.assist.per.capita_{t-1} + \beta_{36} Housing.cost_{t-1} + F_3 + T_{3t} + \varepsilon_{3t}$$

$$Housing.cost_t = \alpha_4 + \beta_{41} Homeless.Percentage_{t-1} + \beta_{42} Inequality_{t-1} + \beta_{43} Unemployment.rate_{t-1} + \beta_{44} Unemployment.rate_{t-1} * Inequality_{t-1} + \beta_{45} Gov.assist.per.capita_{t-1} + \beta_{46} Housing.cost_{t-1} + F_4 + T_{4t} + \varepsilon_{4t}$$

$$Gov.assist.per.capita_t = \alpha_5 + \beta_{51}Homeless.Percentage_{t-1} + \beta_{52}Inequality_{t-1} + \beta_{53}Unemployment.rate_{t-1} + \beta_{54}Unemployment.rate_{t-1} * Inequality_{t-1} + \beta_{55}Gov.assist.per.capita_{t-1} + \beta_{56}Housing.cost_{t-1} + F_5 + T_{5t} + \varepsilon_{5t}$$

4. 2 Hypothesis Testing

Hypothesis 1: The higher income inequality is associated with a higher homeless percentage.

H_0: $\beta_{12} = 0$ H_a: $\beta_{12} > 0$

Hypothesis 2: The higher unemployment rate is associated with a higher homeless percentage.

H_0: $\beta_{13} = 0$ H_a: $\beta_{13} > 0$

Hypothesis 3: The higher government assistance per capita is associated with a lower homeless percentage.

H_0: $\beta_{15} = 0$ H_a: $\beta_{15} < 0$

Hypothesis 4: The higher housing cost is associated with a higher homeless percentage.

H_0: $\beta_{16} = 0$ H_a: $\beta_{16} > 0$

4. 3 Optimal Lag

We conducted a VARselect test to choose the optimal lag used in the panel var model. The results shown in Table 9 imply 2 lags that minimize Akaike Information Criterion (AIC), 2 lags that minimize the Hannan-Quinn criterion (HQ), 1 lag that minimizes the Schwarz criterion (SC), and 2 lags that minimize the Final Prediction Error (FPE). We chose 1 lag based on SIC because of its ability to strike a balance between model fit and model complexity, penalizing models with more parameters to avoid overfitting, and also because we have a relatively short panel.

5. Empirical Results

Table 5 reports the pooled OLS result. The coefficient on inequality is insignificant. However, government assistance and subsidies do have a significant effect on reducing homelessness percentage, and housing costs can significantly increase the homelessness rate.

Then, we compute the clustered standard errors to identify heterogeneity. Table 6 computes and compares the clustered standard errors with the conventional ones. The robust standard errors increase almost twice, indicating likely within-group correlation.

So, we construct the fixed effects model and random effects model. Table 7 compares the results given by the pooled OLS, fixed effects model, and random effects model. Correspondingly, we conduct the Hausman test (Table 8) based on the fundamental assumption that the random effects ω_{it} are considered to be independent of the explanatory variables. The small p-value indicates that we shall reject the null, concluding that exogeneity is violated and the random effects model gives biased estimates. So, we should choose the fixed effects model over the random effects model.

In the fixed effects model, neither inequality nor the unemployment rate has a significant effect on the homelessness rate. Again, government assistance and subsidies have a significant negative effect on homelessness percentage. However, the coefficient on housing cost gives contra-intuition results. This may be due to the fact that the fixed effects model can only deal with omitted variable bias. The endogeneity problem arising from the simultaneous equations system still exists, causing biased estimators. So, we decided to introduce the panel vector auto-regression (VAR) framework and include two-way fixed effects.

The VAR test results are reported in Table 10 in the Appendix. Based on our results of the panel var model, one interesting found is that the coefficient that estimates the relationship between the homeless percentage and the lagged homeless percentage is negative and significant(-0.5009), indicating that a higher homeless percentage in the previous year would lead to a lower homeless percentage in the current year. A striking result arises by further examining the effects of other potential factors: the estimated coefficient of income inequality on homeless percentage also implies a negative and significant relationship. The result didn't confirm our previous prediction that higher income inequality is associated with a higher homeless percentage. Both the unemployment rate and the interaction term between the unemployment rate and income inequality measure have a positive sign, suggesting a higher unemployment rate is associated with a higher homeless percentage, and the positive impact of the unemployment rate on homelessness becomes more robust at higher levels of inequality and dominated the negative effect of income inequality. As we predicted in our previous hypothesis, the negative and significant coefficient on the government assistant per capita infers that higher subsidies received by people would reduce the homeless percentage on the street. When estimating the effect of the housing cost, we obtained a positive and significant impact on the homeless percentage, which is consistent with our hypothesis 4, that a higher housing cost is associated with a higher homeless percentage.

6. Conclusion & Limitation

Despite the interventions and support provided by the U.S. government, homelessness remains a pervasive issue. In this study, we examined the impact of inequality, unemployment rate, government assistance and subsidies, and housing costs on the homeless percentage in each state in the United States from the year 2009 to the year 2020. Our analysis revealed strong and statistically significant results to support Hypotheses 2, Hypotheses 3, and Hypotheses 4. Specifically, higher unemployment rates and higher housing costs would exacerbate the homeless problem, while higher government assistance would alleviate it. The unexpected result from our study is the significant negative impact of inequality on the homeless percentage, which is contrary to our Hypothesis 1 that higher inequality is associated with a higher homeless percentage. These findings emphasize the crucial role of economic factors in contributing to the homeless problem across the country. Ultimately, we can develop effective strategies to address the root of this pressing issue by deepening our understanding of the factors that cause homelessness.

Although this study offers valuable insights into the relationship between these explanatory variables and homelessness, it still has limitations. First of all, we used data from 2009 to 2020 as we skipped the financial crisis, and some variables have missing data after 2020, which is only 12 years, resulting in a short and wide panel. With fewer time periods, the model provides limited information to analyze the dynamic relationship among variables and may suffer from biases or inconsistencies. A short, wide panel also fails to capture the long-term relationship or structural changes among variables, which would be an obstacle in the analysis of future trends and government policies. Secondly, this paper mainly focused on inequality and the other three control variables, while there are more complicated factors that may also have a significant influence on homelessness. Without taking these variables into consideration, our model may lack explanatory power. In conclusion, it is important and necessary to recognize the limitations of the study so we can address them in future studies by adding more time periods and including additional relevant variables. Thus, we can develop a more comprehensive understanding of the complicated dynamics of homelessness.

7. Reference

Bullen, J. (2015). Governing homelessness: The discursive and institutional construction of homelessness in Australia. *Housing, Theory and Society*, *32*(2), 218-239.

Byrne, T. H., Henwood, B. F., & Orlando, A. W. (2021). A rising tide drowns unstable boats: How inequality creates homelessness. *The ANNALS of the American Academy of Political and Social Science*, *693*(1), 28-45.

Byrne, T., Baggett, T., Land, T., Bernson, D., Hood, E., Kennedy-Perez, C., Monterrey, R., Smelson, D., Dones, M., & Bharel, M. (2020). A classification model of homelessness using integrated administrative data: Implications for targeting interventions to improve the housing status, health and well-being of a highly vulnerable population. *PLoS ONE*, *15*(8). https://doi.org/10.1371/journal.pone.0237905

Mosley, J. E., & Park, S. (2022). Service Providers' Influence in Collaborative Governance Networks: Effectiveness in Reducing Chronic Homelessness. *Journal of Public Administration Research and Theory*, *32*(1), 130-149. https://doi.org/10.1093/jopart/muab013

Tompsett, C. J., Toro, P. A., Guzicki, M., Manrique, M., & Zatakia, J. (2006). Homelessness in the United States: Assessing changes in prevalence and public opinion, 1993 to 2001. American Journal of Community Psychology, 37, 47–61.

Toro, P. A. (2007). *Toward an International Understanding of Homelessness. Journal of Social Issues, 63(3), 461–481.* doi:10.1111/j.1540-4560.2007.00519.x

Calvo, F., Carbonell, X., & Badia, M. (2018). Homelessness and unemployment during the economic recession: the case of the city of Girona. *European Scientific Journal*, *14*(13), 1857-7881.

Richard J. Cebula & James William Saunoris. (2021). Determinants of homelessness in the U.S.: new hypotheses and evidence applied Economics, DOI: 10.1080/00036846.2021.1927970

8. Appendix

Table 1: Descriptions of Variables In Model

Variable	Definitions	Data Sources
Homeless.Percentage	The number of homeless as a percentage of the total population of the state (%)	HUD's Point-in-Time (PIT) Count including sheltered and unsheltered
Inequality(GINI)	Gini coefficient is a measure of income inequality that ranges between 0 and 1. The closer the Gini coefficient is to 1, the more unequal the income or wealth distribution is considered to be.	U.S. Census Bureau
Unemployment rate	Unemployment rate (%)	U.S. Census Bureau
Housing cost	Housing Price Index (HPI) is a measure of the change in home prices over time.	Federal Housing Finance Agency (FHFA)
Gov.assist.per.capita	The social assistance spending in government expenditure per capita	U.S. Census Bureau

Table 2: Descriptive Statistics of Variables In Model

Variable	Obs	Mean	Variance	Skewness	Kurtosis	Min	Max
Homeless.Percentage	600	0.16	0.01	1.76	2.69	0.04	0.55
Inequality(GINI)	600	0.46	0.00	-0.06	-0.20	0.41	0.52
Unemployment rate	600	6.14	5.44	0.55	-0.34	2.30	13.70
Housing cost	600	519.24	28176.63	1.42	2.49	284.45	1275.05
Gov.assist.per.capita	600	140.55	7556.79	1.19	2.15	15.60	564.31

Table 3: Correlations of Variables

Variables	Homeless.Percentage	Inequality	Unemployment.rate	Gov.assist.per.capita	Housing.cost
Homeless.Percentage	1				
Inequality	-0.01	1			
Unemployment.rate	0.19	0.08	1		
Gov.assist.per.capita	0.10	0.45	0.15	1	
Housing.cost	0.54	0.03	-0.16	0.24	1

Table 4: Maddala-Wu test

Maddala-Wu (MadWu) test		
Variables	Chisq	P-values
Homless.Percentage	1316.1	< 2.2e-16
Inequality	2158.4	< 2.2e-16
Unemployment Rate	1306.9	< 2.2e-16
Inequa_Unemp	1450.3	< 2.2e-16
Gov.assist.per.capita	1262.8	< 2.2e-16
Housing.cost	2027.4	< 2.2e-16

Table 5: Pooled OLS

	Pooled OLS
Intercept	-1.9877e-01
	(1.9235e-01)
Inequality	5.5410e-01
	(4.1826e-01)
Unemployment.rate	6.3317e-02*
	(3.0135e-02)
Inequa_Unempl	-1.2201e-01
	(6.5529e-02)
Gov.assist.per.capita	-5.0692e-04***
	(3.1710e-05)
Housing.cost	2.5094e-04***
	(1.6359e-05)

Table 6: Comparison between conventional and robust standard errors

	Dependent variable:		
		y	
	OLS	robust	robustsss
	(1)	(2)	(3)
Intercept	-0.199	-0.199	-0.199
	(0.192)	(0.384)	(0.390)
Inequality	0.554	0.554	0.554
	(0.418)	(0.845)	(0.858)
Unemployment.rate	0.063**	0.063	0.063
	(0.030)	(0.052)	(0.152)
Inequa_Unempl	-0.122*	-0.122	-0.122
	(0.066)	(0.111)	(0.112)
Gov.assist.per.capita	-0.001***	-0.001***	-0.001***
	(0.00003)	(0.0001)	(0.0001)
Housing.cost	0.0003***	0.0003***	0.0003***
	(0.00002)	(0.00005)	(0.00005)

Table 7: Comparison between Pooled OLS, FE, and RE

	Dependent Variable:		
		y	
	OLS (1)	FE (2)	RE(3)
	(1)	(2)	(3)
Inequality	0.554	-0.140	0.019
	(0.418)	(0.306)	(0.301)
Unemployment.rate	0.063 **	0.013	0.019
	(0.030)	(0.015)	(0.017)
Inequa_Unempl	-0.122 *	-0.023	-0.034
	(0.066)	(0.033)	(0.036)
Gov.assist.per.capita	-0.001 ***	-0.0003 ***	-0.0003 ***
	(0.00003)	(0.00003)	(0.00003)
Housing.cost	0.0003 ***	-0.0001 ***	0.00002
	(0.00002)	(0.00002)	(0.00002)
Constant	-0.199		0.162
	(0.192)		(0.141)

Table 8: Hausman test

Hausman Test
data: y ~ x1 + x2 + x3 + x4 + x5
chisq = 695.7, df = 5, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent

Table 9: Optimal lag selection

VARselection			
AIC(n)	HQ(n)	SC(n)	FPE(n)
2	2	1	2

Table 10: Panel VAR Model

Panel VAR Model

	Homeless.Percentage	Inequality	Unemployment.rate	Inequa_Unempl	Gov.assist.per.capita	Housing.cost
Lag1_Homeless.Percentage	-0.5009 **	-0.0945 ***	1.3639 *	-0.5512 **	1.0981 **	-0.9773 *
	(0.1771)	(0.0283)	(0.6401)	(0.1701)	(0.3783)	(0.4427)
Lag1_Inequality	-0.0509 **	0.2171 ***	-3.3154 **	0.2612	-0.8978 **	2.1885 ***
	(0.0183)	(0.0629)	(1.0078)	(0.2344)	(0.3090)	(0.6410)
Lag1_Unemployment.rate	57.4819 **	4.2691 *	-9.1567 **	15.8295 *	-3.7956 **	-20.4060 ***
	(18.5230)	(2.1431)	(2.9422)	(7.0208)	(1.4217)	(2.8972)
Lag1_Inequa_Unempl	25.8815 **	2.8147 *	-3.0592	15.5684 ***	-3.7474 ***	14.0720 *
	(8.3657)	(1.2019)	(5.5072)	(4.3837)	(1.1204)	(5.7377)
Lag1_Gov.assist.per.capita	-2.9743 *	2.6218	-0.1863	0.8376	0.4412 **	-0.0294
	(1.1713)	(5.4338)	(0.7638)	(1.6641)	(0.1482)	(0.0511)
Lag1_Housing.cost	2.4760 **	1.6561	0.0670	-0.0939	-0.0044	0.7978 ***
	(0.8619)	(4.0230)	(0.3657)	(0.7566)	(0.0306)	(0.0316)

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$