Economic Factors Affecting Homelessness in the United States

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Abstract

As the cost of housing in the United States rises while wages have stagnated, homelessness becomes a more pressing issue with every passing year. This paper seeks to identify economics characteristics, natural attributes, and government policies that have a significant influence on the rate of homelessness in each state. Several regression models have been developed to analyze these variables and correlate them to the rate of homelessness. Using these methods, a positive relationship was observed between policy variables directed toward low-income citizens and homelessness, while a negative relationship was observed between the Gross State Product and homelessness. These findings support certain legislative measures that could combat the growing problem of homelessness.

I. Introduction

Homelessness is a topic that has garnered much concern and research from both an ethical and economic perspective. From a social point of view, leaving humans on the streets to fend for themselves can be seen as an immoral act which leads to the idea that society should care for these people. Natural empathy lends itself towards their cause and is one of the major reasons that charitable donors often specify "ending homelessness" as one of their main reasons for donating (Kaplan 2016). The rate of homelessness in a community can be an important factor in its economic prosperity and a key determinant for the health of the community. Almost every person has witnessed this phenomenon in some capacity, but rarely consider the economic causes or consequences of the homeless seen on the side of the road or sidewalk or brainstorm solutions to the ever-present problem.

While important socially, the issue of homelessness is also very important from an economic perspective. Previous estimates have predicted that care for a homeless person in the U.S. could cost the government anywhere between $35,000 (Flaming 2009) and $150,000 (Laird 2010) dollars annually and that figure is projected to have risen since then. These figures are important because there could be legislation passed that would help free these people from the eternal struggle of homelessness and be less expensive than the stopgap measures in place simply to sustain life. In addition, any money spent more efficiently that reduces homelessness rates helps bring more people into the workforce, increases spending on goods, and helps bolster the economy as a whole. By funding projects to help the homeless like construction of low cost housing, increased funding for public works, and providing meals and health care to all people, the homeless can become less dependent on society which frees up resources for many other projects. In addition, the weakness of the lowest income class due to homelessness creates a drain on lower and middle class workers who also need government resources to thrive in the U.S. economy.

The purpose of this study is to determine what variables have an effect on homelessness and examine the legislative differences that have lead to lower homeless rates in states. Each of the factors being considered in the regression models can be grouped into three main categories: economics characteristics, natural attributes, and legislative factors. The economic characteristics and natural attributes serve the purpose of correcting for the homeless rate in different areas using the natural conditions found so that the legislative decisions made by each state can be correlated to the homelessness rate more effectively. Economic characteristics are defined by the current economic status of the state in terms of its wealth, economic distribution, and productivity compared to other states. Natural attributes are grouped similarly but are non-economic factors and look at natural conditions like weather, population patterns, and culture of occupants. These two groups are incorporated to evaluate their effect on the homelessness rate for the factors not easily controlled by legislators. In this way, these correlations can be used to determine which methods of economic regulation can be utilized to lower the homelessness rate and which actions should be taken by politicians to combat the extremely prevalent issue of homelessness. As an initial hypothesis using the data presented in the literature review, average temperature, cost of living, and minimum wage are predicted to have the highest correlation with homeless rate with temperature and cost of living having a negative coefficient and minimum wage a positive coefficient. In this way, the team expects to find that states with higher temperatures, higher costs of living, and lower minimum wage will have a higher homeless rate than the inverse.

II. Literature Review

Before examining variables and running regression models, the team looked at research and studies already conducted about key variables and their effect on homelessness to get a better understanding of the issue. Instead of just looking at the typical variables that might seem to predict homelessness like housing costs and poverty rate, the primary goal of the research was to look at more unknown variables like mental illnesses, family traits, veteran spending, disability spending, drug abuse rates, and temperature to see how each affected the homeless rate. Each of these studies will be described in detail over the next section and will lead directly to the regression models proposed by this paper to predict homeless rates.

In the first major study examined, Elliott and Krivo (1991) analyze the factors associated with homelessness beyond what had become the standard of unemployment and individual factors, such as addiction. Instead, they picked several structural factors, including low-cost housing, mental health care, and familial structures, and contrasted those with the homelessness rate of various metropolitan regions. These variables help provide a holistic look at homelessness by covering both government actions for low-cost housing and mental health spending as well as social details like familial characteristics. They expected that by providing more insight to all the factors affecting homelessness, its causes would be better understood and correction would be possible. Their model was made through OLS regression and determined that both availability of low cost housing and mental health care spending were the primary indicators of the homelessness rate. In addition, another strong predictor of high homelessness was the percentage of families with a single mother in an area. Besides just looking at the specific group of single mothers and mental health patients, another key demographic examined was veterans since they too have a high rate of homelessness.

In another study, Metraux et al (2014) discuss the disparities between self-identified veterans and the Veterans Affairs Department's records of veterans in homeless shelters in Columbus, Ohio and New York, New York. Looking at these key cities, one of their primary goals was to look at the benefits in place for veterans and see whether the actions being taken were actually helping veterans at risk of becoming homeless. One interesting observation was finding significantly more false-negatives, where someone qualified for veteran assistance self identifies as not being a veteran, than false-positives, where a non-veteran self identifies as being a veteran. They posit that this could be due to a myriad of factors like lack of awareness about the conditions for being a veteran, refusal for "charity", or possible embarrassment at needing help, all of which would lead to veterans not taking advantage of many of the benefits offered to them. The authors suggest shifting from a self-reporting system to a cross-referencing system between homeless shelters and the Veterans Affairs office to ensure that everyone is being supported. This would afford more homeless veterans increased access to resources through the VA while simultaneously reducing the burden on city programs, allowing them to focus their efforts on other homeless populations. By looking at this effect, the authors were able to examine the effectiveness of current legislation and determine why current actions are less effective than predicted.

John Quigley and Steven Raphael examine the different effects of social and economic variables affecting the U.S. homelessness rate in their article "The Economics of Homelessness: The Evidence from North America". Instead of following the traditional assumption that a variety of social factors lead to the higher than expected rate of homelessness, the authors look to support the hypothesis that homelessness is actually more correlated with variations in the housing market and distribution of income. The drug epidemic, reduction in mental health hospitals, and prison populations are often thought to be closely related to the homelessness rate, but the data actually suggest that the housing market has more influence. By examining the prison and mental health populations and showing how a minor percentage of the new homeless population could actually be caused by these changing rates, the authors support their hypothesis that there must be other major factors at play affecting the rate of homelessness. Looking at other variables like rental vacancy, average rent, temperature, unemployment rate, and disability pensions, four separate regression models were generated to calculate each variable's effect upon an area's homelessness rate. Similar to the hypothesis presented in this paper, they concluded that housing costs and the ratio of rent to income have a strong positive effect on homelessness, average temperature has a moderate positive correlation, and rental vacancy rate has a moderately negative effect. The results of this article support the validity of the variables chosen in this paper since there is some overlap between the two..

When looking at different variables that affect the homelessness rate, one of the most common solutions to solving the growing issue is increased government spending on low-income and subsidized housing. While this does seem beneficial, research done on the benefits of such a program do not entirely support the supposition that the venture is worth the cost compared to other measures. Dirk Early's article delves deep into the role that subsidized housing has in lowering the rate of homelessness. The spending on subsidized housing is directly related to the cost of living and housing assistance per household, a variable being tested in this paper. Early also examines a wide range of other variables like race, age, mental health and drug abuse spending, temperature, quality of homeless shelters, and lowest quality of housing available to track each variable's effect on the rate. From the analysis, several of the hypotheses for the independent variables under investigation seem to be valid with Early's data showing that income, cash assistance, mental health spending, and drug abuse spending are slightly negatively correlated to the homelessness rate, while the price of housing and happiness level are both positively correlated. Overall, Early uses the data presented to show how slight an effect the low income housing development has on the homeless rate and that government money should be spent in other areas.

While these sources look at a wide variety of variables that affect the rate of homelessness all over the United States, one of the primary goals of the regression analysis performed was to use both economic and noneconomic characteristics of each state coupled with the economic policy in place to examine possible legislative action to reduce homeless rates. The other studies would often use either very broad data over the entire United States or a more specific data set like Metraux et al (2014) examining veterans in key cities. Since a lot of the economic legislation that affects the homelessness rate is passed and implemented by state governments, this paper strives to look at the legislative differences between states to see which actions would suggest a decrease in homelessness. Variables that are natural, uncontrollable characteristics of each state were used as controls in regression models to create an even plane upon which the policy decisions effects can be viewed more clearly. A wide variety of variables were considered for the regression models, all of which will all be thoroughly discussed in the next section.

III. Data

Variable Type	Variable	Abbreviation	Unit	Year	Data Source
Independent	Homeless People per 10,000	homeless	N/A	2015	Department of Housing and Urban Development
Dependent	Minority Percentage by State	minority	%	2015	Kaiser Family Foundation
Dependent	Cost of Living Index	costLiving	N/A	2015	Missouri Department of Economic Research
Dependent	Poverty Rate	pov	%	2015	U.S. Census Bureau
Dependent	Gross State product	GSP	Billions of $	2015	U.S. Bureau of Economic Analysis
Dependent	Gross State Product per Capita	GSP	Millions of $	2015	U.S. Bureau of Economic Analysis
Dependent	Median Household Income	medincome	$	2015	U.S. Census Bureau
Dependent	Total Housing Assistance	houseassist	Millions of $	2014	Center on Budget and Policy Priorities
Dependent	Housing Assistance per Household	assistperhouse	$	2014	Center on Budget and Policy Priorities
Dependent	Minimum Wage	minwage	$/hour	2017	U.S. Department of Labor
Dependent	Gini Index	gini	N/A	2015	U.S. Census Bureau

Figure 1: Independent and Dependent Variables

In order to determine the causal factors of homelessness, several models were developed using a number of different explanatory variables, all of which are detailed in Figure 1. The data include observations from all fifty states but exclude the District of Columbia and all U.S. territories (Puerto Rico, American Samoa, etc.). The dependent variable in this research is the number of homeless people per 10,000, which is an estimate made by the Department of Housing and Urban Development (HUD). A potential source of error in this research is the homelessness rate itself, as this number is likely an underestimation of the actual homelessness rate. The independent variables include two populations that are particularly at risk of homelessness, namely minorities and people living below the poverty line. States with a lower minimum wage, lower median household income, and lower amounts of housing assistance further endanger low-income and impoverished citizens, which would likely increase the rate of homelessness.

While not all states have a minimum wage set at or above the federal minimum wage, all workers covered under the Fair Labor Standards Act receive at least the federal minimum wage of $7.25, with the exception of service workers who receive tips and a few other select populations. This results in differences between the minimum wage depending on if a state voted to raise it or not. Similarly, there is a disparity between states in terms of their cost of living. In order to account for the cost of living, an index created by the Missouri Economic Research and Information center was used, which includes such factors as cost housing, transportation, food, utilities, healthcare, and a miscellaneous category. Another source of disparity between states is the Gini index, which is a measurement of the distribution of wealth within states and countries. It ranges from zero to one, where zero represents a perfectly equal distribution of wealth among all citizens, and one represents perfect inequality.

Data sources are comprised almost entirely of federal agencies, and were chosen for their reliability, and where possible, their sampling methods. Hence, the majority of the data sources are departments of the U.S. federal government, as these agencies are able to collect far-reaching, accurate, and relatively unbiased data.

Variable	**Units**	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
homeless	People/10,000	50	15.7	9.7	6.6	53.7
minwage	$/hour	50	8.3	1.2	7.3	11.0
minority	%	50	30.94	16.03	6.00	81.00
medincome	$	50	56022.3	9206.0	40593.0	75847.0
pov	%	50	14.2	3.1	8.2	22.0
GSPcapita	Millions of $/capita	50	0.053	0.010	0.030	0.073
assistperhouse	$/household	50	6649.2	1749.6	4013.0	10279.0
gini	N/A	50	0.464	0.018	0.425	0.514
GSP	Billions of $	50	355.3	448.3	22.9	2481.3
houseassist	Millions of $	50	741.5	1064.53	33.8	5424.7

Figure 2: Descriptive Statistics

Figure 2 shows the mean, standard deviation, minimum, and maximum values for all the variables that are used in this research. Variables that are particularly noteworthy are *GSP* and *houseassist*, as these variables exhibit large standard deviations when compared to their means. This means that there is a high degree of variation in the data, which indicates that there is a large amount of variation between states of the amount of federal housing assistance provided to households, which could be tied to the state poverty rate, the cost of living, the median income, or a number of other factors. This is also represented by the difference between the maximum and minimum housing assistance per household. The variables *homeless* and *pov* have fairly large ranges, which indicates that these variables are somewhat volatile and heavily dependent on location.

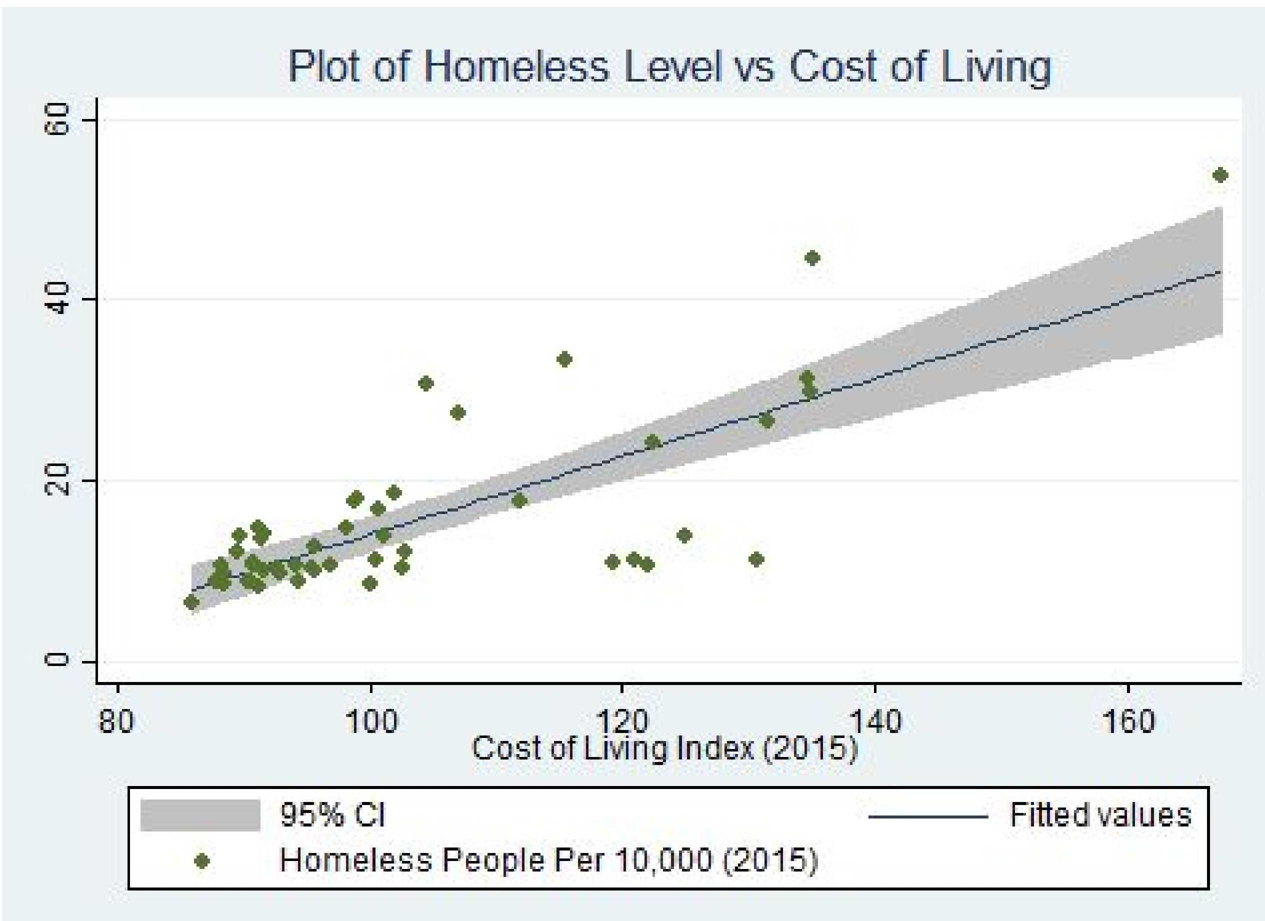

Figure 3: Homelessness vs. Cost of Living

Figure 3 shows the positive correlation between the rate of homelessness and the cost of living in each state. The data exhibit a coefficient of determination (R^2) of 0.583, indicating a relatively strong relationship between the two variables. However, this relationship could be misleading as the data used for cost of living is an indexed quantity, meaning that the results are influenced by the weight the factors that form the index. The ramifications of using an indexed quantity in this research will be discussed in the results section.

The data used in this project very likely does not fully meet the Gauss-Markov assumptions that form the backbone of multiple linear regression. The data meet the first Gauss-Markov assumption that the chosen models are linear in parameters. The data used also meet the second Gauss-Markov assumption, namely that the data are collected using random sampling methods. This is supported by the descriptions of sampling methodology provided with the original data sets. However, the Gauss-Markov assumption that the expected value of the error is zero ($E[u|x] = 0$) is not met in any of our models, as each of our models leave out explanatory variables that are likely not independent of the included variables. However, the remaining Gauss-Markov assumptions are met because none of the explanatory variables are perfectly collinear, as shown in Figure 6, and the variance of the error term will be constant for any random sample.

IV. Results

Models	
Model 1	homeless = $\beta_0 + \beta_1$minwage + u
Model 2	homeless = $\beta_0 + \beta_1$minwage + $\beta_2$minority + $\beta_3$medincome + $\beta_4$pov + u
Model 3	homeless = $\beta_0 + \beta_1$minwage + $\beta_2$minority + β_3GSPcapita + $\beta_4$assistperhouse + u
Model 4	homeless = $\beta_0 + \beta_1$minwage + $\beta_2$minority + $\beta_3$gini + β_4GSP + $\beta_5$houseassist + u

Figure 4: Regression Models

Initially the Cost of Living Index was used as an independent variable since had such a strong correlation with the rate of homelessness, as one would expect. However, the cost of living does not reveal all of the details going on in the economic and social environment or the individual factors. Since the cost of living is an index composed of many factors, the index is influenced by the creator's understanding of what predominantly influences cost of living. This causes the variable to be highly associated with many of the other variables used in the models, while revealing little of the actual economic and social environments. Thus, cost of living is not included as a variable in the regression models tested and presented since it reduces the impact of the other variables in the regression models.

Dependent Variable - homeless				
Independent Variables	Model 1	Model 2	Model 3	Model 4
minwage	4.968*** (0.966)	4.745*** (1.061)	4.017*** (1.164)	3.443*** (0.835)
minority	--	0.302*** (0.105)	0.130 (0.084)	0.256*** (0.063)
medincome	--	-4.07E-4 (3.8E-4)	--	--
pov	--	-1.617 (1.038)	--	--
GSPcapita	--	--	-54.365 (134.589)	--
assistperhouse	--	--	0.001 (0.001)	--
gini	--	--	--	-221.173*** (63.612)
GSP	--	--	--	-0.016*** (0.005)
houseassist	--	--	--	0.009*** (0.002)
Intercept	-25.661*** (8.115)	12.565 (29.858)	-26.436*** (8.416)	80.585** (30.798)
R^2	0.355	0.489	0.464	0.627
Observations	50	50	50	50
Significance Level: * = 10%, ** = 5%, *** = 1%				
Standard errors are listed below each estimate				

Figure 5: Regression Estimates

Model 1 (Figure 4)

In the simple regression model, homelessness was regressed as the dependent variable with the minimum wage as the independent variable. The t-value for the minimum wage coefficient is 5.14, as seen in Figure A1, which is larger than the critical value at 99% confidence ($c.v._{0.01}$ = 2.704), meaning that the coefficient is significant even at 1%, as shown in Figure 5.

Model 2 (Figure 4)

For the second model, three new variables were introduced, as seen in Figure 4. The minimum wage coefficient maintains significance to 1%, as shown in Figure 5. The percent minority had a t-value of 2.88 (Figure A2), larger than the critical value ($c.v._{0.01} = 2.704$), resulting in 99% confidence, as shown in Figure 5. When a t-test is conducted for median income the t-value is -1.10 ($c.v._{0.10} = |1.684|$), as seen in Figure A2, the test fails to reject the null hypothesis and coefficient for median income is insignificant. When a t-test is conducted for the poverty rate the t-value is -1.56 ($c.v._{0.10} = |1.684|$), as seen in Figure A2, the t-test fails to reject the null hypothesis and the coefficient is insignificant, as shown in Figure 5. Thus, both variables are excluded in future models.

Model 3 (Figure 4)

In the third model the GSP per capita and the assistance per house receiving housing aid are considered along with the percent minority and minimum wage. The coefficient for minimum wage retains significance with a 99% confidence interval, as shown in Figure 5. The p-value for the coefficient of GSP per capita is 0.688, a value of no statistical significance in the model, as shown in Figure 5. The p-value for the coefficient of assistance per house is 0.279, also of no statistical significance in the model, as shown in Figure 5. Alongside these new variables, the coefficient of minimum wage only has a p-value of 0.128, which is not quite significant at 10% (Figure 5). Because of the reduction in the significance of the coefficient of minimum wage, an F-test was performed removing GSP per capita and the assistance per house from the equation to test their joint significance. When considered alone with minimum wage, the percent minority has a significance of 1%. The F-value was calculated to be 0.605 ($F_{2,40}$, $c.v._{0.10} = 2.84$) which fails to reject the null hypothesis, meaning they are statistically insignificant even when they are considered together (Figure A5).

Model 4 (Figure 4)

In the final model, homelessness was regressed against minimum wage, percent minority, the Gini index, total GSP, and aggregate housing assistance. With a p-value of 0.000 the coefficients of minimum wage, percent minority, and aggregate housing assistance were all significant to 1%, as shown in Figure 5. The coefficient of the Gini index had a p-value of 0.001, indicating 99% confidence while the coefficient of the GSP had a p-value of 0.002, also indicating 99% confidence, as shown in Figure 5.

Correlation Coefficients of Independent Variables									
	minwage	minority	medincome	pov	GSPcapita	assistperhouse	gini	GSP	houseassist
minwage	1.000								
minority	0.113	1.000							
medincome	0.465	0.202	1.000						
pov	-0.290	0.220	-0.851	1.000					
GSPcapita	0.459	0.195	0.730	-0.554	1.000				
assistperhouse	0.566	0.556	0.696	-0.354	0.598	1.000			
gini	0.062	0.355	-0.250	0.545	-0.013	0.233	1.000		
GSP	0.200	0.425	0.161	0.094	0.330	0.426	0.524	1.000	
houseassist	0.302	0.359	0.214	0.070	0.413	0.527	0.611	0.902	1.000

Figure 6: Correlation Coefficients of Independent Variables

When the correlation coefficients are considered, the total GSP and aggregate housing assistance are strongly correlated with a correlation coefficient of 0.902 (Figure 6), indicating a tendency towards multicollinearity. A regression was run comparing the aggregate housing assistance to the other independent variables in Model 4. The $R^2_{houseassist}$ is calculated to be 0.861, as seen in Figure A6. The variation inflation factor (VIF) is equal to 7.205, which is less than the rule of thumb maximum of VIF = 10.

Some of the coefficients have different than expected results, such as minimum wage having a positive coefficient. Further research must be done to identify causation, but this could be a result of a higher minimum wage reducing employment opportunities or policy makers trying to prevent homelessness due to its prevalence by raising the minimum wage. The percent minority also has a positive coefficient, which is most likely demonstrative of the higher risk of homelessness among minorities. The Gini index has an unexpected negative correlation, as a value equal to one is representative of total income disparity while a value equal zero represents total equality. It was expected that as states tend towards income equality, the rate of homelessness would decrease, but this results of this model show the opposite. This discrepancy could be a result of poor inclusion of the homeless in data taken for economic disparity and poor measurement of homeless populations, which could be better understood through further research. Aggregate housing assistance, like minimum wage, increases as the homeless rate increases. More research could show if this result is a corrective measure due to a high rate of homelessness, or due to another cause. Finally, the GSP increases as the homeless rate decreases, which could be the result of several interactions, such as simply a wealthier state or of more funds to assist those facing economic struggles and homelessness.

Contrary to expectation, the significance found in the model for housing assistance and GSP both concerned the aggregate values rather than the per capita or per beneficiary household variables tested in Model 3 (Figure 4). A possible explanation is that the housing assistance provided per household is insignificant in the models due to the individual amount provided per household not having as much of an effect as it is present in the model. The reason that the aggregate housing assistance provided in the state has a negative coefficient, ash shown in Figure 5, could be a result of reactive policy making where policy makers increase the amount of housing assistance that is provided as the rate of homelessness rises. Further research will need to be done as to why GSP is more significant than the GSP per capita, which is traditionally used as a measure of wealth and productivity for states.

V. Conclusion

As described throughout the paper, the primary goal of looking at legislative actions that could be correlated to a lower homelessness rate by examining different variables associated with homelessness rates, and creating regression models to evaluate effectiveness at predicting homelessness rates. Though other studies have found correlation between homeless rate and average temperature, unemployment rate, urban percentage of population, and/or number of households receiving rental assistance, further examination in the regression models tested in this paper showed little or no significant correlation in these variables. As a result, the models that were developed helped identify minimum wage and housing assistance provided as the two most significant policy decisions that affect the homeless rate by state.

All of the models that contained housing assistance provided and minimum wage showed a positive correlation at the 1% significance level, which was surprising given that increased housing assistance and higher minimum wage are intended to reduce the homelessness rate. There are a few main explanations for this phenomenon.

One likely cause could be the reactive nature of these policy changes instead of preventative. Instead of all states being compared at similar economic, social, political, and geographic levels, these policy decisions could be in response to the growing homelessness problem. This would show that actions by lawmakers were taken to lower the homelessness rate rather than the policies of minimum wage and housing assistance provided causing the homeless rate to be higher. To determine the root causes and examine these issues deeper, a longitudinal study should be conducted on major cities in each state throughout the US to see whether states that have implemented higher minimum wage laws have seen decreased homeless rates based on historical trends.

Another potential explanation for the coefficient on the minimum wage term could be the negative impact of a raised minimum wage on low income jobs. Many studies have shown that an increase in the minimum wage would severely harm both young and low-skill workers by simply lowering the amount of employees hired or leading employer to try replacing jobs with more automation as it becomes more cost effective. In situations where the minimum wage is increased, companies will invest more in high-skill workers and supplement their job with technology rather than relying on low-skill manpower at the higher wage. (Furchtgott-Roth 2016). As the minimum wage is increased and low-skill jobs are cut, this could result in more lower income individuals and families becoming homeless from being unable to afford rent. Thus, this conclusion would suggest that the high homelessness rates are linked to cities with higher minimum wages. However, like the other conclusion, this hypothesis is simple conjecture since no long-term data was examined to try and determine the time effects of minimum wage policy on the homeless rate.

In addition, as there is with any statistical prediction model, there are built in sources of error that range from sampling data issues, to the combinations of variables chosen to form the statistical models. Although the team considered many different variables, some key variables were undoubtedly left out that could end up having a large effect upon the regression models generated. For each data source, only reputable sources that have collected data for many years were used to try and reduce the bias and flaws in the data obtained. Every dataset is flawed in some way though and that could have an effect on the results. While many different simple and multiple regression models were run to test different variable combinations, there is always a chance that an ideal combination was missed or an unseen flaw in the model is reducing the viability of the final models chosen. The final source of error results from the data set failing to meet the Gauss-Markov assumptions, as discussed earlier in the paper.

While this study was looking at the different effects of legislative actions in conjunction with natural conditions and the economic status of each state to predict the homelessness rate, one unintended consequence was seeing how difficult it is to look at this issue over an entire state. Unfortunately, since homeless people do not have a stable dwelling, it is often difficult to get accurate homeless estimates for smaller areas. Even state-wide estimates of the homeless population can be off the true value by large amounts due to polling difficulties. Thus, when examining this issue, the effect of statewide and national policy is hard to measure due to wide variations in the economic, social, and geographical differences within a single state. While correlations were found between minimum wage and the increased housing assistance spending and homeless rate, effect likely varies widely across the state and a more in depth study to get more accurate homeless counts at a county level would be necessary to see the true effects of these changes. Thus, as policy makers are trying to make decisions at the state and national levels to help the homeless population, more accurate studies should be conducted to properly predict the potential benefits of economic plans before passing legislation. Plans where funding is given to local governments to diagnose small scale issues and attempt to help people should be considered too. Though it is easy to forget about the homeless and continue living life as usual, the long and short term effects of a larger homeless population affects everyone and actions need to be taken to curtail the issue.

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VII. Appendix

```
. regress homeless minwage
```

Source	SS	df	MS
Model	1627.01572	1	1627.01572
Residual	2953.59008	48	61.5331266
Total	4580.6058	49	93.481751

Number of obs	=	50
F(1, 48)	=	26.44
Prob > F	=	0.0000
R-squared	=	0.3552
Adj R-squared	=	0.3418
Root MSE	=	7.8443

homeless	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
minwage	4.967563	.9660552	5.14	0.000	3.025178	6.909947
_cons	-25.66106	8.115498	-3.16	0.003	-41.97836	-9.34376

Figure A1: Model 1 Regression

```
. regress homeless minwage minority medincome pov
```

Source	SS	df	MS
Model	2241.41185	4	560.352962
Residual	2339.19395	45	51.9820879
Total	4580.6058	49	93.481751

Number of obs	=	50
F(4, 45)	=	10.78
Prob > F	=	0.0000
R-squared	=	0.4893
Adj R-squared	=	0.4439
Root MSE	=	7.2099

homeless	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
minwage	4.745386	1.061299	4.47	0.000	2.60782	6.882951
minority	.302198	.1047745	2.88	0.006	.0911712	.5132247
medincome	-.0004072	.0003697	-1.10	0.277	-.0011519	.0003374
pov	-1.6168	1.038382	-1.56	0.126	-3.708208	.4746087
_cons	12.5651	29.85782	0.42	0.676	-47.57164	72.70185

Figure A2: Model 2 Regression

```
. regress homeless minwage minority GSPcap assistperhouse
```

Source	SS	df	MS
Model	2126.0482	4	531.512049
Residual	2454.5576	45	54.5457245
Total	4580.6058	49	93.481751

Number of obs	=	50
F(4, 45)	=	9.74
Prob > F	=	0.0000
R-squared	=	0.4641
Adj R-squared	=	0.4165
Root MSE	=	7.3855

homeless	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
minwage	4.017085	1.163726	3.45	0.001	1.673221	6.360948
minority	.130052	.0839364	1.55	0.128	-.0390046	.2991087
GSPcapita	-54.36492	134.589	-0.40	0.688	-325.4411	216.7112
assistperhouse	.0011303	.0010306	1.10	0.279	-.0009453	.003206
_cons	-26.43605	8.416426	-3.14	0.003	-43.3876	-9.484496

Figure A3: Model 3 Regression

```
. regress homeless minwage minority gini GSP houseassist
```

Source	SS	df	MS
Model	2870.65962	5	574.131925
Residual	1709.94618	44	38.8624131
Total	4580.6058	49	93.481751

Number of obs	=	50
F(5, 44)	=	14.77
Prob > F	=	0.0000
R-squared	=	0.6267
Adj R-squared	=	0.5843
Root MSE	=	6.234

homeless	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
minwage	3.442897	.835046	4.12	0.000	1.759973	5.125822
minority	.2557318	.0631931	4.05	0.000	.1283744	.3830892
gini	-221.1734	63.61212	-3.48	0.001	-349.3752	-92.97154
GSP	-.016054	.0049064	-3.27	0.002	-.0259423	-.0061657
houseassist	.0093314	.0022453	4.16	0.000	.0048063	.0138564
_cons	80.58525	30.79835	2.62	0.012	18.51524	142.6552

Figure A4: Model 4 Regression

```
. regress homeless minwage minority

      Source |       SS           df       MS      Number of obs   =        50
-------------+----------------------------------   F(2, 47)        =     19.20
       Model |  2059.70323         2  1029.85162   Prob > F        =    0.0000
    Residual |  2520.90257        47  53.6362248   R-squared       =    0.4497
-------------+----------------------------------   Adj R-squared   =    0.4262
       Total |   4580.6058        49   93.481751   Root MSE        =    7.3237

------------------------------------------------------------------------------
    homeless |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     minwage |   4.675997   .9077608     5.15   0.000     2.849818    6.502176
    minority |   .1865757   .0656897     2.84   0.007     .0544251    .3187262
       _cons |  -29.00736   7.667921    -3.78   0.000    -44.43323   -13.58149
------------------------------------------------------------------------------
```

Figure A5: Restricted Model 3 for F-Test

```
. regress houseassist minwage minority gini GSP

      Source |       SS           df       MS      Number of obs   =        50
-------------+----------------------------------   F(4, 45)        =     69.79
       Model |  47819343.2         4  11954835.8   Prob > F        =    0.0000
    Residual |  7708730.65        45  171305.125   R-squared       =    0.8612
-------------+----------------------------------   Adj R-squared   =    0.8488
       Total |  55528073.9        49     1133226   Root MSE        =    413.89

------------------------------------------------------------------------------
 houseassist |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     minwage |   126.5626   52.13197     2.43   0.019     21.56338    231.5617
    minority |  -4.569714    4.13989    -1.10   0.276    -12.90788    3.768453
        gini |   12114.86   3817.773     3.17   0.003     4425.469    19804.25
         GSP |   1.884276   .1649686    11.42   0.000     1.552012     2.21654
       _cons |  -6464.461   1803.468    -3.58   0.001    -10096.83   -2832.089
------------------------------------------------------------------------------
```

Figure A6: Regression of houseassist for Multicollinearity Testing