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The Geography of Homelessness

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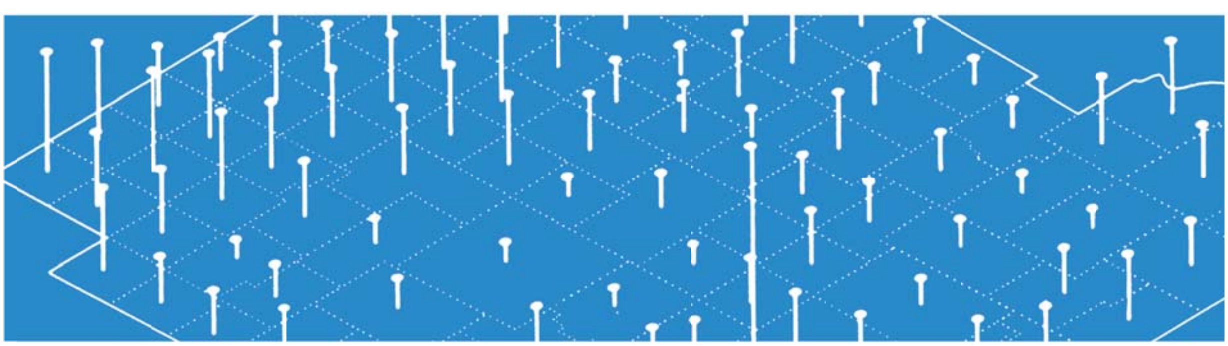

Abstract

The level and extent of homelessness varies substantially across cities and metropolitan areas in the United States. This study examines homelessness variation at a regional level across 97 metropolitan areas. The findings of a multivariate analysis show that climate is among the strongest variables in determining homelessness per capita, together with housing cost and density. Economic variables such as income, poverty and unemployment we find to be insignificant. We find no statistical association between homelessness and social factors such as mental health, disability, or uninsured.

JEL: I3, J19, R0

Keywords: homelessness, socio-economic structures, housing

Introduction

Homelessness is a pressing economic and social problem, with substantial variation in its level and extent across metro areas. While nearly two-thirds of the sheltered homeless population live in central cities, according to data from the U.S. Department of Housing and Urban Development, more than one-third (36 percent) live in rural and suburban areas (Department of Housing and Urban Development, 2011). There is considerable variation in homelessness across cities and metro areas.

A landmark 1992 study by Burt (1992) examined the key factors associated with the geographic variation in homelessness across metros. It found that the lack of affordable housing, household formation, and government expenditures are associated with the geographic variation. Subsequent studies (Bohannon, 1991; Elliott and Krivo, 1991; Honig and Filer, 1993; Grimes and Chressanthis, 1997; Quigley, Raphael, and Smolensky, 2001; Lee, Price-Spratlen, and Kanan, 2003; Ji, 2006) found homelessness across US metros to be associated with a series of housing characteristics - lack of affordable housing and rent-to-income ratios, as well as household size, unemployment, high poverty rates, lack of health care facilities, and climate.

Our research builds upon this literature to examine the key factors that are associated with the geographic variation of homelessness. We incorporate a new measure of homelessness "point-in-time" counts (PIT counts) from the U.S. Department of Housing and Urban Development. Previous researchers have utilized the rate of homelessness as measured by a point prevalence number of homeless people per 10,000 in the general population (Bohannon, 1991; Burt, 1992; Elliott and Krivo, 1991; Honig and Filer, 1993; Grimes and Chressanthis, 1997; Troutman, Jackson, and Ekelund, 1999; Quigley, Raphael, and Smolensky, 2001; Lee, Price-Spratlen, and Kanan, 2003; Early, 2005; Ji, 2006). By using the

PIT counts data, we lay the framework for conducting this type of analyses consistently across time since the data are collected annually (or bi-annually, in the case of the street count component of the count).

We employ a bivariate correlation analysis and multivariate OLS regression analysis to examine the effect of several key categories of variables, such as income and wage levels; unemployment, poverty and inequality; race; regional size and density; housing type and costs; climate and temperature; drinking, imprisonment, mental health, AIDs incidence and other factors on the geographic variation in homelessness across metro areas.

The results of a simple correlation analysis find that population size, wage levels, unemployment, housing costs, the housing cost-to-income ratio, housing density, winter climate, non-white share of the population, and AIDS rates are all significantly correlated to homelessness. The findings from our multivariate analysis find that three key factors in the variation of homelessness are winter climate, housing cost and housing density (the average number of occupants per room in each housing unit).

Theory and Concepts

Research on determinates of homelessness in metropolitan areas is well established. Causal explanations of homelessness might broadly be categorized into two theoretical frames. There are those that use a theoretical framework that explain homelessness based on individual-level reasons, such as substance abuse or mental illness, and then those that explain homelessness based on structural reasons, such as housing structures and employment opportunities. The former approach, which focuses on micro-level explanations, might appeal to researchers on an intuitive level because of the emphasis on the individual circumstances, or those conditions that would propel someone into a position where they could lose their job, the ability to afford rent, and wind up on the streets. The latter approach focuses on macro-level explanations, which appeals to the understanding that, in order to examine the reasons for the variation in the pattern of regional levels of homelessness, the social, economic, and institutional threads that makeup regions must be attended to.

Early research on determinates of homelessness across geographies focused on explanatory models that used structural factors to explain the variation in homelessness (Bohannon, 1991; Elliott and Krivo, 1991; Burt, 1992). More recently, though, researchers have used models that blend together individual with structural explanations (Honig and Filer, 1993; Grimes and Chressanthis, 1997; Troutman, Jackson, and Ekelund, 1999; Quigley, Raphael, and Smolensky, 2001; Early, 2005). Generally, the rationale behind applying this blend is based on empirical evidence: there is now a clearer understanding of which characteristics put someone at-risk of entering into homelessness (including experience with an institution such as prison or foster care, poor physical or mental health that interferes with employment, and alcohol, drug or other substance abuse problems; for more see Lee, Tyler, and Wright (2010)) and there is wide agreement that certain structural factors at the metropolitan level are necessary preconditions for an increase in homelessness to occur (including poor economic conditions and a tight housing market, see Lee, Tyler, and Wright (2010)). Although, to be sure, there have still been investigations which have used models based on structural factors alone to explain and understand geographic variation in homelessness (Lee, Price-Spratlen, and Kanan, 2003; Ji, 2006). Many of the previous investigations, whether applying a blended or a structural model, have found that housing structure variables are the most important explanatory factors when it comes to determining where rates of homelessness will be highest.

A foundational study on determinants of metropolitan homelessness is from Burt (1992). Burt used data on homeless shelter beds as a proxy for a count of the population collected from 147 primary cities (with populations over 100,000). She found that numerous housing variables were significant, including the shortage of affordable housing (measured by the Fair Market Rent for a 1 bedroom apartment and high rental vacancy rates) as well as household formation (measured by percentage of one-person households and the average number of persons per household). Burt also found higher levels of government expenditures, general welfare assistance, per capita county government revenues, and per capita county government expenditures on housing were significant and associated with lower homelessness rates.

Bohannon (1991) examined variation in the rate of homelessness among 60 metropolitan areas through a cross-sectional analysis and found that homelessness was most significantly explained by median rent cost and unemployment, but household size was also significant. Elliott and Krivo (1991) also employed a cross-sectional analysis to examine the variation among 60 metropolitan areas and found that lack of affordable housing units and lack of community health care facilities were the strongest predictors of higher rates of homelessness. High poverty rates were also found to predict higher homelessness rates.

Grimes and Chressanthis (1997) examined whether rent price control laws had an effect on homelessness. While they found that rent price controls do increase a city's shelter population, they also found that a lack of affordable housing units is associated with higher rates of shelter and overall homelessness. Honig and Filer (1993) examined causes of variation in homelessness, but they also looked at causes in variation of "crowded" and "doubled-up" households and they found that high rental housing cost was associated with higher homelessness.

Quigley, Raphael, and Smolensky (2001) looked at variation in homelessness among regions, including national variation and variation among local Californian jurisdictions. Their study found that median housing rents and rent-to-income ratios are significant explanatory variables, and climate is also a significant predictor, where colder weather conditions are associated with lower rates of homelessness.

A comprehensive study on structural determinants of homelessness in 335 metropolitan areas by Lee, Price-Spratlen, and Kanan (2003) found that median rent had the most effect on homelessness rates. Their study also found that the percentage of single-person households also had a positive relationship, with more single-person households in a region correlating to higher rates of homelessness. Ji (2006) conducted a multiple regression study of 52 metropolitan areas and found that the poverty rate is strongly related to the homelessness rate; no other risk factors included in the model were found to be statistically significant predictors.

Variables, Data, and Methods

Our research conducts an empirical analysis of the factors that are associated with the geographic variation in homelessness. The first section outlines and describes the variables as well as the data sources. We will thereafter run a bivariate correlation analysis followed by a multiple regression analysis.

Dependent Variable

Homelessness: The dependent variable is the number of homeless individuals per 10,000 capita. This variable includes point-in-time (PIT) counts of people who are homeless, defined as an individual or member of a family who is living in emergency shelter, transitional housing, or on the streets and other places unintended for human habitation (such as cars, abandoned buildings, etc.). The variable comes from the Metropolitan Statistical Area dataset of the Homelessness Research Institute at the National Alliance to End Homelessness and is based on PIT counts data reported by Continua of Care (CoC) homeless assistance systems to the Department of Housing and Urban Development (HUD) and is for the year 2011. Individual-level characteristics are not associated with the PIT counts data. Some communities collect individual-level characteristics data and manage these data through a data management software system called a Homeless Management Information System (HMIS) (see: Poulin, Metraux, and Culhane, 2008; U.S. Department of Housing and Urban Development, 2011). However, an HMIS-based individual-characteristics data source is not available at the sub-national level. One limitation of these data is that individual-level characteristics data are only captured on the homeless population that "touches" the shelter system.

Independent Variables

A range of independent variables is used in the next analysis.

Regional Size: This is the total population in the region. The data is from the 2007-2009 American Community Survey.

Income: We would expect income patterns to be related to the likelihood of becoming homeless. We employ three different income related measures to capture such effects. Income is the sum of the amounts reported separately for wage or salary income including net self-employment income; interest, dividends, or net rental or royalty income or income from estates and trusts; social security or railroad retirement income; Supplemental Security Income (SSI); public assistance or welfare payments; retirement, survivor, or disability pensions; and all other income. It is measured on a per capita basis and is from the 2007-2009 American Community Survey.

Wage level: This variable is only related to work performance and includes wages, salary, armed forces pay, commissions, tips, piece-rate payments, and cash bonuses earned before deductions were made for taxes, bonds, pensions, union dues, etc. It is measured on a per worker basis and is gathered from the 2010 Bureau of Labor Statistics.

Income Inequality: This is measured as the Gini coefficient. This variable captures the distribution of incomes from the bottom to the top. We use the three-year estimate of the coefficient provided by the 2007-2009 American Community Survey.

Poverty: This variable measures the share of the population that is below the poverty line. It is based on data from the American Community Survey for the years 2007-2009.

Unemployment: This is a measure of the unemployment rate: that is, the share of the labor force without an employment. The data is for July 2011 and is from the Bureau of Labor Statistics.

Housing Costs: We use the median housing cost per month based on the American Community Survey for the years 2007-2009.

Housing to Income Ratio: This is a measure of the income share that is spent on housing. We divide the median yearly housing cost by income per capita. Both variables are from 2007-2009 American Community Survey.

Housing Density: This is a measure for the average occupants per room in each housing unit. The variable comes from the American Community Survey and is for the year 2008-2010.

Climate: Two climate variables are employed: average temperature in January, and in July. The data are from the U.S. Geological Survey.

African American share: This is the African-American share of the population based on the 2007-2009 American Community Survey.

Non-white share: This is the non-white share of the population based on the 2007-2009 American Community Survey.

Jail/imprisonment: We would assume the likelihood of becoming homeless to increase after time spent in prison. Since there is no data available for the number of prisoners per capita at the metropolitan level, we employ correctional officers and jailers occupations share of total regional employment as a proxy variable for this. The data is from the Bureau of Labor Statistics and is for the year 2010.

Uninsured: This is the share of the population that does not have health insurance. Data are from the County Health Rankings 2012 as by the Census Bureau's Small Area Health Insurance Estimates (SAHIE). We have aggregated and population weighted these county results to the metro-level.

Mental Health: This is based on the reported number of days, with poor mental health, of the metropolitan population. The estimate is based on questions such as “Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?”. Data are from the County Health Rankings 2012 as reported in the Behavioral Risk Factor Surveillance System (BRFSS). We have aggregated and population weighted these county results to the metro-level.

Excessive Drinking: This is based on the share of the metropolitan population that binge drink or drink heavily as defined by the BRFSS. Data are from the County Health Rankings 2012 as reported in the BRFSS. We have aggregated and population weighted these county results to the metro-level.

Foster Care: This is a variable for the number of foster care emancipation exits per 100,000, and is an average for the years 2009 and 2010. The data is from the U.S. Administration for Children and Families (AFCARS).

AIDS: This is the estimated rate of the population that is living with HIV infection by the end of year 2008. The data is from the Centers for Disease Control and Prevention (CDC).

Disability: This variable is defined as the share of the population with some kind of disability, such as severe vision or hearing impairment, or conditions that substantially limit the basic physical activities. The data is from the 2008-2010 American Community Survey.

Table 1 presents the descriptive statistics for all variables.

(Table 1 about here)

Since the homelessness share data only includes approximately 100 regions, descriptive statistics have been included in Appendix 1 for the US metropolitan regions that could not be included in this analysis due to missing values. The metros in our analysis are among the biggest in the U.S. with a mean population of approximately 2 millions, which could be compared with the mean of approximately 200,000 for the regions that are not included in this study. The regions in our study also have higher income per capita and higher wage levels ($26,471 and $44,035 to be compared to $23,148 and $38,607). On average, income inequality is on approximately the same level (around 0.45), and poverty shares are somewhat lower (0.13 vs. 0.15). Housing costs are clearly higher in our included regions, (1,049 compared to 826) as well as the share of the income that is being spent on housing (0.48 vs. 0.43). Climate is similar on average. In the included regions we have higher shares of African American and non-white populations (0.13 vs. 0.10). We also find higher shares employed as correctional officers and jailers (0.19 vs. 0.0014). The share of uninsured, individuals with poor mental health, that drink excessively, AIDS rates per capita, and foster care shares are all at approximately the same level in our included regions as in the ones we've excluded.

Methods

We employ a number of different statistical methods. First, we run bivariate correlations to identity relationships between homelessness shares and key economic and social factors. Second, we run a multivariate OLS regression analysis to examine the effect from each of the independent variables while controlling for the others.

Findings

We now turn to our findings. To orient the analysis, Figure 1 provides a map of the variation in homelessness shares across U.S. metro areas.

(Figure 1 about here)

Figure 1 is a map that charts the number of homeless per 10,000 across 98 US metropolitan regions. The average rate of homelessness for included metros is 19 homeless people per 10,000. Tampa-St. Petersburg-Clearwater, FL has the highest number of homeless people per 10,000 with 57.25, followed closely by New Orleans-Metairie-Kenner, LA (56.19), Fresno, CA (56.10), Las Vegas-Paradise, NV (49.57), and Honolulu, HI (46.65). The remaining metro areas have below 45 homeless people per 10,000, with twenty metropolitan regions with homeless populations below 10 homeless people per 10,000. Youngstown-Warren-Boardman, OH-PA (3.58) and Provo-Orem, UT (3.96) have the smallest homeless population per 10,000 of the metro areas examined.

Correlation Analysis

We now turn to the findings of the bivariate correlation analysis. It is important to remember that each case of homelessness is highly affected by personal characteristics, and that analyzing this at the regional level may be hiding unevenly distributed structures. This may specifically be the case of jail/imprisonment effects, poor mental health, foster care, AIDS, and disability. There may be regions with low averages across of all these factors, but where the individuals affected by them are still at a probably larger risk of becoming homeless. Still, we find it important to see if overall regional structures of these kinds affect the overall share of homelessness in a region. Table 2 summarizes the correlation analysis results for the key measures.

(Table 2 about here)

Winter climate has the strongest relationship to homelessness (.447). More people are homeless in places where winters are warmer. There is no significant relation though with summer temperatures (.069).

Housing variables appear to play a substantial role as well. The correlation to median monthly housing costs is (.395), and even stronger (.426) in places where people spend a larger share of their income on housing every month. There is a strong and significant relation between homelessness and housing density (.432). There are more homeless people in metros where more people, on average, share housing space.

Homelessness is associated with several economic factors. There is a positive and significant relation with wage levels (.272). We also find a significant relation to unemployment rates (.290). That said, income does not appear to play a substantial role in homelessness, according to our analysis. There is no significant relation to income per capita (.109), income inequality (.099) or poverty (-.037).

Race plays something of a role. We find a significant relation with the share of non-white population (.383), but not a significant relation with the African American share specifically (-.084).

Population size factors in to some extent. There is a positive, but relatively weak, relation between regional size and homelessness (.240), indicating that there are more homeless individuals per capita as metro population increases.

The results for social and health factors are mixed. Homelessness is significantly related to the rate of AIDS infection (.402). It is weakly related with the share of the population that is uninsured (.170), and with excessive drinking (.192). Homelessness is not related to imprisonment (-.161), measured as the regional share of correctional officers and jailers occupations. Nor is it related to levels of poor mental health (-.005) or disability (-.164).

In short, we find homelessness across metros to be related to housing cost and winter climate as well as wage levels, unemployment and the non-white share of the population. To get a better handle on the factors that shape the regional variation in homelessness, we turn to a multivariate analysis.

Regression Findings

We include only variables that were statistically significant, at least at the 10 percent level, in the bivariate correlation analysis in our regressions. We assume a certain degree of inter-relationship between the independent variables, which in turn may introduce multicollinarity issues in our models. To exclude such collinearity effects, we will run several permutations of our models, where we substitute variables that are strongly related to one another. We will also include Variance Inflation Factors (VIF) to control for multicollinearity effects. Thus, several regressions were run, substituting variables that correlate strongly with one another. All variables are logged and the coefficients could thus be interpreted as elasticities.

The first set of models examine the relationship between homelessness and population size, wages, housing cost and housing density. There is a certain inter-relation between the two housing variables and we will therefore employ them separately to avoid multicollinearity problems. Table 3 summarizes the results for these regressions.

(Table 3 about here)

In equation 1, we let homelessness shares be explained by population size, wages and unemployment. Out of the three, only wages is significant at the 5 percent level.

In equation 2, we add median monthly housing cost to the model. It outperforms both wages (now insignificant), and unemployment (now is significant at the 1 percent level). However, relatively high VIF values (above 3) indicate that we may have introduced multicollinearity into the model.

In equation 3, we substitute median monthly housing cost with the housing-to-income ratio. This variable is the strongest in the model, but significant only at the 5 percent level.

In equation 4, we introduce housing density. This variable is significant at the 1 percent level, and increases the R2 Adj from approximately 0.19 to 0.22, indicating that housing density may explain slightly more of the variation in homelessness shares than the other two housing variables (median cost and income-to-housing ratio).

We employ this housing variable in the next set of regressions in Table 4, which also add climate and other socio-economic variables.

(Table 4 about here)

In equation 5 we add non-white share of the population, as well as the share uninsured. Both of these variables are insignificant and the overall result of the regression is very similar to equation 4, with only wage and housing density being significant.

Equation 6 drops these variables and adds excessive drinking. This is significant at the 5 percent level, and it also increases the R2 Adj value slightly.

Equation 7 includes winter climate, a variable that turns out to be the strongest of all included variables so far. The coefficient is around 0.6-0.7 (see eq. 7 and 8). This implies that a 1 percent increase in winter temperature degrees increases homelessness per capita by 0.6 to 0.7 percent. The R2 increased significantly from approximately 0.24 to 0.39, which suggests that winter temperatures explain a large share of the variation in homelessness shares across metros.

Equation 8 adds AIDS rates, which is insignificant in this multivariate context. However, the inclusion of both climate and AIDS rates decrease the number of observations in our regressions (from 97 down to 88 respectively. 68).

To further control for effects from the missing values, we re-run equation 7 and 8 and this time as pairwise regressions. The results are still relatively similar (see Appendix 2). When we re-run equation 7, wages becomes somewhat weaker, while winter climate remains the strongest variable. The R2 Adj is somewhat lower, but still significantly higher than in the 1-6 regressions. When we re-run equation 8 as a pairwise regression, the results once more are similar. We also re-run equation 8 with only the 68 observations but without the AIDS rate variable. This regression generates an R2 Adj of 0.242, significantly lower than in regression 8. In other words, the AIDS variable adds significantly to the explanatory power. Also, when AIDS is excluded in the reduced sample regression, wages become significant at the 5 percent level.

Discussion and Conclusion

This research has examined the factors related to homelessness in the largest metropolitan regions in the US. It focused on place-based characteristics. While homeless individuals may be poor, suffer from mental illness or substance abuse, our research examined the effect of metro level factors on homelessness (see: Bohannon, 1991; Burt, 1992). We examined the roles played by economic factors like wages, income, poverty, and unemployment, housing variables like cost, affordability and density, population size, climate, and social and health factors across 97 metropolitan areas using both bivariate correlation and multivariate regression analysis.

Our findings suggest that three variables play substantial roles in the geographic variation of homelessness. The first is winter climate. Metros with warmer winter temperatures have significantly higher shares of homelessness, according to our analysis. Our findings here align with those of Quigley, Raphael, and Smolensky (2001) and Lee, Price-Spratlen, and Kanan (2003).

We also find homelessness to be associated with housing costs and housing density. Metros where the monthly housing cost is higher, where people spend a larger share of their incomes on housing, and where people live more closely together also have significantly higher shares of homelessness. This is in line with earlier studies (e.g. Bohannon, 1991; Elliott and Krivo, 1991; Honig and Filer, 1993; Grimes and Chressanthis, 1997; Quigley, Raphael, and Smolensky, 2001; Lee, Price-Spratlen, and Kanan, 2003; Ji, 2006). We also find homelessness to be associated with wage levels. However, we suggest that the effect here is indirect, as wages are channeled into increased housing costs at the metro level.

Perhaps more interesting are the variables that are not related to the geographic variation in homelessness. Among these are economic factors like per capita income, inequality, poverty, and unemployment; social factors like jail and imprisonment levels, mental health, foster care and disability shares, as well as population size and summer climate.

Generally speaking, our research, using a new, improved measure of homelessness at the metro level, indicates that just two key factors are the principle causes of the geographic variation of homelessness - housing cost and density and winter climate. We encourage more research on this important subject.

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Appendix 1: Descriptive Statistics for Non-Included Regions

	N	Minimum	Maximum	Mean	Std. Deviation
Regional Size	264	55152	721430	212915	114420
Income per Capita	262	13450	35988	23148	3575
Wage Level	264	29651	55971	38607	4059
Income Inequality	264	.3890	.5300	.4437	.0264
Poverty	264	.0647	.3601	.1490	.0433
Unemployment	262	3.00	30.80	9.03	3.08
Housing Costs	264	504	1591	826	196
Housing to Income Ratio	262	.2594	.7113	.4290	.0770
Housing Density	264	.3500	.6536	.4066	.0455
Winter Climate	253	3.95	65.20	35.26	12.11
Summer Climate	253	61.80	93.70	75.73	5.51
African American Share	264	.0012	.4955	.0961	.1083
Non-White Share	264	.0318	.5236	.1789	.1106
Jail/imprisonment	258	.0000	.0326	.0014	.0037
Uninsured	261	5.00	38.00	17.17	5.15
Mental Health	262	1.80	5.90	3.55	.66
Excessive Drinking	261	5.00	31.47	15.71	4.14
Foster Care	260	.66	55.10	9.397	5.813
AIDS_Rates	6	44.3	500.5	250.0	177.4
Disability_Share	262	5.97	21.18	13.09	3.20

Appendix 2: OLS Regression findings for Homelessness Shares to Compensate for Missing Values

	Pairwise		**Pairwise**	
	Eq 7	**VIF**	**Eq 8**	**VIF**
Constant	-9.788**		-8.470	
	(4.928)		(6.042)	
Wage Levels	.911**	1.178	.800	1.675
	(.448)		(.544)	
Housing Density	1.346**	1.337	1.426**	1.222
	(.528)		(.618)	
Non-White Share	-	-	-	-
Uninsured	-	-	-	-
Excessive Drinking	.609**	1.135	.558**	1.362
	(.237)		(.284)	
Winter Climate	.647***	1.286	.549**	2.669
	(.161)		(.245)	
AIDS Rates			.081	2.331
			(.133)	
R2	.383		.387	
R2 Adj	.353		.338	
N	87		68	

***Indicate significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level

Tables and Figures:

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Homelessness	98	3.58	57.25	18.7563	11.73577
Regional Size	98	508082	18979822	2021962	2624053
Income per Capita	97	16835	44024	26471	4372
Wages	97	35078	68135	44035	5590
Income Inequality	98	.4110	.5370	.4508	.0200
Poverty	98	7.07	.26.58	.1263	2.98
Unemployment	97	4.70	17.50	9.31	2.41
Housing Costs	98	675	1777	1049	252
Housing to Income Ratio	97	.3302	.7760	.4764	.0874
Housing Density	98	.3565	.5681	.4136	.0471
Winter Climate	88	11.69	66.50	38.31	12.26
Summer Climate	88	64.53	91.15	76.50	5.50
African American Share	98	0.53	46.46	12.84	9.99
Non-White Share	98	4.89	76.99	25.20	11.79
Jail/imprisonment	97	0.00	2.28	0.19	0.29
Uninsured	97	4.78	32.00	16.03	5.23
Mental Health	97	2.67	4.27	3.43	.35
Excessive Drinking	97	4.16	24.49	16.57	2.92
Foster Care	97	2.35	25.46	9.842	4.738
AIDS	74	21.5	859.5	256.2	150.4
Disability	97	6.76	16.11	11.24	2.05
Valid N (listwise)	69				

Table 2: Correlation Analysis Findings for Metropolitan Homelessness Shares

Regional Size	.240**
Income per Capita	.109
Wage Levels	.272***
Income Inequality	.099
Poverty	-.037
Unemployment	.290***
Housing Costs	.395***
Housing to Income Ratio	.426***
Housing Density	.432***
Winter Climate	.447***
Summer Climate	.069
Arican American Share	-.084
Non-White Share	.383***
Jail/imprisonment	-.161
Uninsured	.170*
Mental Health	-.005
Excessive Drinking	.192*
Fostercare per 100K Capita	.134
AIDS Rates	.402***
Disability Share	-.164

***Indicate significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level

Table 3: OLS Regression findings for Homelessness Shares, Economic Structures and Regional Size

	Eq 1	VIF	Eq 2	VIF	Eq 3	VIF	Eq 4	VIF
Constant	-11.922**		-1.889		-5.700		-7.004	
	(5.372)		(6.679)		(5.805)		(5.377)	
Regional Size	.057	1.455	.053	1.455	.050	1.457	.031	1.473
	(.078)		(076)		(.073)		(.075)	
Wage Levels	1.160**	1.446	-.379	3.510	.728	1.602	.940*	1.472
	(.546)		(.829)		(.559)		(.527)	
Unemployment	.680	1.023	.535***	1.103	.320	1.493	.368	1.255
	(.221)		(.224)		(.260)		(.234)	
Housing Costs	-	-	.979**	3.145	-		-	-
			(.405)					
Housing to Income	-	-	-	-	.955**	1.625	-	-
					(.387)			
Housing Density	-	-	-	-	-		1.706***	1.304
							(.549)	
R2	.171		. 220		. 222		. 249	
R2 Adj	. 144		. 186		. 188		. 217	
N	96		96		96		96	

***Indicate significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level

Table 4: OLS Regression findings for Homelessness Shares, Economic and Socio-Economic Structures

	Eq 5	VIF	Eq 6	VIF	Eq 7	VIF	Eq 8	VIF
Constant	-6.506		-3.424		-15.138***		-14.193**	
	(6.237)		(4.839)		(5.042)		(9.883)	
Wage Levels	.989*	1.543	.632	1.150	1.377***	1.173	1.261	1.675
	(.535)		(.458)		(.453)		(.905)	
Housing Density	1.523**	1.454	2.320***	1.073	1.078**	1.365	.724	1.222
	(.576)		(.490)		(.516)		(.799)	
Non-White Share	.197 (.129)	1.548	-	-	-	-	-	-
Uninsured	.131	1.740	-	-	-	-	-	-
	(.190)							
Excessive Drinking	-		.537** (.244)	1.127	.602*** (.222)	1.110	.517** (.270)	1.362
Winter Climate	-				.696***	1.293	.615**	2.669
					(.157)		(.258)	
AIDS Rates	-						.087	2.331
							(.144)	
R2	.206		. 265		. 418		. 291	
R2 Adj	. 228		. 241		. 390		. 235	
N	96		96		87		68	

***Indicate significance at the 1 percent level, ** at the 5 percent level, * at the 10 percent level

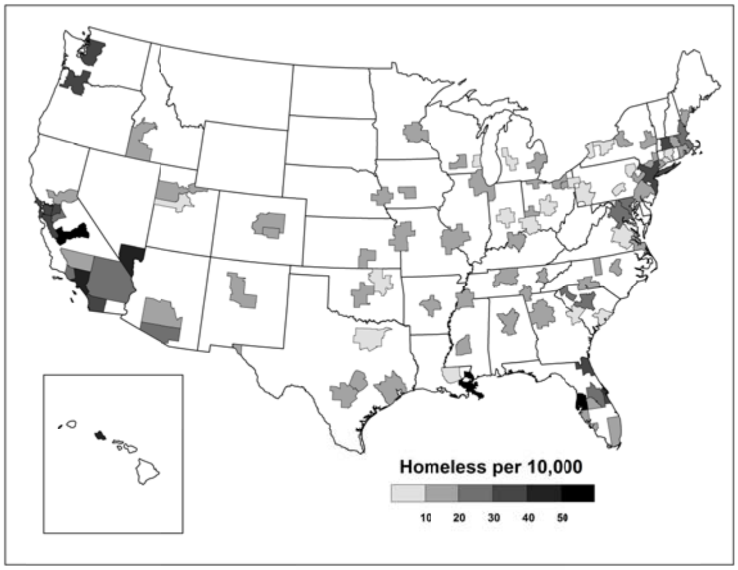

Figure 1: Homelessness Shares in 98 US metropolitan regions

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