Predictors of Homelessness in Midwestern States: A Multiple Linear Regression Analysis

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Abstract

Preliminary bivariate regressions and a subsequent multiple linear regression analysis were performed to quantify the predictors of 2010 homelessness rates in Midwestern states, as measured by the HUD Point-in-Time Count. Twenty-seven variables were investigated. Rates of institutionalization and co-occurring mental health and substance abuse disorders most impacted homelessness rates. Additionally, the unemployment rate and domestic violence indicators were prominent predictors. The racial composition of Midwestern states was also influential. Surprisingly, cross-sectional variation in poverty levels and high school graduation rates explained virtually none of the variation in homelessness rates. Implications of the findings are considered.

Keywords: Homelessness, Midwest, predictors, regression, correlates, econometrics.

Predictors of Homelessness in Midwestern States: A Multiple Linear Regression Analysis

The Midwest is distinct from the other three United States regions in several key ways. For instance, the Midwest accounted for only 21.7% of the nation's total population in 2010 (United States Census Bureau, 2013). The same year, the Midwest was 81.3% white, the least racially diverse of the four regions (United States Census Bureau, 2013). Further, the population density of the Midwest in 2010 was 89.2 persons per square mile, about a quarter of the population density of the Northeast (United States Census Bureau, 2013). Also in 2010, 22.8% of Midwesterners lived in rural areas, over one and a half times the national average (United States Department of Agriculture, n.d.). Regarding its economy, Midwestern states in 2010 accounted for 31.9% of the nation's total full-time and part-time farm employment (United States Bureau of Economic Analysis, n.d.b) and 38.1% of the nation's total Gross Domestic Product from farming (United States Bureau of Economic Analysis, n.d.a). Finally, 64.6% of all harvested land nationwide in 2016 was in the Midwest (United States Department of Agriculture, 2019).

The unique demography, economy, and geography of the Midwest may effect the prevalence and causes of homelessness. Some researchers have conducted regression analyses to quantify the predictors of homelessness both nationwide (Silber, 2019; United States Department of Housing and Urban Development, 2019a; Vyskocil, 2015) and across cities (Bohanon, 1991; Lee et al., 2003). However, to my knowledge, no regression analysis has focused in particular on homelessness across Midwestern states. This is an especially pressing area of investigation given its implications for policy makers, homeless service providers, researchers, community members, and the nearly 62,000 persons who were homeless in the Midwest on a single day in 2019 (United States Department of Housing and Urban Development, 2019b). Responding to this gap in the literature, in this study I present results from a multiple linear regression analysis of several variables on Midwestern homelessness rates in 2010. The variables I investigated in the study were identified from the literature review presented in the remainder of this section.

Race

Black and African-American persons are disproportionately likely to be poor and homeless (Davies, 2016; Jones, 2016), including in rural counties (First et al., 1994). McQuistion et al. (2014) report evidence indicating that black and African-American persons are also further overrepresented in the chronically homeless subsets of homeless populations. Poor access to housing after exit from prison contributes to this racial group's overrepresentation among the homeless (Schneider, 2018). Nationwide, about 40.4% of homeless persons are black or African American (United States Department of Housing and Urban Development, 2015). Given these statistics, it is unsurprising that Greenberg & Rosenheck (2010) identified being black or African American as a risk factor for experiencing adult homelessness. Due to these findings, I expected the regression analysis to yield that 2010 Midwestern homelessness rates were positively correlated with the percent of a state that was black or African American.

Educational Attainment

The available literature indicates that homeless persons tend to have struggled academically due to various life obstacles (Mabhala et al., 2017). Study samples reveal low high school graduation rates among homeless populations (e.g., Basu et al., 2012; McQuistion et al., 2014; Rhoades et al., 2014). This trend appears to remain consistent in rural counties (First et al., 1994), for homeless youth (Curry et al., 2017; Kidd et al., 2016), and for older homeless persons (Brown et al., 2015). Accordingly, Silber (2019) identified an inverse relationship between homelessness rates and high school graduation rates across the nation. A similar relationship between educational attainment and homelessness rates was predicted to exist in the Midwest.

Crime

Past and present criminal activities are documented as pathways to experiencing homelessness (Mabhala et al., 2017; Snow & Anderson, 1990). Likewise, incarceration is a strong risk factor for experiencing adult homelessness (Greenberg & Rosenheck, 2010). Studies report that criminal records are common among homeless populations (e.g., Fischer & Ross, 1993; Lee & Greif, 2008; McQuistion et al., 2014), including for youth (Barman-Adhikari et al., 2016; Curry et al., 2016; Ferguson et al., 2011) and especially for drug users (Coumans & Spreen, 2003) and persons with a serious mental illness (Viron et al., 2014). Exemplifying the significant overlap between crime and homelessness, when one county expanded their definition of *homeless* to include persons in jail who were homeless before arrest, the total number of documented homeless persons increased by 57.9% (Troisi & The Coalition for the Homeless of Houston/Harris County, 2016). In light of these findings, I anticipated discovering a positive relationship between criminal activity and Midwestern homelessness.

Mental Illnesses

Mental illnesses are one cause of homelessness (Fitzpatrick, 2005; Snow & Anderson, 1990). One study suggests that persons diagnosed with a mental illness are 10 to 20 times more likely to experience homelessness (Susser et al., 1997). Accordingly, research documents the prevalence of mental illness diagnoses and mental health problems among homeless populations (e.g., Basu et al., 2012; Ferguson et al., 2011; Greenberg & Rosenheck, 2010; Lee & Greif, 2008; Nishio et al., 2017; Rhoades et al., 2014; Toro et al., 2014; Viron et al., 2014), including for homeless youth (Curry et al., 2016; Perlman et al., 2014; Taylor et al., 2006), older homeless persons (Brown et al., 2015), indigenous homeless persons (Whitbeck et al., 2012), and homeless veterans (Byrne et al., 2016; Creech et al., 2015). Of the nearly 80,000 documented persons experiencing homelessness in the Midwest on a single day in 2010, 17.7% were reported to be severely mentally ill (United States Department of Housing and Urban Development, 2011). Given these data, I expected to find a positive correlation between rates of mental illnesses and Midwestern homelessness.

Substance Use

Baseline results from studies of homeless persons and interviews with homeless persons reveal that substance use is both a pathway to experiencing homelessness (Mabhala et al., 2017) and common among homeless populations (e.g., Lee & Greif, 2008; Rhoades et al., 2014; Toro et al., 2014), especially for those who struggle with a serious mental illness (Viron et al., 2014). This pattern prevails for homeless youth (Barman-Adhikari et al., 2016; Ferguson et al., 2011; Salomonsen et al., 2008; Taylor et al., 2006), older homeless persons (Brown et al., 2015), indigenous homeless persons (Whitbeck et al., 2012), and homeless veterans (Byrne et al., 2016; Creech et al., 2015). About 20.2% of the homeless persons counted in the Midwest in early 2010 suffered from chronic substance abuse (United States Department of Housing and Urban Development, 2011). For these reasons, substance use was expected to positively correlate with Midwestern homelessness rates.

Housing Affordability and Poverty

The relevant literature identifies several socioeconomic forces that cause homelessness. Housing affordability and accessibility are widely recognized as one of such forces (e.g., Cronley, 2010; Fitzpatrick, 2005; Kneebone & Wilkins, 2016; Main, 1996; Neale, 1997; Snow & Anderson, 1990). Data indicate, for example, that rent level positively correlates with homelessness (Lee et al., 2003). Poverty and low-wage jobs are also recognized as socioeconomic forces causing homelessness (e.g., Cronley, 2010; Fitzpatrick, 2005; Lee et al., 2003; Main, 1996; Snow & Anderson, 1990). For instance, Curry et al. (2017) observed that homeless youth are more likely to come from households with lower annual income than non-homeless youth. Additionally, the receipt of welfare payments, a proxy-measurement for poverty, has been found to be a risk factor for experiencing adult homelessness (Greenberg & Rosenheck, 2010). For these reasons, I anticipated poverty and poor housing affordability to positively relate to Midwestern homelessness rates.

Domestic Violence

In a survey of 25 cities from across the nation, 28% of mayors cited domestic violence as one of the three main causes of homelessness for families with children (United States Conference of Mayors, 2012). Domestic violence is commonly recognized as a pathway to homelessness for women (Thurston et al., 2013). Further, homeless women have been found to experience high levels of rape, sexual harassment, sexual assault, physical abuse, physical assault, and other traumas (Hudson et al., 2010; Tsai et al., 2012). Finally, of the nearly 80,000 persons counted as experiencing homelessness on a single day in the Midwest in 2010, 12.6% were also victims of domestic violence (United States Department of Housing and Urban Development, 2011). Due to these findings, I anticipated discovering a positive correlation between domestic violence and Midwestern homelessness rates.

Weather

Unsheltered homeless persons are particularly vulnerable to extreme heat in the summer, frigid cold in the winter, and heavy precipitation (Cusack et al., 2013; Petrovich et al., 2017). As one homeless interviewee explained, “There is nowhere to dry your clothes if… you get wet, you stay wet” (Cusack et al., 2013, p. 253). Homeless persons who could otherwise remain undetected in communities with moderate weather may be forced to seek refuge at a homeless shelter in communities with more extreme, inclement weather. Because sheltered homeless persons are easier to enumerate than unsheltered homeless persons, I expected adverse winter weather conditions to be associated with higher counted levels of Midwestern homelessness.

Methods

This study is based on a cross-sectional analysis of 2010 data describing Midwestern states. All data were obtained from United States government publications. To control for varying populations among Midwestern states, the response (dependent) variable was the total homelessness count from the 2010 *Point-in-Time* (PIT) *Count* as a percent of the total population of the state. A PIT Count is an attempt to count the number of persons in a given jurisdiction (known as a *Continuum of Care*) who are homeless on a given day. To receive funding from the United States Department of Housing and Urban Development, PIT Counts must be conducted early in the year, usually at the end of January, on at least a biennial basis. The date of the count is specially chosen to maximize its accuracy. For more information on the methodology of the PIT Count, see United States Department of Housing and Urban Development (2014).

Predictor (independent) variables were identified from the literature review in the introduction. They comprised: demographic and racial statistics; housing affordability, economic, and educational metrics; substance abuse, mental health, and crime data; and weather patterns.

When appropriate, predictor variables were also converted to a percent of the total population of the state to control for varying population sizes.

I conducted preliminary bivariate linear regressions of each predictor variable on the response variable. Predictor variables included in the subsequent multiple linear regression analysis needed to account for approximately 10% or more of the variance in the response variable, $r^2 \gtrsim .1$. Preference was given to predictors that (a) explained greater amounts of the variance in the response variable, (b) were of greater statistical significance, and (c) described a characteristic of a state not captured by other qualifying predictors.

After selecting predictor variables for inclusion in the multiple regression analysis, the initial model was reduced. Predictor variables were removed in a backward-stepwise fashion according to the significance level at which their coefficients were estimated. The model was reduced until it exclusively comprised coefficients of predictors that were estimated at the 1% significance level. Finally, post-hoc tests were conducted to check the assumptions of the model. Namely, I tested for multicollinearity, heteroscedasticity, and non-normally-distributed residuals.

Results

Baseline Results

Table 1 shows the total population and PIT Count results for each Midwestern state in 2010. On average, about .1199% of a Midwestern state was counted as homeless on a single day in early 2010, or nearly 12 for every 10,000 persons. Nebraska's PIT Count as a percent of the total population was 77.0% larger than the average. The Nebraska datum was classified as an outlier since it exceeded the upper-outlier threshold of .1834%, the product of 1.5 and the interquartile range above the third quartile, $Q_3 + 1.5 \cdot [Q_3 - Q_1]$. Nebraska data were excluded

Table 1

Point-in-Time Count Homelessness Rates in Midwestern States, 2010

State [a]	PIT Homelessness Count [b]	Total Population [a]	Percent of Population Experiencing Homelessness
Illinois	14,395	12,830,632	0.1122%
Indiana	6,452	6,483,802	0.0995%
Iowa	3,014	3,046,355	0.0989%
Kansas	2,024	2,853,118	0.0709%
Michigan	13,058	9,883,640	0.1321%
Minnesota	7,869	5,303,925	0.1484%
Missouri	8,122	5,988,927	0.1356%
Nebraska	3,877	1,826,341	0.2123%
North Dakota	799	672,591	0.1188%
Ohio	12,569	11,536,504	0.1089%
South Dakota	731	814,180	0.0898%
Wisconsin	6,333	5,686,986	0.1114%

Note. Data are from United States Census Bureau (2012b) [a] and United States Department of Housing and Urban Development (2011) [b].

from both the bivariate linear regressions and the subsequent multiple linear regression analysis due to their disparate impact on the results. For example, removing the Nebraska data from the bivariate linear regressions changed the observed *r* value, on average, by a magnitude of 0.244. (See Appendix A.)

Preliminary Bivariate Linear Regressions

In total, I separately regressed 27 variables on 2010 Midwestern PIT Counts as a percent of the total population of the state. The complete data as well as the results of the predictor variables regressed on the response variable are available as follows: demographic variables in Appendix B; racial metrics in Appendix C; housing affordability metrics in Appendix D;

economic and educational metrics in Appendix E; substance abuse, mental health, and criminal justice system data in Appendix F; and weather data in Appendix G. Tables 2-4 present condensed bivariate linear regression results of the nine predictor variables chosen for inclusion in the subsequent multiple linear regression analysis and two predictor variables (poverty and high school graduation rates) that exhibited unexpected relationships with homelessness rates.

Multiple Linear Regression Analysis

The multiple linear regression analysis contained all variables presented in Tables 2-4 except for measures of poverty and high school graduation. Table 5 shows the initial and reduced equations generated by the multiple linear regression analysis. The reduced equation estimates at the 1% significance level the coefficients of the following model:

$$PIT\ Homelessness\ \widehat{Count},\ \%\ of\ Population\ =\ \beta_0\ +\ \beta_1 Unemployment_i\ +\ \beta_2 Institutionalization_i +\ \beta_3 CoOccurringDisorders_i\ +\ \beta_4 DomesticViolence_i\ +\ \epsilon_i$$

The summary output, ANOVA output, and residual output of the reduced multiple linear regression analysis are presented, respectively, in Tables 6-8. Holding constant rates of institutionalization, co-occurring mental health and substance abuse disorders, and domestic violence, a 1% increase in the unemployment rate would decrease counted levels of homelessness as a percent of a state's population by an estimated .00838%, or nearly 84 for every one million persons living in a Midwestern state. Holding the other three predictors constant, a 1% increase in a Midwestern state's institutionalization rate would decrease PIT Count results as a percent of the state's total population by a projected .12444%, or more than 12 for every ten thousand persons living in the state. All other considered variables held constant, a .1% increase in the percent of a Midwestern state's population that has a co-occurring mental

Table 2

Condensed Bivariate Linear Regression Results of Selected Economic, Educational, and Housing Affordability Data on Midwestern PIT Count Homelessness Rates, 2010

State	Percent of Population Experiencing Homelessness	Percent of Occupied Housing Units Renter-Occupied [a]	Unemployment Rate [b]	Percent of Population in Poverty [c]	Percent of Population Age 25 and Older Without a High School Diploma or Equivalent [d]
Illinois	0.1122%	32.53%	10.3%	13.8%	13.1%
Indiana	0.0995%	30.14%	10.2%	15.3%	13.0%
Iowa	0.0989%	27.91%	6.1%	12.6%	9.4%
Kansas	0.0709%	32.24%	7.0%	13.6%	10.8%
Michigan	0.1321%	27.87%	12.5%	16.8%	11.3%
Minnesota	0.1484%	26.99%	7.3%	11.6%	8.2%
Missouri	0.1356%	31.23%	9.6%	15.3%	13.1%
Nebraska [e]	0.2123%	32.78%	4.7%	12.9%	9.7%
North Dakota	0.1188%	34.58%	3.9%	13.0%	9.6%
Ohio	0.1089%	32.42%	10.1%	15.8%	11.9%
South Dakota	0.0898%	31.87%	4.8%	14.4%	10.4%
Wisconsin	0.1114%	31.94%	8.3%	13.2%	9.9%
r Value		-0.39	0.31	-0.01	-0.11
r^2 Value		0.15	0.10	0.00	0.01
Coefficient p Value		0.237	0.354	0.988	0.749

Note. Data are from or calculated from data available at United States Census Bureau (2012b) [a], United States Bureau of Labor Statistics (2011) [b], United States Census Bureau (2012a) [c], and United States Census Bureau (n.d.b) [d]. Nebraska data [e] are not included in the bivariate linear regressions. The complete results of the bivariate linear regressions for these selected variables are available in Appendices D and E.

Table 3

Condensed Bivariate Linear Regression Results of Selected Substance Abuse, Mental Health, and the Criminal Justice System Data on Midwestern PIT Count Homelessness Rates, 2010

State	Percent of Population Experiencing Homelessness	Percent of Persons Age 12 and Older Using Marijuana in the Past Month [a]	Percent of Population Institutionalized [b]	Percent of Population With Co-Occurring Mental Health and Substance Abuse Disorders [c]	Projected Percent of Population Lifetime Victims of Rape, Physical Violence, and/or Stalking by an Intimate Partner [d]
Illinois	0.1122%	6.9%	1.25%	0.1570%	24.14%
Indiana	0.0995%	7.2%	1.47%	0.1829%	25.17%
Iowa	0.0989%	5.0%	1.42%	0.1867%	19.27%
Kansas	0.0709%	5.1%	1.45%	0.1334%	19.31%
Michigan	0.1321%	9.0%	1.11%	0.3093%	25.17%
Minnesota	0.1484%	6.1%	1.06%	0.2176%	21.66%
Missouri	0.1356%	5.3%	1.56%	0.3039%	29.05%
Nebraska [f]	0.2123%	5.4%	1.29%	0.2616%	23.82%
North Dakota	0.1188%	4.1%	1.44%	0.2849%	19.33%
Ohio	0.1089%	6.6%	1.44%	0.2434%	25.16%
South Dakota	0.0898%	4.4%	1.82% [e]	0.2130%	24.07%
Wisconsin	0.1114%	5.7%	1.31%	0.2618%	21.21%
r Value		0.33	-0.58	0.67	0.37
r^2 Value		0.11	0.34	0.44	0.14
Coefficient p Value		0.320	0.061	0.025	0.261

Note. Data are from or calculated from data available at Substance Abuse and Mental Health Services Administration (2016) [a], United States Census Bureau (2012b) [b], Substance Abuse and Mental Health Services Administration (2014) [c], and Centers for Disease Control and Prevention (2011) [d]. Outliers [e] are marked for easy reference. Nebraska data [f] are not included in the bivariate linear regressions. The complete results of the bivariate linear regressions for these selected variables are available in Appendix F.

Table 4

Condensed Bivariate Linear Regression Results of Selected Demographic and Weather Data on Midwestern PIT Count Homelessness Rates, 2010

State	Percent of Population Experiencing Homelessness	Percent of Population Black or African American [a]	Total January Precipitation (in) [b]
Illinois	0.1122%	14.55%	1.44
Indiana	0.0995%	9.12%	1.52
Iowa	0.0989%	2.93%	1.30
Kansas	0.0709%	5.88%	0.48
Michigan	0.1321%	14.17%	0.95
Minnesota	0.1484%	5.17%	0.89
Missouri	0.1356%	11.58%	2.12
Nebraska [c]	0.2123%	4.54%	0.37
North Dakota	0.1188%	1.18%	0.79
Ohio	0.1089%	12.20%	1.76
South Dakota	0.0898%	1.25%	0.61
Wisconsin	0.1114%	6.32%	0.89
r Value		0.31	0.34
r^2 Value		0.10	0.12
Coefficient p Value		0.355	0.304

Note. Data are from or calculated from data available at United States Census Bureau (2012b) [a] and National Centers for Environmental Information (n.d.) [b]. Nebraska data [c] are not included in the calculations. The complete results of the bivariate linear regressions for these selected variables are available in Appendices C and G.

health and substance abuse disorder would increase PIT Count homelessness rates by an estimated .01067%, or more than 1 for every ten thousand persons in the state. Finally, holding all other considered variables constant, a 1% increase in the percent of a Midwestern state's

Table 5

Regression of Predictor Variables on Midwestern PIT Count Homelessness Rates, 2010

Predictor	Initial Equation		Reduced Equation	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept, B_0	0.00125*	0.00015	0.00152****	0.00014
Percent of Population Black or African American	-0.00086	0.00027		
Percent of Occupied Housing Units Renter-Occupied	-0.00032	0.00020		
Median Monthly Rent (USD)	3.43E-07	1.40E-07		
Unemployment Rate, B_1	-0.00807**	0.00058	-0.00838****	0.00110
Percent of Population Institutionalized, B_2	-0.11023**	0.00623	-0.12444****	0.01072
Percent of Persons Age 12 and Older Using Marijuana in the Past Month	0.00179	0.00081		
Percent of Population with Co-Occurring Mental Health and Substance Abuse Disorders, B_3	0.13087*	0.01160	0.10671***	0.02703
Projected Percent of Population Lifetime Victims of Rape, Physical Violence, and/or Stalking by an Intimate Partner, B_4	0.00633**	0.00033	0.00771****	0.00090
Precipitation in January (in)	0.00011*	0.00001		

* $p < .1$. ** $p < .05$. *** $p < .01$. **** $p < .001$.

Table 6

Summary Output of Reduced Multiple Linear Regression Equation

Regression Statistics	
Multiple R	0.989
R Square	0.978
Adjusted R Square	0.963
Standard Error	4.22E-05
Observations	11

Table 7

ANOVA Output of Reduced Multiple Linear Regression Equation

	df	SS	MS	F	Significance F
Regression	4	4.74E-07	1.18E-07	66.55	4.21E-05
Residual	6	1.07E-08	1.78E-09		
Total	10	4.84E-07			

population that is projected to be a victim of rape, physical violence, and/or stalking by an intimate partner at least once in their lifetime would increase homelessness rates by a projected .00771%, or more than 77 for every one million persons in the state.

Ultimately, the multiple linear regression analysis I conducted relates four predictor variables and an intercept to explain 97.8% of the variance in 2010 PIT Counts of homelessness as a percent of the Midwestern state's total population. The reduced model predicts the response variable with an average absolute percent error of 2.45% and a standard error of about 0.00004%, or 4 homeless person for every ten million persons living in a Midwestern state.

The regression sufficiently passed a series of post-hoc tests, which are documented in Appendix H. Presented in Table H1 are the Variance Inflation Factors (VIFs) of the four predictor variables, $\frac{1}{1-R^2}$. A VIF greater than 5 was regarded as sufficiently multicollinear to

Table 8

Residual Output of Reduced Multiple Linear Regression Equation

Observation	Predicted Percent of Population Experiencing Homelessness	Actual Percent of Population Homeless	Residuals
Illinois	0.1129%	0.1122%	-0.0008%
Indiana	0.0967%	0.0995%	0.0028%
Iowa	0.0921%	0.0989%	0.0068%
Kansas	0.0755%	0.0709%	-0.0045%
Michigan	0.1356%	0.1321%	-0.0035%
Minnesota	0.1485%	0.1484%	-0.0002%
Missouri	0.1337%	0.1356%	0.0019%
North Dakota	0.1193%	0.1188%	-0.0005%
Ohio	0.1078%	0.1089%	0.0011%
South Dakota	0.0935%	0.0898%	-0.0037%
Wisconsin	0.1109%	0.1114%	0.0005%
Average Magnitude of Residual:			0.0024%
Average Absolute Percent Error:			2.4497%

be cause for concern (Alin, 2010; Daoud, 2017; Williams, 2015). All the predictors remained within this threshold. Issues of heteroscedasticity do not appear to be present. I easily failed to reject at the 5% significance level the null hypothesis of homoscedasticity after performing the Breusch-Pagan test, as noted in Tables H2 and H3. I also easily failed to reject at the 5% significance level the null hypothesis of normally-distributed residuals after an execution of the Kolmogorov-Smirnov test, which is documented in Table H4. Overall, the reduced equation presented in this study is not considered to substantively violate any of its relevant assumptions.

Discussion

Limitations

There are several limitations to this study. First, a decade has passed since the 2010 Census was taken, so my findings may no longer be relevant for policy work. Second, the PIT Counts used in this study are typically regarded as underestimates of true homelessness rates (National Law Center on Homelessness & Poverty, 2017). After all, it is difficult to count every unsheltered person across an entire state on a single night. Further, many homeless persons sleep in places not visible to counters (Hopper et al., 2008). PIT Counts also do not include all of the homeless persons who are hospitalized, in jail, or temporarily residing with friends or family (National Law Center on Homelessness & Poverty, 2017). Finally, cross-sectional, point-prevalent counts like the PIT Count fail to capture the much larger homelessness rates that yearlong measurements reveal (Metraux et al., 2001).

This study investigated 27 predictor variables in total. I examined this broad “horizon” of variables to minimize the possibility of failing to account for factors that substantially impact homelessness rates (Leamer, 1983). However, the drawback of studying this large “horizon" is the increased likelihood of committing a Type I statistical error: “With multiple tests, there is a chance of a fluke finding” (Harvey & Liu, 2014, p. 110). The remedy is applying a “higher [statistical] threshold” (Harvey & Liu, 2014, p. 109). Importantly, this threshold must take into account the tests of not only every considered variable but also potential (even if not actual) manipulated forms of each variable (see “the garden of forking paths” in Gelman & Loken [2014] and “researcher degrees of freedom” in Wicherts et al. [2016]).

To address this limitation, the threshold of the multiple linear regression analysis was raised from the traditional 5% significance level. Instead, the coefficients of predictor variables needed to be estimated at the 1% significance level to remain in the reduced model.

Nevertheless, the possibility of committing a Type I statistical error remains ever present.

A fourth limitation of this study is its small sample size. Analyzing the cross-sectional variation of only 11 Midwestern states in a single year leaves findings more susceptible to influence from anomalies in the data from that particular year. Of course, some knowledge about the predictors of Midwestern homelessness rates is preferable to none at all, even if that knowledge is limited by a small sample size. Future research can refine the results of this study as new and more complete data become available for analysis.

Preliminary Bivariate Linear Regressions

Most of the results from the preliminary bivariate linear regressions in Appendices B-G align with the relevant literature. It was expected that documented homelessness rates would positively correlate with the following variables: total population size; rates of single-headed female households; population density; the proportion of the population that was black or African American; median monthly rent; measures of economic inequality; marijuana use; co-occurring mental health and substance abuse disorders; domestic violence and sexual assault indicators; and precipitation in January. Homelessness rates were also anticipated to negatively correlate with the percent of the population that was white, the minimum temperature in January, and the average temperature in January. The negative correlation between homelessness rates and institutionalization rates was also expected; some of those who were institutionalized for criminal conduct or mental illnesses may have otherwise became homeless.

Several bivariate linear regression results were unexpected. I was surprised to discover that poverty rates, at least in the bivariate analysis, shared virtually zero association with PIT Count homelessness rates in Midwestern states in 2010. Expanding the analysis to include other variables may reveal a different relationship. These findings conflict with research by the United States Department of Housing and Urban Development (2019a). Their study identified at the 1% significance level a positive relationship between poverty and sheltered homelessness. These findings suggest that, compared to trends at the national level, poverty may relate to homelessness to a lesser extent in the Midwest.

I also did not expect that the percent of the population in a Midwestern state age 25 and older without a high school diploma would have virtually no bearing on 2010 PIT Counts. This finding is especially surprising given that common childhood experiences among homeless populations have been found to negatively impact educational attainment, cognitive development, and personal development (Haskett et al., 2016; Mabhala et al., 2017; Schweitzer et al., 1994). A regression analysis conducted by Silber (2019) found at the 1% significance level a negative relationship between homelessness and high school graduation rates using 2007 to 2015 data from across the nation. Therefore, this study's finding serves as preliminary evidence indicating that education may play a lesser role in affecting homelessness rates in the Midwest compared to the nation as a whole.

Finally, the relationship between race and homelessness deserves attention. Variation in the percent of a state that was black or African American explained 10% of the cross-sectional variation in homelessness rates in the Midwest in 2010. This is a particularly salient finding given the national attention recently garnered by the Black Lives Matter movement. The cause of this relationship may be personal, cultural, or institutional — or, undoubtedly, a mix of the three (as documented in relation to poverty and childrearing practices, for example, by Lareau [2011]). However, there clearly exists a need to better support this demographic.

Multiple Linear Regression Analysis

The model estimated by the available data shows that institutionalization rates, for mental health or criminal reasons, are the most influential predictor of PIT Count homelessness rates in Midwestern states, of the variables considered in this study. The second most influential predictor is the co-occurrence of mental health and drug abuse disorders. These findings underscore the importance of providing supportive, rehabilitative services for persons facing such struggles as mental illnesses, criminal tendencies, and substance abuse. These results align with similar regression analyses of local, state, and national homelessness levels. For example, Bohanon (1991) identified at the 5% significance level a negative correlation between homelessness as a percent of the poor and the number of persons being served in state and local mental hospitals in a regression analysis of 60 cities in 1983. Additionally, Vyskocil's (2015, p. 27) multiple regression analysis of 2014 PIT Count data at the national level yielded an inverse relationship between rates of treated mental illnesses and homelessness (p-value < 0.001).

This study also found that the unemployment rate and domestic violence, albeit to lesser extents, play important roles in predicting Midwestern PIT Count homelessness rates. As expected, higher rates of domestic violence were associated with increases in homelessness rates in the Midwest. This finding highlights the necessity of ensuring that housing, counseling, and strong community support are available for persons leaving abusive relationships and unsafe home environments. Many of such persons are women accompanied by children. In 2019, 41.3% of the Midwestern homeless population were female, 10.7% were victims of domestic violence, and 9.1% were youth (United States Department of Housing and Urban Development, 2019b).

The preliminary bivariate linear regression bore that the unemployment rate positively correlated with 2010 Midwestern PIT Count homelessness rates. Interestingly, after controlling for the co-occurrence of mental health and substance abuse disorders, institutionalization rates, and indicators of domestic violence, the Midwestern PIT Count homelessness rates in 2010 inversely related to the unemployment rate. The change in this relationship is puzzling, and the available literature offers little clarification. Vyskocil's (2015, p. 27) multiple regression analysis of 2014 PIT Count data at the national level found homelessness to negatively correlate with unemployment (p-value $= 0.099$). Lee et al. (2003) failed to reject the null hypothesis that unemployment has no effect on homelessness in their analysis of 335 metropolitan areas in 1990. Meanwhile, Bohanon's (1991) analysis of 60 cities in 1983 yielded at the 5% significance level that homelessness positively correlates with unemployment. Further, Silber (2019) found at the 0.1% significance level a positive relationship between unemployment and homelessness from 2007 to 2015 across the nation. Clearly, there is a lack of consensus in the econometric literature regarding the effect of unemployment on homelessness.

Future Research

Future research should compare the predictors of homelessness between the four United States regions. This study should also be replicated with 2020 Census data. The influence of the considered variables may have changed over the past decade, especially given the current COVID-19 pandemic which has already had and will continue to have widespread economic consequences. Future research should also aim to better discern how homelessness relates to unemployment and underemployment. This is a particularly pressing area of investigation given its policy implications and due to the confounding results presented in the available literature. Most importantly, future research should strive to better understand what mitigates, based on the findings of this study, the potentially disparate impact of mental illnesses, criminal tendencies, substance use, and race but not poverty and education on Midwestern PIT Count homelessness rates. Finally, future research should assess the fragility of this study's findings, as proposed by Leamer (1983) for the evaluation of econometric research.

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Appendix A

Average Magnitude of Difference of r Value without Nebraska Data

Table	Column	*r* Value with Nebraska Data	*r* Value without Nebraska Data, All Other Outliers Included	Magnitude of Difference
B1	B	-0.063	0.309	0.371
	C	-0.082	0.141	0.223
	D	-0.140	0.155	0.295
	E	0.185	-0.424	0.609
C1	B	0.025	0.309	0.284
	C	-0.197	-0.220	0.023
	D	0.106	0.341	0.236
	E	0.015	-0.150	0.165
C3	B	0.131	-0.125	0.256
	C	0.143	-0.240	0.383
	D	-0.132	-0.253	0.121
	E	0.038	-0.285	0.323
D1	B	-0.031	-0.389	0.358
	C	-0.068	-0.071	0.003
	D	0.142	0.360	0.218
E1	B	-0.134	0.310	0.444
	C	-0.192	-0.005	0.187
	D	0.198	0.286	0.089
	E	-0.140	0.175	0.315
	F	-0.245	-0.109	0.136
F1	B	-0.451	-0.580	0.130
	C	0.099	0.331	0.232
	D	0.526	0.666	0.140
	E	0.276	0.371	0.095
G1	B	-0.111	-0.278	0.167
	C	-0.071	-0.335	0.264
	D	-0.163	0.341	0.505
Average Magnitude of Difference of *r* Value				0.243

Appendix B

Table B1

Demographic Data by Midwestern State, 2010

State	Total Population [a]	Percent of Households with Female Householder, No Husband Present [a]	Average Number of Persons per Square Mile [a]	The Natural Log of the Ratio of Republican Votes to Democratic Votes for Governor in 2010 or Most Recent Gubernatorial Election [b]
Illinois	12,830,632	12.87%	231.1	-0.02
Indiana	6,483,802	12.40%	181	0.37
Iowa	3,046,355	9.31%	54.5	0.20
Kansas	2,853,118	10.41%	34.9	0.68
Michigan	9,883,640	13.21%	174.8	0.38
Minnesota	5,303,925	9.52%	66.6	-0.01
Missouri	5,988,927	12.30%	87.1	-0.39
Nebraska [d]	1,826,341	9.81%	23.8	1.04
North Dakota	672,591	8.18%	9.7	1.15 [c]
Ohio	11,536,504	13.08%	282.3	0.04
South Dakota	814,180	9.65%	10.7	0.47
Wisconsin	5,686,986	10.26%	105	0.12

Note. Data are from or calculated from data available at United States Census Bureau (2012b) [a] and United States Census Bureau (2012c) [b]. Outliers [c] are marked for easy reference. Nebraska data [d] are not included in the bivariate linear regressions.

Table B2

Expanded Bivariate Linear Regression Results of Demographic Data on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Total Population	Percent of Households with Female Householder, No Husband Present	Average Number of People per Square Mile	The Natural Log of the Ratio of Republican Votes to Democratic Votes for Governor in 2010 or Most Recent Gubernatorial Election
Original	*r* Value	0.31	0.14	0.16	-0.42
	r^2 Value	0.10	0.02	0.02	0.18
	Intercept	0.00102	0.00092	0.00107	0.00118
	Coefficient	1.66E-11	0.00173	3.72E-07	-0.00023
	Coefficient *p* Value	0.356	0.679	0.648	0.193
Excluding Outliers, if Applicable	*r* Value				-0.72
	r^2 Value				0.52
	Intercept				0.00121
	Coefficient				-0.00055
	Coefficient *p* Value				0.019

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix C

Table C1

Selected Races by Midwestern State, 2010

State	Percent of Population Black or African American [a]	Percent of Population American Indian and Alaska Native [a]	Percent of Population Asian [a]	Percent of Population White [a]
Illinois	14.55%	0.34%	4.57% [b]	71.53% [b]
Indiana	9.12%	0.28%	1.58%	84.33%
Iowa	2.93%	0.36%	1.74%	91.31% [b]
Kansas	5.88%	0.99%	2.38%	83.80%
Michigan	14.17%	0.63%	2.41%	78.95%
Minnesota	5.17%	1.15%	4.04% [b]	85.30%
Missouri	11.58%	0.46%	1.64%	82.80%
Nebraska [c]	4.54%	1.01%	1.77%	86.12%
North Dakota	1.18%	5.44% [b]	1.03%	90.02%
Ohio	12.20%	0.22%	1.67%	82.69%
South Dakota	1.25%	8.82% [b]	0.93%	85.90%
Wisconsin	6.32%	0.96%	2.27%	86.20%

Note. Data are calculated from data available at United States Census Bureau (2012b) [a]. Outliers [b] are marked for easy reference. Nebraska data [c] are not included in the bivariate linear regressions.

Table C2

Expanded Bivariate Linear Regression Results of Selected Races on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Percent of Population Black or African American	Percent of Population American Indian and Alaska Native	Percent of Population Asian	Percent of Population White
Original	*r* Value	0.31	-0.22	0.34	-0.15
	r^2 Value	0.10	0.05	0.12	0.02
	Intercept	0.00101	0.00115	0.00097	0.00164
	Coefficient	0.00138	-0.00175	0.00652	-0.00062
	Coefficient *p* Value	0.355	0.515	0.304	0.659
Excluding Outliers, if Applicable	*r* Value		0.14	-0.00	-0.14
	r^2 Value		0.02	0.00	0.02
	Intercept		0.00107	0.00107	0.00206
	Coefficient		0.00948	-7.88E-05	-0.00110
	Coefficient *p* Value		0.715	0.996	0.723

Note. Nebraska data are not included in the bivariate linear regressions.

Table C3

Additional Races by Midwestern State, 2010

State	Percent of Population Pacific Islander [a]	Percent of Population Some Other Race [a]	Percent of Population Two or More Races [a]	Percent of Population Hispanic or Latino (of any race) [a]
Illinois	0.03%	6.71% [b]	2.26%	15.80% [b]
Indiana	0.04%	2.67%	1.97%	6.01%
Iowa	0.07%	1.84%	1.75%	4.97%
Kansas	0.08%	3.86%	3.01% [b]	10.52% [b]
Michigan	0.03%	1.49%	2.33%	4.41%
Minnesota	0.04%	1.94%	2.36%	4.72%
Missouri	0.10% [b]	1.34%	2.08%	3.55%
Nebraska [c]	0.07%	4.33%	2.16%	9.17%
North Dakota	0.05%	0.52%	1.76%	2.00%
Ohio	0.04%	1.13%	2.06%	3.07%
South Dakota	0.05%	0.92%	2.12%	2.72%
Wisconsin	0.03%	2.39%	1.83%	5.91%

Note. Data are calculated from data available at United States Census Bureau (2012b) [a]. Outliers [b] are marked for easy reference. Nebraska data [c] are not included in the bivariate linear regressions.

Table C4

Expanded Bivariate Linear Regression Results of Additional Races on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Percent of Population Pacific Islander	Percent of Population Some Other Race	Percent of Population Two or More Races	Percent of Population Hispanic or Latino (of any race)
Original	r Value	-0.12	-0.24	-0.25	-0.29
	r^2 Value	0.02	0.06	0.06	0.08
	Intercept	0.00117	0.00118	0.00145	0.00121
	Coefficient	-0.11444	-0.00302	-0.01552	-0.00156
	Coefficient p Value	0.715	0.478	0.453	0.395
Excluding Outliers	r Value	-0.66	-0.47	0.51	-0.01
	r^2 Value	0.43	0.22	0.26	0.00
	Intercept	0.00147	0.00132	0.00029	0.00117
	Coefficient	-0.86350	-0.01116	0.04213	-0.00018
	Coefficient p Value	0.038	0.172	0.130	0.973

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix D

Table D1

Housing Affordability Metrics by Midwestern State, 2010

State	Percent of Occupied Housing Units Renter-Occupied [a]	Percent of Rental Housing Units Vacant [a]	Median Monthly Rent (USD) [b]
Illinois	32.53%	9.1%	$848 [c]
Indiana	30.14%	10.9%	$683
Iowa	27.91%	8.5%	$629
Kansas	32.24%	10.1%	$682
Michigan	27.87%	11.5%	$730
Minnesota	26.99%	7.8%	$764
Missouri	31.23%	11.1%	$682
Nebraska [d]	32.78%	9.3%	$669
North Dakota	34.58%	7.1%	$583
Ohio	32.42%	10.9%	$685
South Dakota	31.87%	9.1%	$591
Wisconsin	31.94%	8.0%	$715

Note. Data are from or calculated from data available at United States Census Bureau (2012b) [a] and United States Census Bureau (n.d.a) [b]. Outliers [c] are marked for easy reference. Nebraska data [d] are not included in the bivariate linear regressions.

Table D2

Expanded Bivariate Linear Regression Results of Housing Affordability Metrics on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Percent of Occupied Housing Units Renter-Occupied	Percent of Rental Housing Units Vacant	Median Monthly Rent (USD)
Original	r Value	-0.39	-0.07	0.36
	r^2 Value	0.15	0.01	0.13
	Intercept	0.00223	0.00121	0.00040
	Coefficient	-0.00360	-0.00104	1.04E-06
	Coefficient p Value	0.237	0.835	0.277
Excluding Outliers, if Applicable	r Value			0.49
	r^2 Value			0.24
	Intercept			-0.00019
	Coefficient			1.94E-06
	Coefficient p Value			0.154

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix E

Table E1

Economic and Educational Metrics by Midwestern State, 2010

State	Unemployment Rate [a]	Percent of Population in Poverty [b]	Median Household Income (USD) [c]	Gini Index of Inequality [c]	Percent of Population Age 25 and Older Without a High School Diploma or Equivalent [d]
Illinois	10.3%	13.8%	$52,972	0.465	13.1%
Indiana	10.2%	15.3%	$44,613	0.440	13.0%
Iowa	6.1%	12.6%	$47,961	0.427	9.4%
Kansas	7.0%	13.6%	$48,257	0.445	10.8%
Michigan	12.5%	16.8%	$45,413	0.451	11.3%
Minnesota	7.3%	11.6%	$55,459 [e]	0.440	8.2%
Missouri	9.6%	15.3%	$44,301	0.455	13.1%
Nebraska [f]	4.7%	12.9%	$48,408	0.432	9.7%
North Dakota	3.9%	13.0%	$48,670	0.433	9.6%
Ohio	10.1%	15.8%	$45,090	0.452	11.9%
South Dakota	4.8%	14.4%	$45,904	0.442	10.4%
Wisconsin	8.3%	13.2%	$49,001	0.430	9.9%

Note. Data are from or calculated from data available at United States Bureau of Labor Statistics (2011) [a], United States Census Bureau (2012a) [b], United States Census Bureau (2011) [c], and United States Census Bureau (n.d.b) [d]. Outliers [e] are marked for easy reference. Nebraska data [f] are not included in the bivariate linear regressions.

Table E2

Expanded Bivariate Linear Regression Results of Economic and Educational Metrics on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Unemploy-ment Rate	Percent of Population in Poverty	Median Household Income (USD)	Gini Index of Inequality	Percent of Population Age 25 and Older Without a High School Diploma or Equivalent
Original	r Value	0.31	-0.01	0.29	0.18	-0.11
	r^2 Value	0.10	0.00	0.08	0.03	0.01
	Intercept	0.00090	0.00113	0.00027	-0.00038	0.00127
	Coefficient	0.00259	-7.37E-05	1.77E-08	0.00336	-0.00145
	Coefficient p Value	0.354	0.988	0.393	0.606	0.749
Excluding Outliers, if Applicable	r Value			-0.17		
	r^2 Value			0.03		
	Intercept			0.00166		
	Coefficient			-1.23E-08		
	Coefficient p Value			0.637		

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix F

Table F1

Substance Abuse, Mental Health, and the Criminal Justice System Data by Midwestern State, 2010

State	Percent of Population Institutionalized [a]	Percent of Persons Age 12 and Older Using Marijuana in the Past Month [b]	Percent of Population With Co-Occurring Mental Health and Substance Abuse Disorders [c]	Projected Percent of Population Lifetime Victims of Rape, Physical Violence, and/or Stalking by an Intimate Partner [d]
Illinois	1.25%	6.9%	0.1570%	24.14%
Indiana	1.47%	7.2%	0.1829%	25.17%
Iowa	1.42%	5.0%	0.1867%	19.27%
Kansas	1.45%	5.1%	0.1334%	19.31%
Michigan	1.11%	9.0%	0.3093%	25.17%
Minnesota	1.06%	6.1%	0.2176%	21.66%
Missouri	1.56%	5.3%	0.3039%	29.05%
Nebraska [f]	1.29%	5.4%	0.2616%	23.82%
North Dakota	1.44%	4.1%	0.2849%	19.33%
Ohio	1.44%	6.6%	0.2434%	25.16%
South Dakota	1.82% [e]	4.4%	0.2130%	24.07%
Wisconsin	1.31%	5.7%	0.2618%	21.21%

Note. Data are from or calculated from data available at United States Census Bureau (2012b) [a], Substance Abuse and Mental Health Services Administration (2016) [b], Substance Abuse and Mental Health Services Administration (2014) [c], and Centers for Disease Control and Prevention (2011) [d]. Outliers [e] are marked for easy reference. Nebraska data [f] are not included in the bivariate linear regressions.

Table F2

Expanded Bivariate Linear Regression Results of Substance Abuse, Mental Health, and the Criminal Justice System Data on Midwestern PIT Count Homelessness Rates, 2010

Data	Statistic	Percent of Population Institutionalized	Percent of Persons Age 12 and Older Using Marijuana in the Past Month	Percent of Population With Co-Occurring Mental Health and Substance Abuse Disorders	Projected Percent of Population Lifetime Victims of Rape, Physical Violence, and/or Stalking by an Intimate Partner
Original	*r* Value	-0.58	0.33	0.67	0.37
	r^2 Value	0.34	0.11	0.44	0.14
	Intercept	0.00196	0.00081	0.00055	0.00052
	Coefficient	-0.06092	0.00513	0.24756	0.00259
	Coefficient *p* Value	0.061	0.320	0.025	0.261
Excluding Outliers, if Applicable	*r* Value	-0.51			
	r^2 Value	0.26			
	Intercept	0.00207			
	Coefficient	-0.06896			
	Coefficient *p* Value	0.128			

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix G

Table G1

Winter Weather Patterns by Midwestern State, 2010

State	Minimum Temperature in January (°F) [a]	Average Temperature in January (°F) [a]	Total January Precipitation (in) [a]
Illinois	14.8	21.5	1.44
Indiana	17.5	23.9	1.52
Iowa	6.9	13.6	1.30
Kansas	17.6	27.2	0.48
Michigan	15.1	21.3	0.95
Minnesota	0.5	8.8	0.89
Missouri	17.8	25.5	2.12
Nebraska [b]	12.8	22.1	0.37
North Dakota	2.0	9.7	0.79
Ohio	18.9	25.0	1.76
South Dakota	6.5	14.8	0.61
Wisconsin	7.4	15.1	0.89

Note. Data are from National Centers for Environmental Information (n.d.) [a]. Nebraska data [b] are not included in the bivariate linear regressions.

Table G2

Expanded Bivariate Linear Regression Results of Winter Weather Patterns on Midwestern PIT Count Homelessness Rates, 2010

Statistic	Minimum Temperature in January (°F)	Average Temperature in January (°F)	Total January Precipitation (in)
r Value	-0.28	-0.33	0.34
r^2 Value	0.08	0.11	0.12
Intercept	0.00122	0.00133	0.00094
Coefficient	-8.97E-06	-1.12E-05	0.00015
Coefficient p Value	0.408	0.314	0.304

Note. Nebraska data are not included in the bivariate linear regressions.

Appendix H

Table H1

Variance Inflation Factors of Regressed Predictor Variables

Predictor Variable	Unadjusted Multiple R Square	Variance Inflation Factor
Unemployment Rate	0.7884	4.73
Percent of Population Institutionalized	0.6474	2.84
Percent of Population with Co-Occurring Mental Health and Substance Abuse Disorder	0.3044	1.44
Projected Percent of Population Lifetime Victims of Rape, Physical Violence, and/or Stalking by an Intimate Partner	0.7792	4.53

Table H2

Summary Output of Breusch-Pagan Test for Heteroscedasticity

Regression Statistics	
Multiple R	0.581
R Square	0.338
Adjusted R Square	-0.104
Standard Error	1.47E-09
Observations	11

Table H3

ANOVA Output of Breusch-Pagan Test for Heteroscedasticity

	df	SS	MS	F	Significance F
Regression	4	6.63E-18	1.66E-18	0.76	0.59
Residual	6	1.30E-17	2.17E-18		
Total	10	1.96E-17			
Lagrange Multiplier (LM)	3.71354				
Significance LM	0.446				

Table H4

Kolmogorov-Smirnov Test for Normality of Residuals

State	Residuals	Expected Cumulative Distribution	Inverse Standard Normal Cumulative Distribution	(Rank-1)/n	Actual Standard Normal Cumulative Distribution	Magnitude of Difference
Kansas	-0.0045%	0.0909	-1.3352	0.0000	0.0819	0.0819
South Dakota	-0.0037%	0.1818	-0.9085	0.0909	0.1276	0.0367
Michigan	-0.0035%	0.2727	-0.6046	0.1818	0.1444	0.0374
Illinois	-0.0008%	0.3636	-0.3488	0.2727	0.4092	0.1364
North Dakota	-0.0005%	0.4545	-0.1142	0.3636	0.4407	0.0771
Minnesota	-0.0002%	0.5455	0.1142	0.4545	0.4805	0.0260
Wisconsin	0.0005%	0.6364	0.3488	0.5455	0.5595	0.0140
Ohio	0.0011%	0.7273	0.6046	0.6364	0.6369	0.0005
Missouri	0.0019%	0.8182	0.9085	0.7273	0.7169	0.0104
Indiana	0.0028%	0.9091	1.3352	0.8182	0.8047	0.0134
Iowa	0.0068%	1.0000		0.9091	0.9815	0.0724
					Maximum	0.1364
					Critical Value *	0.3912

* Kolmogorov-Smirnov critical value at the 5% significance level for $n = 11$.