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Predictors of urban homeless rates.

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PREDICTORS OF URBAN HOMELESS RATES

By

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B.A., Macalester College, 1990
M.P.A., University of Louisville, 2006
M.M.A.S., U.S. Army Command and General Staff College, 2011

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ABSTRACT

PREDICTORS OF URBAN HOMELESS RATES

Andrew J. Bates

July 9, 2020

This dissertation analyzes the differences among homeless rates in urban and suburban “continuums of care” (service areas for homelessness in the United States) over the period of 2014-2018. The purpose is to determine which variables are useful to predict the rates of two definitions of homelessness: the more extreme “Category One” homelessness as defined by the U.S. Department of Housing and Urban Development (HUD): those unsheltered or living in homeless shelters; and the broader Department of Education definition of homelessness: families with children that are homeless, including those in Category One but also those living in hotels, staying temporarily with other families, or in other inadequate housing that is not their own. Comparing these two forms of homelessness helps to provide insight into the overall spectrum of homelessness in U.S. cities.

This study provides a parsimonious model that can predict the rate of Category One homelessness in a community with relative accuracy: a coefficient of multiple determination (R-Squared) of 0.49. The model includes five variables: median income,

median home value, homeownership, the share of resources devoted to rapid-rehousing compared to other forms of housing units for the homeless, and the relative amount of prior federal funding awarded to each continuum of care provider network.

A different model can predict the number of students in homeless families, according to the broader definition of homelessness reported by school systems. A model with four variables can predict the school-reported homeless rate with a coefficient of determination of 0.18. This less accurate model is not as useful for forecasting but helps to reveal some of the community characteristics associated with the broader but less visible forms for school-reported homelessness. The four significant predictors of school-reported homelessness are median income, median rent, rent control, and drug/alcohol induced deaths.

This study finds that housing affordability is a significant predictor of both Category One and school-reported homelessness. A comparison of the data for both forms of homelessness indicates that less affordable communities tend to have higher ratios of Category One homelessness compared to school-reported homelessness. The model for Category One homelessness also suggests that continuums of care networks have lower rates of homelessness when they devote a greater share of resources to rapid rehousing programs. The findings of this study do not support the popular belief that the homeless tend to migrate to areas that are warmer or have better homeless services.

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INTRODUCTION

This dissertation identifies and analyzes economic and policy factors that predict the sizes of homeless populations in American cities. This study serves two purposes. The first purpose is to provide a practical tool that will enable planners to forecast changes in the homeless populations of their communities. The second purpose is to contribute to the theoretical debate about the causes of homelessness and the most effective policies for local governments to address the issue.

Homelessness is an important challenge for cities. From a humanitarian perspective, homelessness is the most extreme form of poverty, physically harming and psychologically traumatizing those who suffer in it. From a more cynical economic perspective, homelessness is expensive for cities, as the homeless disproportionately drain the resources of first responders, jails, and hospitals. From a political perspective, voters perceive homelessness to be a problem, either sympathizing with the homeless or viewing them as a nuisance, but in either case expect local leaders to address the issue (Clifford & Piston, 2017; Culhane et al., 2011; Fang, 2009; Moore, Sink, & Hoban-Moore, 1988; Swan, 2015).

The sizes of homeless populations vary drastically among American cities. For example, in 2018 there were three homeless per ten thousand residents in Overland Park, Kansas but 124 homeless per ten thousand in Washington, DC. Scholars have attempted since the 1980s to explain why some cities have larger relative homeless populations than others. There is still disagreement among experts about the local factors that contribute to homelessness and about whether specific polices reduce homelessness. Previous studies have proposed various combinations of variables and have used multiple measures of homelessness. This dissertation intends to compare a comprehensive list of independent variables including many proposed by previous scholars, using a robust model with recent data from urban and suburban "continuums of care": service areas for federally-funded homelessness programs.

This dissertation may hopefully contribute to the three-decade debate regarding the causes of variations in homeless rates by comparing two forms of homelessness: the more extreme form of "Category One" homelessness that is measured by the U.S. Department of Housing and Urban Development, and the broader but less visible form of "school-reported" homelessness that is measured by school systems. By comparing the data for these two forms of homelessness, this dissertation explores some of the conditions that explain the variations in homeless rates.

CHAPTER I

LITERATURE REVIEW

Aspects of homelessness have been analyzed by multiple fields of scholarship. Psychologists have studied the characteristics of homeless individuals (Pluck et al., 2008), anthropologists have studied the culture of the homeless (Glasser & Bridgman, 1999; Oliveira & Burke, 2009; Thrasher & Mowbray, 1995), and the field of social work has studied the effectiveness of various methods to assist the homeless (Larkin et al., 2016; Manthorpe et al., 2015; Zufferey & Kerr, 2004). This literature review will focus primarily on previous works that compared the sizes of homeless populations in cities.

Since the 1980s, there has been a debate among scholars about the causes of homelessness. Authors have compared the sizes of homeless population among American cities to isolate conditions that contributed to larger homeless populations. Studies of this topic often refute the claims of earlier studies, and later studies introduce new variables and consider more comprehensive data.

The scholars in this line of research can be roughly divided into two opposing theoretical camps. One side emphasizes economic factors that contribute to homelessness, especially related to housing; with the implication that government could intervene to mitigate those factors. The second camp is generally skeptical of government intervention, and either blames homelessness on government policies or argues that government policies have failed to effectively reduce homelessness.

The availability of data has been a limitation on this area of research, and so studies can also be grouped into generations by the data sources they have used. When a new data source became available, scholars of both theoretical camps would publish new studies, and the cycle would repeat with the appearance of the next data source. The following graph depicts the variety of studies and their relationships to data sources over time.

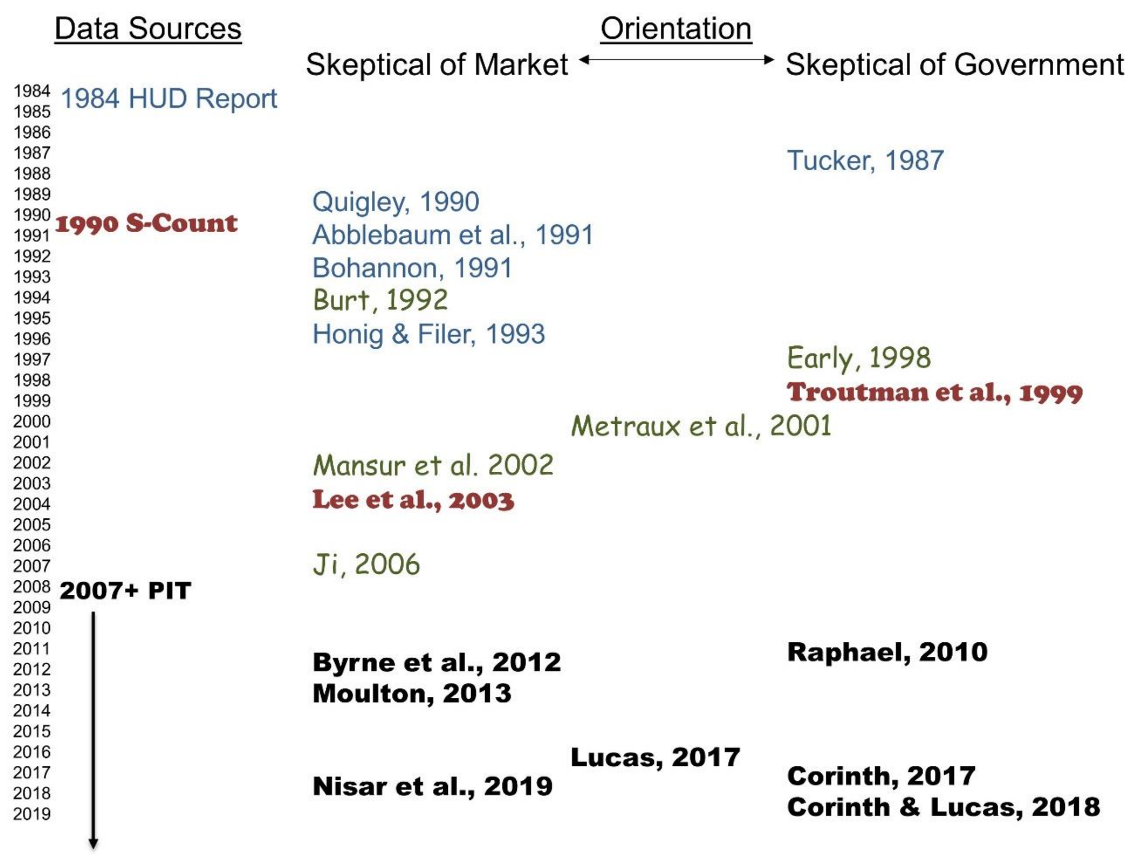

Figure 1: Graph of Studies that Compare Cities' Homeless Populations

1984 HUD Report

The first data source to allow researchers to compare the homeless populations of cities was the Department of Housing and Urban Development (HUD)'s 1984 document "A Report to the secretary on the homeless and emergency shelters." The data in this report was analyzed in a 1987 article in *The National Review* by journalist William Tucker. Tucker's article was not written for an academic audience, but used regression analysis performed by Jeffery Simonoff. Tucker's study considered the independent variables of poverty, unemployment, public housing, population, mean temperature, vacancy rate, and rent control. He concluded that the most important factor is rent control. "Truly widespread homelessness does not occur, however, until a city imposes rent control," he wrote. "…This pushes homelessness to pathological levels—about two and a half times what it would be without rent control." Tucker continued his campaign against rent control in editorials and in a book published by the Heritage Foundation (Tucker, 1987, 1988a, 1988b, 1990).

Others followed Tucker in analyzing HUD's 1984 data. Two academic articles specifically refuted Tucker's argument: Quigley in 1990 and Appelbaum et al. in 1991. Both argued that Tucker's statistical regression was flawed. Better regression models, using Tucker's data and variables, make rent control irrelevant in explaining homelessness. Bohanon in 1991 compared the HUD 1984 homeless estimates to some new and some differently operationalized independent variables. Bohanon's regression included the unemployment rate, average welfare payments, median rent, January temperature, annual precipitation, number institutionalized for mental or psychological care, average household size, and rent control. Bohanon concluded that only median rent was significantly correlated with homelessness at the one percent level. Honig and Filer in 1993 examined the same 1984 HUD data on homelessness. In addition, they included dependent variables of “crowding” and “doubling up” (now defined as HUD’s Category Three homelessness). Honig and Filer evaluated a list of independent variables, including rent, rent control, vacancy rates, labor market statistics, various benefits, and demographic characteristics. They concluded that rent was the most important predictor.

1990 Census Bureau “S-Night” Count

The next data source for comparing cities’ homeless populations was provided the Census Bureau in the form of the “S-Night” homeless count that was conducted in conjunction with the 1990 census. Teams of enumerators were dispatched to count and, when possible, to interview the homeless in shelters on March 20 and on the streets between 2am and 4am on March 21, 1990 (Martin, 1992).

In 1999 Troutman, Jackson, and Ekelund analyzed both the 1990 S-Night count and the earlier 1984 HUD study. Like the works of Tucker and Early, this article carries the perspective of classical economics, as exemplified by their assumption in the introduction: “…we assume that individuals, either homeless or at risk of becoming so, make rational decisions…” (197). Troutman, Jackson, and Ekelund found that public policies to lower the cost of housing have the counter-intuitive result of increasing homelessness. Their article is an important contribution for its focus on the effect of government efforts to address homelessness in addition to broader economic variables.

They found that the two most significant variables to increase homelessness were mean temperature and greater federal housing assistance.

Continuing the ideological back-and-forth, in 2003 Lee, Price-Spratlen, and Kanan analyzed the same 1990 S-count data but reached different conclusions. Although they did not cite Troutman et al., the authors of the 2003 study included similar variables. While they agreed that climate is a significant predictor of homeless population, they disagreed on the variables that have policy implications. Lee, Price-Spratlen, and Kanan found that rent level is the greatest predictor of homelessness.

Other Data Sources

During the period that the S-count data was available, some studies attempted to use other data sources. The studies that used other data sources were constrained by a relatively small sample size or by the use of less rigorous proxy measures of homelessness. Despite these limitations, the studies that used alternative data sources nevertheless helped to shape the debate regarding homelessness. The independent variables they introduced could later be reproduced with newer and more rigorous data sources.

In 1992 Burt compared the homeless populations of cities using the number of shelter beds as a proxy for the homeless population. Burt expressed dissatisfaction with this proxy measure, writing that "..it is axiomatic that any rates based only on shelter bed counts will underestimate the true numbers of homeless people…" and "…any estimates based on shelter bed counts will exaggerate the growth of the total homeless population" (p 140). Yet Burt determined that that shelter bed counts would suffice as a proxy for homeless population. Burt employed an exhaustive list of independent variables, including multiple measures of housing, population, poverty and income, education and employment, public benefits, climate, and other factors. She found that rent, vacancy rates, and other housing variables had significant relationships to the number of homeless beds. Higher per capita public housing (including Section 8) was correlated with higher shelter beds, as were public benefits. Higher expenditures and admission rates for drug and alcohol treatment were correlated with more shelter beds.

In 1998 Early analyzed data from a 1987 project by the Urban Institute that surveyed homeless people in 20 cities. Early compared these observations of the homeless to observations of low-income residents in unsubsidized housing from the American Housing Survey. Early was therefore analyzing individual-level data combined with aggregate city-level data. Early concluded that 4.53% of the population in subsidized housing would become homeless in the absence of a subsidy. He interpreted this as a refutation of the relationship between housing subsidies and homelessness. Interestingly, Early found a positive relationship between homelessness and "quality of homeless shelters," arguing that higher-quality shelters contribute to higher homeless populations. Early explained this with the claim that "…availability and quality of shelters will draw families out of conventional housing" (691). He based this claim on the analysis of Robert Ellikson, who compared multiple surveys and data sources to conclude that approximately 40% of the population in homeless shelters comes from the street, with the other 60% coming from unstable housing situations. However, Early's method of operationalizing quality provides an alternative explanation. He measures quality of homeless shelters by the cost per bed. This means that his measure for quality of shelter can serve as a proxy measure for scarcity of shelter. Consider two hypothetical cities with the same budget for serving the homeless. The city with half as many beds would have double the "quality." Quality by this measure, in other words, could just as easily be portrayed as lack of efficiency in shelter. Furthermore, the per-unit cost of homeless shelter beds would be driven in part by property values, wages for staff, and other expenses for the shelters that would reflect the overall cost of living in the city, a variable that other studies find to be a significant predictor of homelessness.

Lacking a recent nationwide survey of cities' homeless populations, some studies during this period analyzed smaller samples. A 2001 study by Metraux et al. compared the homeless population of nine communities- eight cities and one state - that participated in a 1998 HUD study. Their primary conclusion was that per-capita homeless populations vary widely. A 2002 study by Mansur, Quigley, Raphael, and Smolensky compared four California cities using a housing market model, arguing that government intervention in housing markets reduces homelessness, explicitly refuting Early and other authors.

In 2006 Eun-Gu Ji followed Burt's example of using the number of homeless beds as a proxy for the homeless population. Ji found that the best predictor of the local homeless population was the poverty rate, followed by lack of affordable housing. Since some communities have empty shelter beds while others have large unsheltered populations, the number of shelter beds is a dubious proxy for homeless population (Burt, 1992, p. 131). Like Burt, Ji had to settle for the data that was available.

HUD Point in Time (PIT) Data

In 2007, HUD conducted the first national Point-In-Time homeless census (PIT), a practice it has continued every year since. HUD's "continuum of care" regulations require all of the homeless-serving agencies that receive HUD funds in each community to coordinate their efforts and submit a joint funding application to HUD (Burt et al., 2002; U.S. Dept. of Housing and Urban Development, 2019a). HUD requires each local continuum of care ("CoC") to conduct the census according to national guidelines. Each CoC is required to conduct the count during one night in the last ten days of January. The count includes unsheltered homeless and persons living in emergency shelters and transitional housing projects. Methods of conducting the survey vary among CoCs within guidelines required by HUD (Byrne et al., 2013). The PIT receives criticism mostly from advocacy groups for its strict criteria for counting the homeless, since it does not include incarcerated people or those doubled up with other families (Barmann, 2019; Boone, 2019; National Law Center on Homelessness and Poverty, 2017; Schoolhouse Connection, 2020).This nationwide repeated census became the primary data source for comparisons of cities' homeless populations.

The first study to compare homeless rates using the PIT was by Raphael (2010). Raphael compared the homeless rates of all fifty states using 2007 PIT data, concluding that regulation of housing markets is partly responsible for the rise of homelessness by reducing the availability of affordable housing and thereby increasing the ratio of rent to income. Raphael included the additional independent variables of each state's poverty rate, January temperature, and demographics of African-American race, Hispanic ethnicity, age under eighteen and age over sixty-five in his regression formula.

In 2012, Byrne, Munley, Fargo, Montgomery and Culhane considered variables used in fourteen earlier studies, ranging from the work of Tucker in 1987 to Raphael in 2010. They conducted a simple ordinary least squares (OLS) linear regression of the 2009 PIT homeless census with fourteen independent variables. They found that the most significant predictors of the homeless population in metropolitan CoCs were rent, homeownership, the Hispanic population, baby boomers, and one-person households. Because this study included both statewide and metro COCs, it did not include any weather or climate variables, although climate was found to be a significant factor by earlier studies such as and Troutman, Jackson, and Ekelund (1999) and Lee et al. (2003).

Multiple scholars have compared the PIT data of CoCs, using different methods and reaching different conclusions. Moulton in 2013 used panel data of the initial years of the PIT to determine that permanent supportive housing programs reduce chronic homelessness. Lucas in 2017 concluded that federal funding for homelessness increases the sheltered homeless population without reducing the unsheltered homeless population. However, Lucas also concluded that other housing and safety net programs were correlated to lower rates of homelessness. In 2017, Corinth used PIT count data to consider the effectiveness of permanent supportive housing programs, concluding that their impact is less than promised: reducing the homeless population by only 1/10 the number of permanent supportive housing beds. Corinth's article is the closest to this dissertation in methodology: using the PIT homeless census data of CoCs for multiple years in a panel (longitudinal, multidimensional) dataset.

Corinth and Lucas contributed another important article to the study of homeless in 2018. Using PIT data for homeless counts, Corinth and Lucas focused on the effects of climate on homeless rates in cities. They argued that warmer climates are associated with higher homelessness. Corinth and Lucas found that variables such as housing prices, religiosity, and poverty rates, have a stronger correlation with homelessness in warmer cities than in colder cities. However, Corinth and Lucas operationalized cities' income and housing characteristics with only two variables: the poverty rate and median rent, whereas this dissertation considers multiple variables that have different correlations to climate. Corinth and Lucas consider the number of emergency shelter, transitional housing, and permanent supportive housing units, but do not include rapid rehousing units or overall continuum of care funding. Consequently this dissertation reaches a different conclusion than Corinth and Lucas on the overall effect of climate on homelessness.

The most recent study to compare communities' homeless rates is a 2019 project for HUD by Nisar, Vachon, Horseman, and Murdoch. This team compared all CoCs using 2017 PIT survey data with a broad array of economic, geographic, and demographic independent variables. They considered variables for safety net programs including HUD-assisted housing but did not consider the effects of CoC policies to address homelessness. Overall, they found that median rent and overcrowding had the strongest correlation to homelessness, but that population density had a negative correlation. This study used an ordinary least squares regression model, not compensating for positive skew in the dependent variables, though this dissertation and other studies of PIT data demonstrate positive skew (as shown in Research Methods, below). Researchers should compensate for skew since it may cause measures of significance to be inaccurate (Yanagihara & Yuan, 2005). For example, Troutman, Jackson, and Ekelund (2005), compensate for skew by using a natural log of the dependent variables whereas Corinth and Lucas (2018) use a Poisson distribution. The authoritativeness of the 2019 HUD study is limited by its lack of compensation for skew.

Over the course of three decades, dozens of scholars have been unable to reach a consensus regarding the effects of local conditions and policies on the sizes of cities' homeless populations. Prior to the introduction of the annual PIT count in 2007, studies were hampered by a lack of consistent data. Even in recent studies, scholars have included different variables and used varying statistical methods. A secondary goal of this dissertation is to compare previous conflicting claims in a single comprehensive framework.

CHAPTER II

THE CATEGORIES OF HOMELESSNESS

This study considers two types of homelessness in its dependent variables: "Category One" as established by the U.S. Department for Housing and Urban Development (HUD), and the broader definition of homelessness used for school children by the U.S. Department of Education, which includes both HUD Category One and HUD Category Three. In this section, I will describe the differences between all four HUD categories of homelessness and explain the importance of studying the broader form of school-reported homelessness in addition to the more extreme form considered by previous studies.

The categories of homelessness were not established by HUD to provide a comprehensive examination of all facets of the homeless problem, but rather for administrative classification of federally-funded project types. HUD's Homelessness Category Two, for example, is a misnomer: people in this category are not yet homeless, and, if the programs that serve them are successful, they will not become homeless. This dissertation focuses on extreme homelessness, defined by HUD as Category One, and the broader definition of homelessness reported by the Department of Education, corresponding to HUD's Categories One and Three. Nevertheless, a brief explanation of each category is provided to provide a more thorough understanding. HUD's current categories of homelessness were established in the Federal Register Vol. 76, No. 233 (December 5, 2011) as follows:

> The categories are: (1) Individuals and families who lack a fixed, regular, and adequate nighttime residence and includes a subset for an individual who resided in an emergency shelter or a place not meant for human habitation and who is exiting an institution where he or she temporarily resided; (2) individuals and families who will imminently lose their primary nighttime residence; (3) unaccompanied youth and families with children and youth who are defined as homeless under other federal statutes who do not otherwise qualify as homeless under this definition; and (4) individuals and families who are fleeing, or are attempting to flee, domestic violence, dating violence, sexual assault, stalking, or other dangerous or life-threatening conditions that relate to violence against the individual or a family member.

Category One: Literally Homeless

HUD further clarified the definitions in *Criteria and Recordkeeping Requirements for Definition of Homeless*, published in January 2012, in which it labelled Category One as "literally homeless," and provided the following Category One criteria:

> Individual or family who lacks a fixed, regular, and adequate nighttime residence, meaning: (i) Has a primary nighttime residence that is a public or private place not meant for human habitation; (ii) Is living in a publicly or privately operated shelter designated to provide temporary living arrangements (including congregate shelters, transitional housing, and hotels and motels paid for by charitable organizations or by federal, state and local government programs); or (iii) Is exiting an institution where (s)he has resided for 90 days or less and who resided in an emergency shelter or place not meant for human habitation immediately before entering that institution

The Category One homeless population is counted annually in the Point-In-Time census (PIT). HUD does not conduct an equivalent of the PIT for the other three categories of homelessness. Category One has therefore been the focus of previous scholarship on this topic.

Category Two: Pending Homelessness

HUD Homelessness Category Two is for people who are not yet homeless but are pending imminent homelessness. Category Two provides eligibility criteria and recordkeeping classification for recipients of HUD-funded eviction prevention programs. If the programs are successful, then by definition many of those classified as Category Two will not become homeless. However, homeless prevention programs are not always successful, and they are often unavailable for many of those in need of assistance (Culhane, Byrne, & Metraux, 2011). HUD only provides funding and receives reports for a minority of eviction-prevention programs. Most such programs are funded at the state and local level (National Low Income Housing Coalition, 2019). Therefore there is no national database of those served by programs to prevent homelessness.

While there is no database of Category Two homelessness - people at risk of losing their homes – there are data sources for people who have lost their homes through foreclosure or eviction. This dissertation exploits the research of the 2018 Princeton University Eviction Lab project, which provides data on evictions at the county level since 2000. One should not assume that everyone who loses their home through eviction will become homeless, or at least not Category One homeless. Those who cannot obtain other housing of their own might have resources or relationships to avoid living outdoors or in a homeless shelter. By examining the eviction lab data as an independent variable, this dissertation considers the relationships between the rate of people leaving Category Two Homelessness through eviction and the rates of Category One and Category Three homelessness.

Category Three: Unstable Housing

HUD's Category Three is a broader definition of homelessness than Category One. It includes families with children that are "doubled up" (living with another family), living in a hotel, or in other unstable living arrangements. HUD's 2012 *Criteria and Recordkeeping Requirements for Definition of Homeless*, provides the following criteria for Category 3:

> Unaccompanied youth under 25 years of age, or families with children and youth, who do not otherwise qualify as homeless under this definition, but who: (i) Are defined as homeless under the other listed federal statutes; (ii) Have not had a lease, ownership interest, or occupancy agreement in permanent housing during the 60 days prior to the homeless assistance application; (iii) Have experienced persistent instability as measured by two moves or more during in the preceding 60 days; and (iv) Can be expected to continue in such status for an extended period of time due to special needs or barriers.

The overcrowding, frequent moves, and insecurity of Category Three homelessness are associated with multiple harmful outcomes (Bailey et al, 2016). The Department of Education primarily uses a broad definition of homelessness for homeless students that includes all those in HUD's Category Three plus Category One. However, almost all previous studies of the homeless populations of cities have included only Category One. The reasons appear to be practical rather than philosophical: Category One homeless data is easily available, it drives funding, and it has clearer criteria.

Perhaps most importantly for scholars, Homelessness Category One is the definition used for the PIT, which is the most prominent source of data on the homeless population. PIT data is easily available from HUD's website for each year since 2007. The Department of Education also collects data annually on homeless school children, including both Category One and Three, but it is less accessible. The Department of Education website only provides data since 2013 and it is organized by school district, which requires the researcher to then match school districts to counties or other jurisdictions, a time-consuming process. PIT data is not only more defensible, it is less laborious to gather.

The PIT also appears to be a more important survey of homelessness because it drives funding. Funding to local CoCS homeless service networks is based partly on need, as determined by the PIT. HUD uses the PIT data, based on Category One homelessness, to determine its official statistics for the homeless population of each CoC area. HUD regulations also prevent CoCs from serving anyone who doesn't meet the definition of Category One. Therefore, local providers of service to the homeless are most interested in the number of Category One homeless. Studies of Category One homelessness have a ready audience in CoC service providers. In order for a study to have value for local planners, it should use the same units of measure as the resources that the planners would employ.

In addition to its importance for HUD resources, the criteria for Category One homelessness is clear: those without shelter other than a homeless shelter. For Category Three, the criteria are more ambiguous. As the HUD Criteria document states after defining Category One, "Other definitions of homelessness are broader, and can include anyone who lacks fully safe and secure housing with rights of tenancy or ownership. There is room for subjectivity along that continuum between sleeping in the open and renting or owning a home." (US Dept of Housing and Urban Development, 2012). The concept of being "doubled up," for example, could be stretched to include adult children still living with their parents, or retired seniors living with their adult children. If someone is not named on the lease or mortgage, at exactly what point do they shift from being a member of the household to "doubled up" and therefore homeless?

There are good reasons to employ such a broad definition of homelessness within the realm of American public education. School districts are often locally funded, and school districts serve those who live within their boundaries. Therefore the education of a child is jeopardized if his or her family does not have an established residence in their own name. Schools can deny admission to a local child unless the child's family can prove residency in the school's district. A child's education will be disrupted if their family is forced to frequently relocate due to housing instability: even if allowed to attend school in each new district, it may follow a different lesson plan than the previous school, so the child will become lost when dropped into unfamiliar classes midyear. Homeless children, using the broader Category Three definition, suffer academically (Aviles de Bradley, 2011; Biggar, 2001).

Therefore, from the perspective of school regulators, it makes sense to use a broader definition of homelessness that includes unstable housing. However, given the scale of the problem of homelessness, it also makes sense for HUD to limit their attention to those who are most obviously homeless: sleeping outdoors or in homeless shelters. In other words, different definitions of homelessness suit different purposes.

Category Four: Fleeing Domestic Violence

HUD Homelessness Category Four consists of those fleeing domestic violence. This category allows applicants fleeing domestic violence to qualify for HUD-funded services if they do not meet the eligibility criteria of other homeless categories. Category Four overlaps with Categories One and Three. Homeless persons in Category Four are counted in the PIT census but are not differentiated from the rest of the Category One population. Domestic Violence is also one of the possible causes for families to enter Category Three Homelessness and to be counted in the school-reported homeless populations.

This study considers both Category One homelessness from HUD's annual PIT census; and school-reported homelessness, which includes both Category One and Category Three, from surveys conducted for the Department of Education by local school districts. Category Two – imminent homelessness – is also represented through consideration of eviction rates. Homelessness is a complex problem at the community level, and I believe that much can be gained by considering the interactions between the most extreme form of homelessness – Category One – and the broader homeless population represented for families with children by school-reported homeless rates.

CHAPTER III

RESEARCH QUESTIONS

GAPS IN PREVIOUS SCHOLARLY WORK

Despite the multitude of scholars that have compared the homeless populations of cities, there is still disagreement about the local factors that contribute to the size of each community's homeless population. The question of which local economic and policy factors contribute to homelessness is important, and perhaps can be more conclusively answered by addressing three gaps in the research: the lack of consideration of Category Three homelessness, the lack of a single study that considers all of the variables that have been proposed to contribute to homelessness; and the lack in most previous studies of an appropriate modeling framework.

Lack of Category Three Homelessness Analysis

Studies since 2007 have relied on the HUD PIT census of Category One homeless populations. Category One represents the most extreme form of homelessness. By excluding the broader definition of homelessness, studies that relied on PIT data may not have fully captured the ways that economic and housing variables or local policies affected the overall homeless population. There are a number of counter-intuitive relationships between the size of each community's Category One homeless population and various independent variables. Perhaps the addition of the Category Three homeless population to the analysis may help to explain them.

For example, Corinth's 2017 study found that a homeless population was only reduced by one person for every ten additional permanent supportive housing beds. Corinth was of course only counting the Category One homeless population. Compare this to Early's 1998 study that found 60 percent of homeless shelter occupants came from unstable housing (i.e. HUD category 3). One could theorize that new Permanent Supportive Housing residents left behind vacant beds in homeless shelters, some of which were filled by homeless people from Category Three rather than Category One. This dissertation explores other implications of the relationship between the more severe homelessness of Category One and the broader homelessness of Category Three.

<u>Lack of Exhaustive Set of Independent Variables</u>

Throughout the debate over variation in cities' homeless populations, scholars have used a variety of variables, and have operationalized them in different ways. A study is vulnerable to the claim that it is incomplete if it excluded a variable that another study found to be significant. For example, Byrne et al. attempted to include all variables of previous studies in their 2012 analysis of PIT data, but excluded the key variable of climate, while others, such as Kevin Corinth, have argued that climate is vital (Corinth, 2017, Corinth & Lucas, 2018). This dissertation attempts to include every possible variable that previous studies have found significant, using the same measures and data sources whenever feasible to consider as many previous theories as possible. Some variables were researched for this dissertation but are discarded during the process of factor analysis or through stepwise removal. Their initial inclusion and later removal is nonetheless informative. In some cases, this can suggest that a variable that was previously found significant is spurious due to multicollinearity with other variables that have more plausible causality.

Lack of Appropriate Statistical Modeling Framework

Most previous studies of cities' homeless population analyzed cross-sectional data. Cross-sectional studies, comparing cities at a single point in time, could not consider how changes in the independent variables might relate to changes in the dependent variables over time. A model using panel data could include longitudinal and cross-sectional data together (Frees, 2010). Only three recent studies, Moulton (2013), Corinth (2017), and Corinth and Lucas (2018), have used panel data. However, these three articles addressed specific questions about homeless policies and did not consider many of the independent variables of previous studies. One purpose for this dissertation is to apply the same methodology while including more independent variables from previous studies that compared cities' homeless populations.

RESEARCH QUESTIONS

This study attempts to answer the questions of how the size of a city's Category One and school-reported homeless populations are affected by local economic, demographic, and geographic conditions as well as by local policies to address homelessness. The following hypotheses were included in the proposal for this dissertation.

Hypothesis One

A city's availability of affordable housing corresponds to a larger ratio of the school-reported homeless population to the Category One homeless population.

A fundamental concept of this dissertation is the need to consider both extreme homelessness (Category One) and the broader (school-defined) form of homelessness. This would not be necessary if the two forms of homelessness had the same relationships to independent variables and were found in the same proportion in all cities. How, then, are the two forms of homelessness different? Most previous scholars on the topic of urban homeless rates have only considered Category One homelessness, and many have concluded that housing costs are a major cause. How, then, would housing costs affect the two forms of homelessness differently?

I believed that the data would reveal that it is relatively easier for people to find unstable housing such as doubling up or living in hotels in cities that are more affordable. Therefore, since community income levels and community housing costs are correlated, school-defined homelessness would be relatively higher in cities with more affordable housing, while Category One homelessness would be relatively higher in less affordable cities. In more expensive cities, the homeless are more likely to be either forced to leave or pushed into more extreme Category One homelessness: living on the street or in a homeless shelter.

Hypothesis Two

A city's percentage of employment in accommodations/food service corresponds to its homeless population.

Previous studies have considered unemployment as an independent variable to explain homeless rates. In addition to the quantity of employment (or rather lack of quantity), could the quality of employment be a factor in homelessness? It seemed likely that employees in the accommodations/food service sector would be more vulnerable to homelessness as is the lowest paying and least stable employment sector (Semuels & Burnley, 2019). Research has found that low-wage service sector jobs have significant income volatility that contributes to economic hardship (Schneider & Harknett, 2017, 2019). Among the studies of city homeless rates in the literature review, only Lee et al. (2003) considered a similar variable: "service and unskilled jobs," which they found to have a positive, nearly-significant relationship to homelessness.

Since it has only been considered by one previous study of the topic of cities' homeless rate and it was found on the verge of significance, the accommodations/food sector variable seemed worthy of additional consideration. In keeping with the overall concept of this dissertation, it was not assumed that the accommodations/food service sector would have the same relationship to both Category One and school-defined homelessness. This dissertation considers accommodations/food service separately for both forms of homelessness.

Hypothesis Three

A city's percentage of HMIS (Homeless Management Information System) participation has a negative correlation to the size of its Category One homeless participation.

As discussed in the literature review, there appears to be a philosophical divide between scholars that are skeptical of markets, who implicitly or explicitly endorse government intervention, versus their opponents who are skeptical of government interference and in some cases argue that government action backfires to exacerbate homelessness. In order to contribute to this debate, this dissertation proposed to consider a specific measurable indicator of government intervention: usage of Homeless Management Information Systems (HMIS).

Homeless Management Information Systems are databases that are shared by homeless providers in continuums of care (CoCs) to synchronize services for specific homeless recipients and to provide more accurate aggregated reports. Usage of HMIS is promoted by HUD and requires cooperation between homeless providers (Poulin, Metraux, & Culhane, 2008). Each CoC is required by HUD to annually report the percentage of its providers that participate in HMIS (U.S. Dept. of Housing and Urban Development, 2020b). Comparing HMIS participation to homeless populations over time in combination with other factors may indicate whether this particular intervention is worthwhile. If HMIS participation corresponds to lower homelessness, it would validate that an intervention funded and promoted by the government can be credited for lower homelessness.

Hypothesis Four

A city's higher ratio of rapid-rehousing beds (relative to other services for the homeless) corresponds to a lower Category One homeless rate.

Rapid rehousing is a recent innovation in program design that has gained support from advocates for the homeless and been promoted by the Federal Government (Byrne et al., 2015). Rapid re-housing is the newer of two forms of "Housing First" programs, the other being “Permanent Supportive Housing” (O’Flaherty, 2018). Housing First programs enable homeless participants to obtain free market housing leases in their own names without meeting any prior behavioral requirements. Prior to Housing First, re-housing programs generally required participants to complete a series of goals and gradually earn the right to occupy transitional housing owned by the provider before acquiring their own housing (Tsemberis, 2004). Permanent Supportive Housing provides long term rental subsidies and case management for formerly homeless participants that are disabled. The newer form of Housing First is rapid rehousing, which is designed for non-disabled participants to become self-sufficient and take responsibility for their own rent after a temporary period of subsidized rent (National Alliance to End Homelessness, 2016).

Previous scholars on the topic of homeless rates have considered housing first in the form of permanent supportive housing, but not in the newer form of rapid rehousing (Moulton, 2013; Lucas, 2017). Other scholars have studied the effectiveness of rapid rehousing by examining outcomes of program participants (Burt et al., 2016; Rodriguez & Eidelman, 2017). As yet, no studies appear to have considered the relationship between rapid rehousing programs and community homeless rates. This dissertation intend to fill that gap. If cities that allocate a greater share of resources to rapid rehousing are experiencing lower homelessness, HUD’s promotion of rapid rehousing would be vindicated.

CHAPTER IV

RESEARCH METHODS

This dissertation primarily consists of a quantitative analysis of Category One and school-reported homeless populations with independent variables including affordable housing availability, poverty, unemployment, accommodations / food service sector employment, climate, drug / alcohol induced deaths, charitable giving, rent control policies, and the allocation of resources for emergency shelter, transitional housing, rapid rehousing, and permanent housing, among others. These independent variables are compared to the Category One homeless rate and school-reported homeless rate as dependent variables. To perform the calculations in this dissertation I used the statistical analysis software Stata 13.1 by StataCorp.

Units of Analysis and Observations

The units of analysis in this study are continuum of care service areas. In situations where multiple CoCs share a county, they are aggregated together into a multi-CoC unit. The dataset includes forty-four of forty-eight CoCs classified by HUD as "major city," forty-six of forty-nine "other urban" CoCs, and 133 of 174 "suburban" CoCs. All 117 "rural" CoCs are excluded. Eight counties include multiple CoCs; the CoCs within each of these counties are aggregated for analysis. Thirty-five non-rural CoCs are excluded because they include counties with populations below 65,000, for which accurate census 1-year estimates are unavailable. Twenty-two more non-rural COCs are excluded due to boundary changes or missing data.

This process yields 208 CoCs and multi-CoC counties for analysis. Appendix B provides a list of the CoCs and multi-COC counties in the dataset. Appendix C provides a list of excluded non-rural CoCs with reasons for exclusion. Each CoC and multi-CoC county is matched with the school district or districts that share(s) its area to obtain homeless student counts. Three observations are included for each CoC: 2014, 2016, and 2018, for a total of 624 observations. A map of the CoCs in the dataset is displayed as Figure 2 on the following page. The CoCs in the dataset are highlighted in red. Non-rural COCs excluded due to low county populations are highlighted in yellow. Non-rural COCs excluded for other reasons are highlighted in orange. Rural CoCs are uncolored.

The 208 CoCs and multi-CoC counties in the dataset include 54% of the US population and 74% of the Category One homeless population. The rate of homelessness among the dataset CoCs and multi-CoC counties is positively skewed with a mean of 0.18% and a median of 0.13%. The overall rate of homelessness in the dataset (total homeless/total population) is 22.8 per 10,000 residents. The CoC with the highest rate of homelessness is the District of Columbia at 99 per 10,000 in 2017. The CoC with the lowest rate of homelessness is Tuscaloosa County, Alabama at 3 per 10,000 in 2017.

Table 1: Comparison of Dataset to USA Total

	CoCs	2017 Population	Category 1 Homeless
Dataset	227	177,060,611	404,673
USA Total	398	327,200,000	552,830

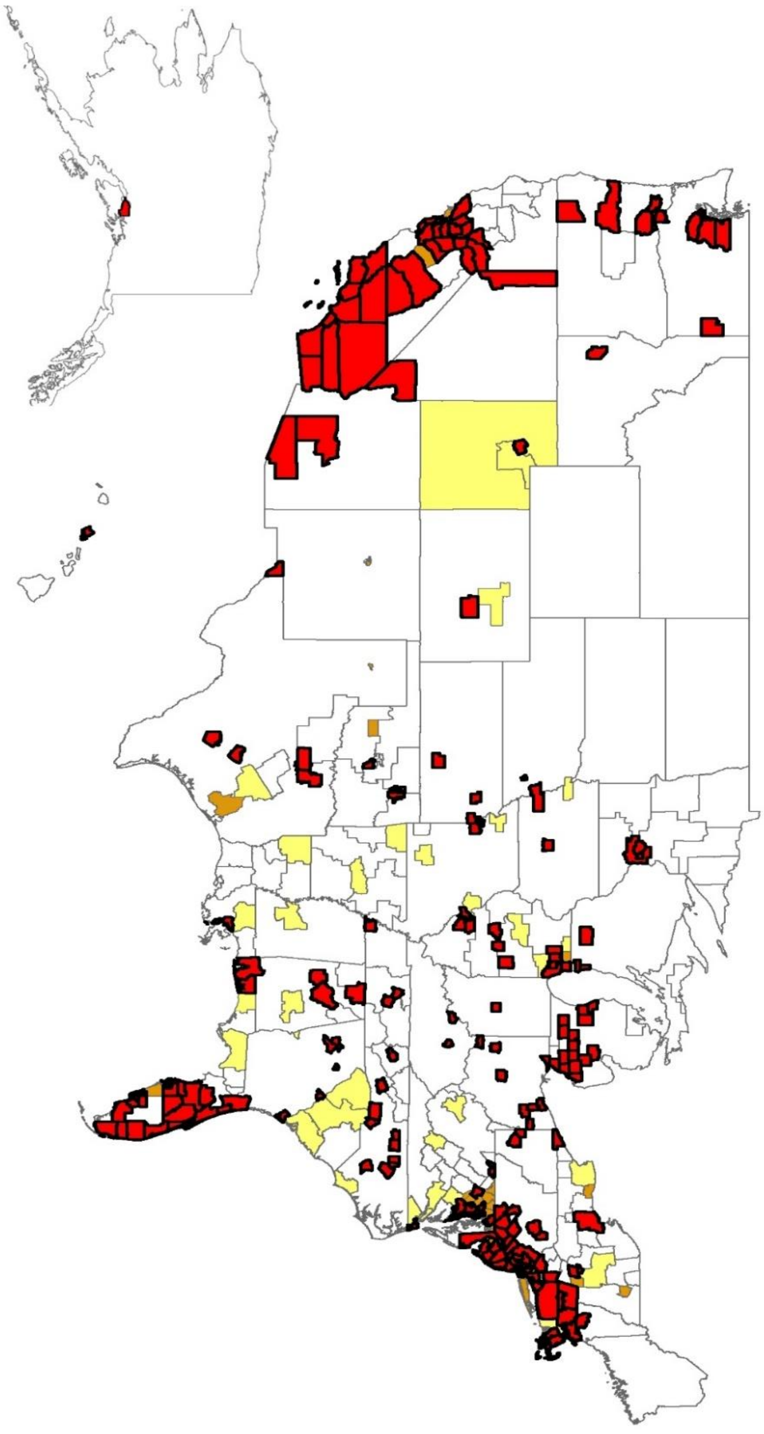

Figure 2: Map of Continuum of Care Areas in Dataset

This map was created using ArcMap 10.6.1 with a shapefile obtained from Byrne (2015).

Dependent Variables

Category One Homeless rate: The Category One homeless population reported in the annual Point-in-Time homeless census ("PIT") as "Overall Homeless," divided by the total population of the CoC reporting area according to the U.S. Census Bureau. The PIT homeless count for January of each year is divided by the ACS population estimate for the previous year: 2014/2013, 2016/2015, 2018/2017.

School-reported Homeless Children Rate: The population of homeless children reported in school districts within the CoC divided by the total population of the CoC reporting area according to the U.S. Census Bureau. The homeless children count for each school year is divided by the ACS population estimate for the initial year: 2013-2014 homeless children /2013 CoC population; 2015-2016/2015, 2017-2018/2017.

Independent Variables

Most independent variables in this study are taken from 2013, 2015, and 2017, the years prior to the dependent variables. Overcrowding data are based on American Community Survey 5-year estimates, since 1-year estimate data were not available. Data regarding funding sources (charitable contributions and HUD continuum of care funding) are collected from two years prior to the dependent variable. The delay for funding variables is partly due to data availability but also allows time for funding that was provided two years prior to the dependent variable to be expended over following year to affect the dependent variables. CoC Housing Inventory Count (HIC) data are taken from the same years as the dependent variables. Additional independent variables remain constant throughout the period such as climate and geographical region. The specific years of data for each variable are provided below. Data sources are provided in Appendix D.

Year: The year of dependent variable data for the observation. As this study uses longitudinal (panel) data, a time period variable is required. By including the year as a variable, the correlation matrix shows the overall direction of change for each variable over the time period of analysis. For school-reported homeless data, it is the end of the school year: 2014 for school year 2013-2014, 2016 for school year 2015-2016, and 2018 for school year 2017-2018.

Population: The total population of the CoC area expressed in hundreds of thousands. It is considered as a possible variable here to validate whether homeless rates could be affected by the population size of communities. There is a common perception that homelessness is a greater problem in larger cities (Henry & Sermons, 2010). Previous scholars have not considered population size as a variable in comparing cities' homeless rates, though journalists have observed differences in changing homeless rates between larger and smaller cities (Nash & Deprez, 2015).

Population Density: The population variable divided by the area variable. Density is a variable considered by previous studies that compare cities' homeless rates. Nisar et al. (2019) found high density to have an association with homelessness within $p \leq 0.1$.

Area: The land area of the CoC in square miles. This is a fixed variable – it does not change over the period of observation. Area data are collected in order to calculate density and is retained in the descriptive statistics and correlation matrix in the interest of thoroughness.

New Residents: Total percentage of residents that moved from a different county, state, or country in the past year. Nisar et al. (2019) found the related measure of net migration rate to have a significant positive relationship to homelessness within $p \leq 0.01$.

Percent African-American: Percentage of the population in the CoC area that selected the race “African-American/Black” in the American Community Survey. Since Honig and Filer (1993), race has been considered as an independent variable by most studies that compared cities’ homeless rates. Honig and Filer provided no specific justification for including race as a variable. Later studies of this topic (including this dissertation) consider race as a variable because it was included in earlier studies. One could justify this variable on the grounds that housing discrimination due to systemic racism could explain higher homeless in cities with higher African-American populations (Korver-Glenn, 2018; Priester, Foster, & Shaw, 2017). However, findings on the relationship between race and homelessness have been unclear. Corinth and Lucas (2018) found a significant negative association between African American population and homelessness whereas Early (1998) found a positive association. Others included the variable but did not find a significant association, including Honig and Filer (1993), Byrne et al. (2012), Moulton (2013), and Nisar et al. (2019).

Percent Hispanic: Percentage of the population in the CoC area that selected the ethnicity “Hispanic.” Hispanic ethnicity has been included as a variable by multiple studies of cities' homeless rates since Early in 1998. Early justified the inclusion of demographic variables including race and ethnicity based on previous non-community-level studies of homelessness. Housing discrimination against Hispanics could explain a positive association between Hispanic populations and homeless rates (Findling et al., 2019). On the other hand, Khadduri et al. (2018) argue that Hispanic families are less likely to experience street homelessness because Hispanic populations tend to have lower measures of housing instability relative to the general population. Byrne et al. (2012) found a significant positive association between Hispanic population and homeless rates. Corinth and Lucas (2018) and Nisar et al. (2019) found a significant negative association. Early (1998) did not find a significant association.

January Low Temperature: The average January low temperature for years 1979-2011 for counties in the CoC area, expressed in Fahrenheit. This is a fixed variable – it does not change over the period of observation. Appelbaum et al. (1991), Troutman et al. (1999), Corinth and Lucas (2018), and Nisar et al. (2019) found significant positive associations between January temperature and homelessness. Bohanon (1991), Early (1998), and Moulton (2013) did not find significant associations between climate and homelessness.

East Coast: Whether the CoC is located in a state on the East Coast (adjacent to the Atlantic Ocean plus Pennsylvania). CoCs that meet the criteria have a value of 1; others have a value of 0. This is a static variable – it does not change over the observation period. Lee et al. (2003) and Nisar (2019) considered city's homeless rates by region, although they categorized cities into four census regions: Northeast, South, Midwest, or

West. This dissertation reclassified region by east-west to minimize the likelihood of multicollinearity with climate.

West Coast: Whether the CoC is in a state on the West Coast (adjacent to the Pacific Ocean including Alaska and Hawaii). CoCs that meet the criteria have a value of 1; others have a value of 0. This is a static variable – it does not change over the observation period. Nisar et al (2019) conducted a subgroup analysis of Western states where homeless rates tended to be higher than other regions. They found that some variables associated with unsheltered homelessness had different coefficients and significance than in other regions.

Median Income: Median household income in the past twelve months, in thousands of 2017 inflation adjusted dollars. Early (1998) found a significant negative association between income and homelessness, whereas Corinth (2017) found a significant positive association.

Gini Index: A popular measure of income inequality, named for the author Corrado Gini, ranging from zero to one. A higher score indicates greater income inequality (Giorgi & Gigliarano, 2017). Nisar et al. (2019) included the Gini Index but did not find a significant association with homelessness.

Poverty Rate: Percentage of the population in the CoC area with income below the poverty level. Ji (2006) and Corinth and Lucas (2018) found a significant positive association between poverty and homelessness. Other studies have included poverty but did not find a significant association.

Unemployment Rate: Percentage of the population in the CoC area that is unemployed. Appelbaum et al. (1991), Bohanon (1991), and Corinth (2017) found significant positive associations between unemployment and homelessness. Ji (2006) and Nisar et al. (2019) found significant negative associations between unemployment and homelessness. Others included unemployment but did not find significant associations.

Employment in Accommodations and Food Service: Percentage of the workforce employed in the accommodations and food service sector by County for 2013, 2015, and 2017. Lee, Price-Spratlen, and Kanen (2003) found the similar measure of "service and unskilled jobs" to have a positive nearly-significant relationship to homelessness. The Accomodations / Food Service tests the second hypothesis of this dissertation: that a positive association would be found between the share of employment in accommodations/ food service and homeless rates.

Drug / Alcohol Induced Deaths: The death rate due to drug / alcohol induced causes per ten thousand residents by County for 2013, 2015, and 2017. Previous studies have considered substance abuse as an independent variable with variation in how it is operationalized. Troutman et al. (1999) found a negative association between homelessness and spending to address alcohol, drug, and mental health. Nisar et al. (2019) found alcohol mortality to have a significant positive relationship to rates of homelessness.

Rental Vacancy Rate: Percentage of rental units that are unoccupied. Appelbaum et al. (1991) and Moulton (2013) found positive associations between rental vacancies and homelessness; but others did not including Early (1998), Ji (2006), Byrne et al. (2012), and Nisar et al. (2019).

Median Home Value: The median home price in thousands of 2017 inflation-adjusted dollars. Nisar et al. (2019) found home price (operationalized as house price index) to be a significant predictor of homelessness.

Median Rent: The median rent in thousands of 2017 inflation adjusted dollars. Several studies have found positive associations between median rent and homelessness including Quigley (1991), Bohanon (1991), Lee et al. (2003), Byrne et al. (2012), Corinth and Lucas (2018), and Nisar et al. (2019). Corinth (2017) did not.

Lower Quartile Rent: The maximum rent paid by the bottom 25% of the renting population, in hundreds of 2017 inflation adjusted dollars. Moulton (2013) included lower quartile rent as a variable but did not find a significant association between lower quartile rent and homelessness.

Homeownership: Percentage of housing units that are occupied by owners. Appelbaum et al. (1991), Byrne et al. (2012), and Nisar et al. (2019) found significant negative associations between homeownership and homelessness.

Rent-Income Ratio: Median Gross Rent as a Percentage of Household Income (GRAPI). It does not appear that previous studies have considered GRAPI as a variable per se, but it is included since it reflects both rent and income which previous studies have found significant.

Overcrowding: Percentage of housing units with more than 1.5 occupants per room. Overcrowding is included as another means to operationalize housing scarcity in comparison with price and vacancy rates. Nisar et al. (2019) found a significant positive relationship between overcrowding and homelessness.

Eviction Rate. The number of evictions per year divided by the number of renters, expressed in percentage points. Eviction rates are an attempt to reflect the interaction of HUD Homelessness Category Two- Imminent Homelessness – with Category One and school-reported homelessness. Nisar et al. (2019) found a significant association between increasing eviction rates and homelessness.

Eviction Filing Rate. The number of eviction filings per year divided by the number of renters, expressed in percentage points. Both eviction rates and filing rates are considered in order to determine which may be a better predictor of homelessness.

Charitable Giving: Total itemized deductions by taxpayers in the CoC area divided by population, expressed in 2017 inflation-adjusted dollars. I compare the dependent variables to the charitable giving data from two years prior. Charitable giving data for 2017 were not yet available, but this two-year delay also allows time for the charitable programs funded by the donations to be implemented in order to have an effect.

Food Stamps: The percentage of households in poverty receiving cash assistance or food stamps in the previous 12 months. Previous studies including Ji (2006), Byrne et al. (2012), and Nisar et al. (2019) have found a positive association between homelessness and the rates of various forms of public assistance.

Public Housing: Percentage of housing units that are provided by the local housing authority and funded by HUD. This includes housing units that are owned by the housing authority plus "housing choice" programs that subsidize the rent of privately owned apartments leased by subsidized tenants. Troutman et al. (1999) and Nisar et al. (2019) found significant positive associations between sheltered homelessness and the share of HUD-assisted units.

Rent Control: Whether the primary municipal government of the CoC area has statutes or ordinances that limit rent increases or limit grounds for eviction as a Yes (1) or No (0) variable. If a CoC includes multiple counties, the rent control value is the number of counties with rent control divided by the total number of counties. Rent control was implemented in three CoCs and repealed in one CoC between 2014 and 2017. Tucker (1987, 1990) and Troutman et al. (1999) found significant positive associations between rent control and homelessness. Tucker's findings were disputed by Quigley (1990) and Appelbaum et al (1991).

Counties Per CoC: The number of counties in the Unit of Analysis divided by the number of CoCs. The purpose of this variable is to determine if the rate of homelessness is associated with the scale of COCs: whether they are multi-county regional COCs, single-county CoCs, or multiple CoCs within counties.

Permanent Supportive Housing: The percentage of CoC-funded units that are dedicated to permanent supportive housing. Moulton (2013) and Corinth (2017) found significant but negative associations between permanent supportive housing and homelessness.

Emergency Shelter: The percentage of CoC-funded beds that are in emergency shelters. Corinth (2017) found a significant positive association between emergency shelter beds and homelessness.

Transitional Housing: Percentage of CoC-funded housing units that are classified as transitional housing. Corinth (2017) found a significant positive association between transitional housing beds and homelessness.

Rapid Rehousing: Percentage of CoC-funded housing units that are classified as rapid rehousing. The rapid rehousing variable tests the fourth hypothesis of this dissertation: that greater implementation of rapid rehousing will predict lower rates of homelessness.

HMIS Participation Rate: The percentage of homeless service agencies that participate in the CoC's shared Homeless Management Information System. The HMIS participation rate variable tests the third hypothesis of this dissertation: that greater implementation of HMIS will predict lower rates of homelessness.

Continuum of Care Funding: The amount of funding awarded to the CoC by HUD in 2012, 2014, and 2016 (two years prior to the dependent variable in the same observation). The CoC funding variable is taken from two years prior to the dependent variable in order to be consistent with the other funding variable of charitable donations. More importantly, since funding is expended in the year after it is awarded, the two-year delay provides time for the funding to be implemented and have an effect. Moulton (2013) found a negative association between new project CoC funding and homelessness. Early (1998) found a positive association between homelessness and funding per homeless shelter bed. CoC funding is reflected in two variables. It is provided relative to the total population and also relative to the homeless population at the time it was awarded (two years prior to the dependent variable). Funding per homeless is in increments of one thousand dollars.

Descriptive Statistics

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Category One Homeless rate	19.18109	16.69404	3	131
School-reported Homeless rate	38.125	28.53744	2	218
Year	2016	1.634303	2014	2018
Population	8.347353	11.0376	0.71615	101.7029
Population Density	1583.022	3054.712	42.3	28490.7
Area	1313.065	2034.87	15	20057
New Residents	6.433654	2.275098	2.4	17.8
African-American	13.56	12.31	0.3	63.7
Hispanic	15.44904	14.34859	0.8	84.3
January Minimum Temperature	29.52292	12.46207	3.4	66
East Coast	0.451923	0.498083	0	1
West Coast	0.192308	0.39443	0	1
Median Income	62.98848	16.54966	32.088	135.842
Gini Index	46.2758	3.171109	36.7	56.2
Poverty	9.898718	4.125429	1.4	24.2
Unemployment	5.486699	1.986091	2.3	32.4
Accommodations and Food Service	7.442628	2.076601	3.8	27
Drug / Alcohol Deaths	20.56117	11.23638	4.852559	101.7794
Rental Vacancy Rate	5.854647	2.776185	0.3	23.6
Median Home Value	262.2637	154.648	81.841	1104.1
Median Rent	1.061532	0.277075	0.509	2.259
Lower Quartile Rent	0.706191	0.208351	0.322	1.587
Rent-Income Ratio	41.8976	5.11797	26.3	58.5
Home Ownership	62.80401	9.43354	29.9	86.1

Variable	Mean	Std. Dev.	Min	Max
Overcrowded	0.81	0.76	0.1	5
Eviction Rate	2.771265	2.248052	0.1	15.1
Eviction Filing Rate	7.494224	9.376455	0.1	113.6
Charitable Giving	0.740192	0.397283	0.2	2.92
Food Stamps	12.12573	4.968669	2.2	26.2
Public Housing	3.221795	1.965743	0.3	13.8
Housing Choice	1.801122	1.033165	0	7.2
Non-Housing Choice	1.420673	1.168956	0	8.3
Rent Control	0.124734	0.328688	0	1
Counties Per CoC	1.279567	0.855462	0.25	7
Permanent Supportive Housing	40.78846	14.59091	0	74.7
Emergency Shelter	28.14199	11.8288	3	86.1
Transitional Housing	22.84519	13.04658	0	92.9
Rapid Rehousing	8.221635	9.343265	0	61.8
HMIS Participation Rate	77.3141	18.7968	0	100
CoC Funding Per Capita	7.058512	6.306129	0	39.30502
CoC Funding per Homeless	4.304	3.376	0	23.58

Correlation Matrix

In the following correlation matrix, positive correlations of +0.1 and higher are highlighted in green, and negative correlations of -0.1 and below are highlighted in red. Associations of 1 are not highlighted.

Table 3: Correlation Matrix

	Category One Homeless rate	School-reported Homeless rate	Year	Population	Population Density	Area	New Residents	African-American
Category One Homeless rate	1.00							
School-Reported Hless rate	**0.27**	1.00						
Year	-0.08	0.00	1.00					
Population	**0.18**	0.07	0.01	1.00				
Population Density	**0.43**	-0.10	0.01	**0.39**	1.00			
Area	-0.01	**0.44**	0.00	**0.27**	**-0.20**	1.00		
New Residents	**0.13**	0.01	0.03	**-0.24**	0.06	**-0.11**	1.00	
African-American	0.06	-0.08	0.01	0.05	**0.28**	**-0.21**	**0.13**	1.00

	Category One Homeless rate	School-reported Homeless rate	Year	Population	Population Density	Area	New Residents	African-American
Hispanic	**0.15**	**0.33**	0.03	**0.35**	0.09	**0.46**	**-0.18**	**-0.22**
January Min Temp	**0.23**	**0.21**	0.00	**0.18**	-0.04	**0.26**	**0.12**	-0.01
East Coast	-0.06	**-0.35**	0.00	-0.08	**0.16**	**-0.23**	0.06	**0.24**
West Coast	**0.33**	**0.43**	0.00	**0.13**	-0.07	**0.34**	-0.03	**-0.37**
Median Income	-0.05	**-0.24**	**0.15**	0.03	**0.12**	**-0.13**	0.02	**-0.27**
Gini Index	**0.30**	0.00	-0.02	**0.25**	**0.37**	-0.06	0.01	**0.35**
Poverty	**0.21**	**0.29**	**-0.20**	**0.14**	**0.16**	**0.20**	-0.08	**0.43**
Unemployment	**0.14**	**0.24**	**-0.36**	0.01	-0.02	**0.22**	**-0.19**	**0.12**
Accomm/ Food Service	**0.15**	**0.13**	0.05	-0.01	-0.08	**0.14**	**0.11**	-0.01
Drug / Alcohol Deaths	-0.02	-0.01	**0.39**	**-0.12**	0.04	**-0.11**	**-0.17**	**0.20**
Rental Vacancy Rate	**-0.16**	-0.03	-0.08	-0.07	**-0.12**	0.00	0.00	**0.34**
Median Home Value	**0.37**	0.00	**0.12**	**0.23**	**0.38**	-0.02	0.05	**-0.25**
Median Rent	**0.22**	-0.06	**0.13**	**0.21**	**0.29**	-0.01	0.09	**-0.15**
Lower Quartile Rent	**0.12**	-0.08	**0.11**	**0.20**	**0.23**	-0.01	**0.11**	**-0.19**
Rent-Income Ratio	**0.19**	**0.20**	**-0.18**	**0.13**	-0.07	**0.19**	**-0.12**	0.08
Home Ownership	**-0.46**	**-0.21**	0.02	**-0.32**	**-0.57**	-0.06	**-0.26**	**-0.36**
Overcrowded	**0.38**	**0.27**	0.05	**0.46**	**0.35**	**0.25**	-0.09	**-0.15**
Eviction Rate	**-0.15**	0.01	-0.08	-0.05	-0.07	0.05	0.02	**0.34**
Eviction Filing Rate	**-0.13**	**-0.16**	-0.04	-0.03	0.06	**-0.10**	0.01	**0.53**
Charitable Giving	**0.12**	**-0.19**	**0.13**	**0.16**	**0.28**	**-0.15**	**0.14**	0.09
Food Stamps	**0.15**	**0.21**	**-0.13**	0.05	**0.11**	**0.10**	**-0.18**	**0.36**
Public Housing	**0.41**	0.04	-0.05	0.08	**0.49**	**-0.21**	-0.04	**0.53**
Housing Choice	**0.39**	**0.11**	-0.04	**0.11**	**0.34**	**-0.12**	-0.09	**0.47**
Non-Housing Choice	**0.35**	-0.03	-0.06	0.04	**0.53**	**-0.24**	0.01	**0.47**
Rent Control	**0.13**	**-0.18**	0.01	**0.23**	**0.35**	-0.07	**-0.18**	0.06
Counties Per CoC	-0.02	-0.06	0.00	**0.19**	0.08	**0.14**	-0.02	0.02
Perm. Supportive Housing	-0.03	-0.06	0.10	**0.14**	0.08	0.00	-0.09	**0.19**
Emergency Shelter	**0.12**	0.02	-0.03	-0.05	**0.13**	-0.07	-0.02	-0.04
Transitional Housing	-0.05	0.05	**-0.38**	-0.10	**-0.20**	0.02	0.07	**-0.12**
Rapid Rehousing	-0.04	0.01	**0.42**	-0.03	-0.01	0.07	0.05	-0.07
HMIS Participation Rate	-0.01	**-0.10**	**-0.19**	0.01	**0.14**	-0.04	0.00	0.05
CoC Funding Per Capita	**0.43**	0.06	0.02	**0.13**	**0.48**	**-0.15**	0.00	**0.38**
CoC Funding per Homeless	**-0.27**	**-0.20**	**0.15**	0.03	0.09	**-0.14**	**-0.20**	**0.18**

	Hispanic	January Min Temp	East Coast	West Coast	Median Income	Gini Index	Poverty	Unemployment
Hispanic	1.00							
January Min Temp	**0.45**	1.00						
East Coast	**-0.15**	0.10	1.00					
West Coast	**0.43**	**0.38**	**-0.44**	1.00				
Median Income	-0.01	-0.09	**0.14**	**0.17**	1.00			
Gini Index	**0.17**	**0.15**	0.05	-0.08	**-0.26**	1.00		
Poverty	**0.31**	**0.14**	**-0.13**	0.01	**-0.76**	**0.43**	1.00	
Unemployment	**0.36**	**0.15**	-0.04	**0.22**	**-0.40**	**0.14**	**0.60**	1.00
Accomm/ Food Service	0.01	**0.30**	-0.05	-0.01	**-0.18**	0.06	0.08	0.01
Drug / Alcohol Deaths	**-0.30**	**-0.19**	0.09	**-0.23**	**-0.22**	0.08	**0.11**	-0.04
Rental Vacancy Rate	**-0.14**	**0.23**	**0.21**	**-0.37**	**-0.33**	**0.11**	**0.20**	0.06
Median Home Value	**0.26**	**0.26**	0.01	**0.51**	**0.75**	0.08	**-0.43**	**-0.22**
Median Rent	**0.28**	**0.31**	**0.16**	**0.40**	**0.82**	-0.03	**-0.49**	**-0.24**
Lower Quartile Rent	**0.27**	**0.27**	**0.14**	**0.38**	**0.83**	-0.09	**-0.54**	**-0.27**
Rent-Income Ratio	**0.34**	**0.40**	0.09	**0.26**	**-0.29**	**0.27**	**0.40**	**0.41**
Home Ownership	**-0.35**	**-0.15**	**0.12**	**-0.22**	**0.20**	**-0.52**	**-0.51**	**-0.15**
Overcrowded	**0.67**	**0.35**	**-0.18**	**0.54**	**0.16**	**0.22**	**0.16**	**0.16**
Eviction Rate	**-0.19**	**-0.13**	-0.07	**-0.32**	**-0.35**	-0.06	**0.29**	**0.10**
Eviction Filing Rate	**-0.15**	**-0.13**	**0.20**	**-0.29**	-0.03	-0.10	0.06	0.04
Charitable Giving	-0.04	0.09	0.10	0.00	**0.55**	**0.29**	**-0.37**	**-0.33**
Food Stamps	**0.12**	-0.03	-0.06	-0.09	**-0.76**	**0.29**	**0.84**	**0.51**
Public Housing	-0.06	**-0.23**	0.09	**-0.16**	**-0.30**	**0.47**	**0.51**	**0.20**
Housing Choice	0.04	-0.09	-0.01	0.01	**-0.21**	**0.42**	**0.43**	**0.18**
Non-Housing Choice	**-0.14**	**-0.30**	**0.15**	**-0.28**	**-0.32**	**0.42**	**0.48**	**0.17**
Rent Control	**0.16**	-0.03	**0.25**	0.03	**0.30**	**0.15**	**-0.10**	0.03
Counties Per CoC	-0.04	0.01	**0.13**	**-0.11**	-0.01	-0.08	-0.01	0.01
Perm. Supportive Housing	**-0.12**	**-0.13**	-0.07	-0.02	-0.03	**0.20**	0.06	-0.08
Emergency Shelter	**0.14**	-0.04	0.09	**-0.13**	-0.02	**-0.10**	0.09	**0.11**
Transitional Housing	0.00	**0.15**	-0.02	0.05	-0.04	**-0.11**	-0.04	**0.11**
Rapid Rehousing	0.01	0.04	0.02	**0.11**	**0.13**	-0.03	**-0.14**	**-0.17**
HMIS Participation Rate	-0.07	**-0.11**	**0.15**	-0.10	**0.10**	0.04	-0.06	-0.02
CoC Funding Per Capita	**-0.11**	**-0.14**	-0.03	0.01	-0.09	**0.40**	**0.27**	0.02
CoC Funding per Homeless	**-0.18**	**-0.36**	0.05	**-0.23**	0.01	**0.13**	-0.01	**-0.11**

	Overcrowded	Eviction Rate	Eviction Filing Rate	Charitable Giving	Food Stamps	Public Housing	Housing Choice	Non-Housing Choice
Overcrowded	1.00							
Eviction Rate	**-0.26**	1.00						
Eviction Filing Rate	**-0.14**	**0.45**	1.00					
Charitable Giving	**0.13**	**-0.18**	0.06	1.00				
Food Stamps	-0.03	**0.27**	0.06	**-0.46**	1.00			
Public Housing	0.10	0.06	0.06	-0.01	**0.51**	1.00		
Housing Choice	**0.19**	-0.01	0.02	0.03	**0.40**	**0.88**	1.00	
Non-Housing Choice	-0.01	**0.11**	0.09	-0.05	**0.51**	**0.91**	**0.59**	1.00
Rent Control	**0.32**	**-0.21**	**0.20**	**0.15**	**-0.17**	**0.12**	0.09	**0.11**
Counties Per CoC	-0.06	-0.05	-0.05	0.00	0.03	0.02	0.00	0.03
Perm. Supportive Housing	0.02	0.05	0.00	0.09	**0.10**	**0.23**	**0.26**	**0.17**
Emergency Shelter	0.04	0.04	0.06	-0.04	0.05	0.05	-0.04	**0.11**
Transitional Housing	-0.05	-0.02	-0.01	**-0.10**	**-0.11**	**-0.26**	**-0.22**	**-0.23**
Rapid Rehousing	-0.01	**-0.10**	-0.07	0.04	-0.07	-0.07	-0.04	-0.08
HMIS Participation Rate	-0.06	0.04	0.09	0.01	0.00	0.09	0.03	**0.12**
CoC Funding Per Capita	**0.13**	-0.05	-0.05	**0.11**	**0.32**	**0.68**	**0.59**	**0.61**
CoC Funding per Homeless	**-0.16**	0.02	0.07	-0.01	**0.12**	**0.26**	**0.18**	**0.28**

	Rent Control	Counties Per CoC	Permanent Supportive	Emergency Shelter	Transitional Housing	Rapid Rehousing	HMIS Participation Rate	CoC Funding Per Capita
Rent Control	1.00							
Counties Per CoC	-0.01	1.00						
Perm. Supportive Housing	**0.11**	0.00	1.00					
Emergency Shelter	0.06	0.10	**-0.54**	1.00				
Transitional Housing	**-0.12**	-0.07	**-0.52**	**-0.17**	1.00			
Rapid Rehousing	-0.07	-0.03	**-0.16**	**-0.19**	**-0.37**	1.00		
HMIS Participation Rate	0.03	-0.04	0.08	**-0.14**	0.01	0.03	1.00	
CoC Funding Per Capita	**0.14**	-0.06	**0.44**	**-0.21**	**-0.28**	-0.04	**0.12**	1.00
CoC Funding per Homeless	0.05	-0.02	**0.48**	**-0.31**	**-0.28**	0.04	**0.15**	**0.51**

Histograms of Dependent Variables

Histograms of the dependent variables of Category One Homelessness and school-reported Homelessness are displayed below, with the ranges of observations for both divided into twenty columns.

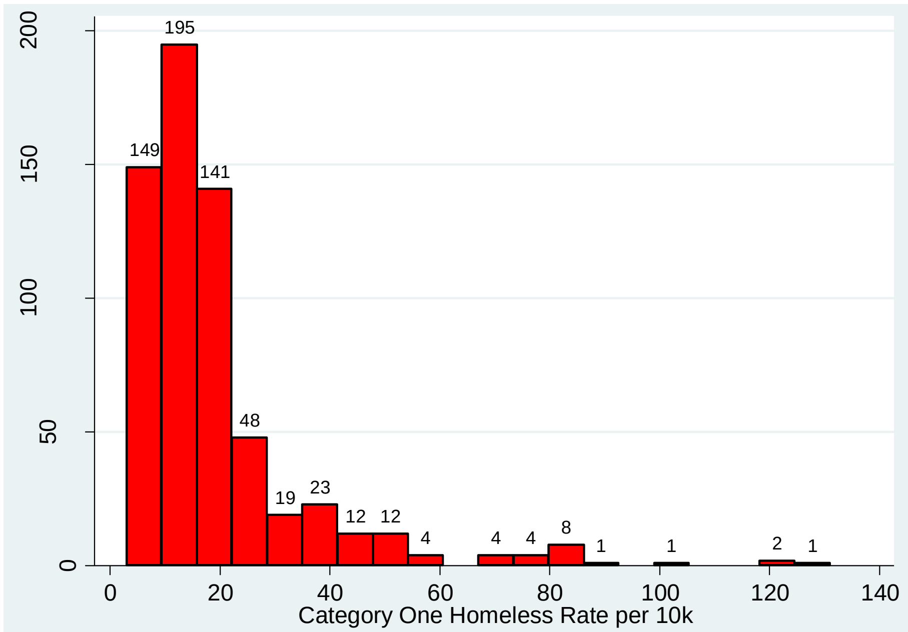

Figure 3: Histogram of Category One Homeless rate

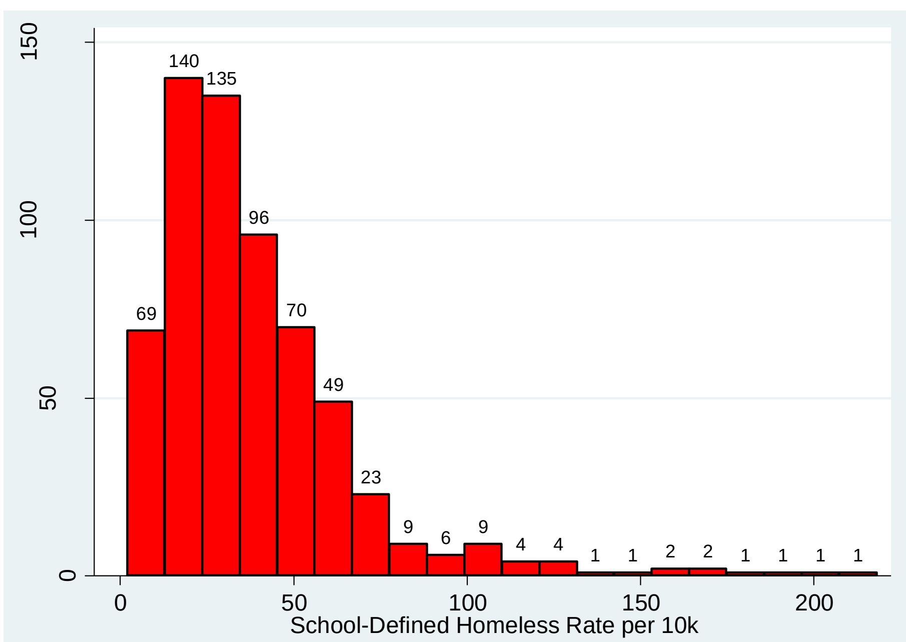

Figure 4: Histogram of School-Reported Homeless Rate

As Figures 3 and 4 illustrate, both dependent variables are positively skewed. Normality tests confirm skewness scores of 2.95 for the Category One homeless rate and 2.38 for the school-reported homeless rate. In order to account for skew, this study uses a natural log to transform the dependent variables (Bland, 1996).

Method of Analysis

In order to compare CoCs to each other while also considering changes over time in each CoC, this study uses a longitudinal generalized-least-squares random-effects linear model. Each continuum of care (or county cluster of small continuums of care) is a panel. The model includes differences in observations over time within each panel ("within") and also differences among panels ("between"). In Stata, the command code "Xtreg" runs this model.

Interpolated Data

In processing the data for this dissertation, the extent to which school system boundaries fail to correspond to county boundaries in some American states became apparent. In order to determine school-reported homeless data for county-based units of analysis, I was required to partially interpolate data for school systems that overlapped continuums of care. Homeless numbers for overlapping school districts are counted relative to the share of the school district's population living in the CoC area. Using Arcmap GIS software, I cross-referenced a layer of county boundaries, a layer of school system boundaries, and a layer of 2010 population census tracts. The number of homeless students in each school system was multiplied by the percentage of the school system's population in the census tracts of each overlapping county, and the products of all overlapping school systems was summed for each county. 43 of 208 continuum of care areas (129 of 624 observations) required some degree of interpolation. The school-reported homeless statistics for these 124 are therefore “coarse data” (Kim & Hong, 2012). The possible effects of interpolated data are investigated in Chapter V: Findings.

Multicollinearity

Having applied a “kitchen sink” approach in order to include a comprehensive list of variables considered by previous studies, the approach of this dissertation inevitably results in many variables that are redundant and collinear, as demonstrated in the correlation matrix. Topics such as income and housing are each represented by multiple variables. The purpose of this redundancy is to determine which aspects of each topic are the best predictors of the homeless rate. This approach requires a process to determine which variables should be eliminated for a more accurate model.

Instead of selecting the most representative variable, another option would have been to combine related variables into an index or composite variable. Both methods have pros and cons and there are advocates for and against the use of indices (Nardo et al., 2008; Saisana, Saltelli, & Tarantola, 2005). One purpose of this dissertation is to provide a formula that planners could use to help forecast homeless rates in their communities. For simplicity and ease of use I will therefore reduce the number of independent variables rather than combining them into indices. The refinement process will be shown in detail to justify the selection of specific variables over others that were used by previous scholars.

Within each category of variables related to the same topic, factor analysis helps to determine which variables should be retained in the model. The factor analysis is conducted in separate categories to reduce redundant measurements of the same community characteristic. For example, Median Home Price, Median Rent, and Lower Quartile Rent are all measurements of housing cost and are highly correlated with each other (median home price and median rent at 0.91, median rent and lower quartile rent at 0.97). In this step, the median home price is found to be a better predictor of Category One Homelessness so it is retained while median rent and lower quartile rent are removed. On the other hand, Median Rent and Median Income are also correlated with each other (0.75), but measure aspects of the economy that are distinct - albeit related. As the findings of this dissertation will demonstrate, income and housing costs have a strong positive association with each other but have opposite effects on homeless rates so it is important for both to be represented. The separation into categories for factor analysis enables these distinctions to be made more systematically.

The independent variables are grouped into four categories: location/demographics, economy, housing, and interventions. Factor analysis is conducted within each category to determine which variables can best represent the category. These four categories are based on previous studies of cities' homeless rates. Byrne et al. (2013) categorized variables under economic conditions, demographic composition, safety net, climate, and transience. Nisar et al. (2019) used the categories of housing market, economic, safety net, demographic, and climate. This dissertation uses only one climate variable (January Min Temperature) and one transience variable (New Residents) so the climate and transience categories are combined with other categories. The “safety net” category is re-labelled with the broader term “interventions” since it includes government policies such as rent control and HMIS use that are not direct-benefit programs one would typically consider “safety net.”

The location/demographics category includes Population, Population Density, Area, African-American, Hispanic, January Minimum Temperature, East Coast, and West Coast.

The economy category includes Median Income, Poverty, Unemployment, Gini, and Accommodations and Food Service Sector.

The housing category includes Median Rent, Lower Quartile Rent, Gross Rent as a Percent of Income (GRAPI), Median Home Value, Homeownership, Rental Vacancy Rate, Eviction Rate, Eviction Filing Rate, and Overcrowding.

The interventions category includes Food Stamp Utilization, Public Housing Units, Rent Control, Charitable Giving, Emergency Shelter, Transitional Housing, Permanent Supportive Housing, Rapid Rehousing, HMIS Utilization Rate, and Counties per CoC.

The refinement process used below to reduce multicollinearity is to find groups of variables within each category that have low uniqueness values and are closely associated in the same factor. From each such group I generally retain the independent variable that has the highest correlation with the dependent variable, though this process requires some judgement based on the nature of the variables, as described below.

Location/ Demographics

Table 4 below illustrates the results of a factor analysis of the location and demographics variables. In this initial factor analysis, three variables have uniqueness values below 0.5.

Table 4: Initial Factor Analysis of Location/Demographic Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	5
Rotation: (unrotated)	Number of params	=	35

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	1.991	0.996	0.635	0.635
Factor 2	0.995	0.452	0.317	0.952
Factor 3	0.543	0.229	0.173	1.125
Factor 4	0.314	0.239	0.100	1.225
Factor 5	0.075	0.149	0.024	1.249
Factor 6	-0.073	0.052	-0.023	1.225
Factor 7	-0.126	0.094	-0.040	1.185
Factor 8	-0.220	0.142	-0.070	1.115
Factor 9	-0.361	.	-0.115	1.000

LR test: independent vs. saturated: chi2(36) = 1280.64, Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Population	0.362	0.517	-0.268	-0.021	0.042	0.528
Population Density	-0.100	0.601	-0.126	0.249	-0.057	0.547
Area	0.590	-0.034	-0.016	-0.187	0.153	0.593
New Residents	-0.172	-0.030	0.366	0.257	0.084	0.763
African-American	-0.380	0.378	0.090	0.038	0.151	0.680
Hispanic	0.692	0.228	0.041	-0.098	-0.051	0.456
January Min Temp	0.471	0.219	0.481	-0.033	-0.007	0.498
East Coast	-0.386	0.312	0.276	-0.259	-0.104	0.600
West Coast	0.693	-0.157	0.062	0.267	-0.059	0.417

Population, Population Density, and Area are intrinsically collinear as components of the same mathematical equation. Area has the lowest correlation to homelessness, so it is removed. Population and Population Density are retained.

The Hispanic population is related to January Minimum Temperature and the West Coast in Factor 1. The relationship between January Minimum Temperature and West Coast is physically inherent since they are both static geographical variables. However, the relationship between Hispanic and January Minimum Temperature is moderate (correlation of 0.4484) and not fixed: I.e. people who identify as Hispanic tend to live in certain areas but are not bound there. Since climate is relevant to all cities, January Minimum Temperature is retained and West Coast is removed. Conducting a new factor analysis after removing Area and West Coast confirms that the remaining variables have uniqueness scores greater than 0.5, as shown below.

Table 5: Final Factor Analysis of Location/Demographic Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	4
Rotation: (unrotated)	Number of params	=	21

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	1.122	0.334	0.639	0.639
Factor 2	0.788	0.330	0.449	1.087
Factor 3	0.458	0.392	0.261	1.348
Factor 4	0.066	0.177	0.038	1.385
Factor 5	-0.111	0.090	-0.063	1.322
Factor 6	-0.200	0.165	-0.114	1.208
Factor 7	-0.366	.	-0.208	1.000

LR test: independent vs. saturated: chi2(21) = 629.86 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Population	0.584	0.223	-0.224	0.016	0.559
Population Density	0.245	0.554	-0.126	0.075	0.612
New Residents	-0.219	0.153	0.363	0.171	0.768

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
African-American	-0.108	0.504	0.062	-0.025	0.730
Hispanic	0.672	-0.188	0.095	0.005	0.505
January Min Temp	0.447	-0.036	0.458	-0.032	0.589
East Coast	-0.103	0.344	0.195	-0.171	0.804

Higher uniqueness values could be obtained by removing East Coast, either Population or Population Density, and either Hispanic Population or January Minimum Temperature, as shown in Table 6 below. Even if all were retained at this point, all would be eliminated during later steps of model refinement. None of the location/demographic variables will survive the process of stepwise removal for inclusion in the parsimonious model. Only Hispanic Population has a significant P-score in the initial model. After the other variables have been eliminated one-by-one during stepwise removal, Hispanic Population loses its significance and is also eliminated.

Table 6: Alternate Factor Analysis of Location/Demographic Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	1
Rotation: (unrotated)	Number of params	=	3

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	0.408	0.485	2.467	2.467
Factor 2	-0.077	0.088	-0.469	1.999
Factor 3	-0.165	.	-0.999	1.000

LR test: independent vs. saturated: chi2(3) = 55.40 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Uniqueness
New Residents	0.326	0.894
African-American	0.368	0.865
Hispanic	-0.408	0.833

Economy

The Economy category includes variables related to employment and income. The correlation matrix reveals a very strong and unsurprising correlation between Poverty and

Median Income, and a substantial correlation between Poverty and Unemployment. Median Income and Unemployment have a moderate correlation to each other.

Table 7: Initial Factor Analysis of Economic Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	3
Rotation: (unrotated)	Number of params	=	10

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	1.947	1.774	0.991	0.991
Factor 2	0.173	0.062	0.088	1.079
Factor 3	0.111	0.168	0.056	1.135
Factor 4	-0.057	0.151	-0.029	1.106
Factor 5	-0.208	.	-0.106	1.000

LR test: independent vs. saturated: chi2(10) = 986.56 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Median Income	-0.778	0.138	0.151	0.352
Gini Index	0.393	-0.155	0.260	0.755
Poverty Rate	0.913	0.034	0.058	0.161
Unemployment	0.581	0.284	-0.037	0.581
Accomm/Food Service	0.126	-0.219	-0.127	0.920

The factor analysis shows that Median Income and Unemployment are strongly related to Poverty in Factor 1. This necessitates a choice between either removing Poverty or removing both Median Income and Unemployment. I chose to retain Median Income and Unemployment since they allow us to consider different aspects of poverty. Conducting a new factor analysis after removing Poverty confirms that the retained variables have uniqueness scores greater than 0.63, as shown in Table 8 below.

Table 8: Final Factor Analysis of Economic Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	2
Rotation: (unrotated)	Number of params	=	6

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	0.757	0.701	1.512	1.512
Factor 2	0.056	0.098	0.112	1.624
Factor 3	-0.042	0.227	-0.085	1.539
Factor 4	-0.270	.	-0.539	1.000

LR test: independent vs. saturated: chi2(6) = 176.01 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Uniqueness
Median Income	-0.603	-0.019	0.636
Gini Index	0.344	0.025	0.881
Unemployment	0.491	-0.117	0.746
Accomm/Food Service	0.184	0.203	0.925

Housing Conditions

The Housing Conditions category includes variables related to housing costs, both rental and ownership, housing scarcity, and overcrowding. Table 9 shows that several of these variables have very low uniqueness values since they reflect closely related characteristics of the underlying demand for housing.

Table 9: Initial Factor Analysis of Housing Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	5
Rotation: (unrotated)	Number of params	=	35

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	3.490	2.681	0.745	0.745
Factor 2	0.809	0.163	0.173	0.918
Factor 3	0.646	0.441	0.138	1.056
Factor 4	0.205	0.193	0.044	1.100
Factor 5	0.012	0.051	0.003	1.103
Factor 6	-0.038	0.005	-0.008	1.094
Factor 7	-0.044	0.152	-0.009	1.085
Factor 8	-0.196	0.006	-0.042	1.043
Factor 9	-0.202	.	-0.043	1.000

LR test: independent vs. saturated: chi2(36) = 3921.13 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Rental Vacancy Rate	-0.378	0.046	0.117	0.216	0.055	0.792
Median Home Value	0.939	0.033	0.009	-0.132	0.049	0.098
Median Rent	0.947	0.237	0.145	0.090	0.046	0.017

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Lower Quartile Rent	0.918	0.295	0.156	0.070	-0.067	0.036
Rent Income Ratio	0.101	-0.265	0.035	0.329	-0.013	0.810
Homeownership	-0.265	0.552	-0.158	0.121	-0.003	0.586
Overcrowded	0.627	-0.527	0.062	0.046	-0.008	0.324
Eviction Rate	-0.470	-0.026	0.481	-0.042	0.008	0.545
Eviction Filing Rate	-0.179	0.096	0.571	-0.040	-0.011	0.631

Median home Value, Median Rent, Lower Quartile Rent, and Overcrowding are all closely related in the first factor. Since Median Home Value has the strongest correlation to homelessness, Overcrowding and Median- and Lower Quartile Rent are removed. Conducting a new factor analysis confirms that the retained variables have uniqueness scores greater than 0.55, as shown in Table 10 below.

Table 10: Final Factor Analysis of Housing Variables

Factor analysis/correlation Number of obs = 624
Method: principal factors Retained factors = 3
Rotation: (unrotated) Number of params = 10

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	0.991	0.851	1.329	1.329
Factor 2	0.140	0.119	0.187	1.516
Factor 3	0.020	0.158	0.027	1.543
Factor 4	-0.138	0.129	-0.185	1.358
Factor 5	-0.267	.	-0.358	1.000

LR test: independent vs. saturated: chi2(10) = 277.84 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Rental Vacancy Rate	0.477	0.041	0.067	0.766
Rent Income Ratio	-0.040	0.216	0.089	0.944
Homeownership	0.262	-0.272	0.042	0.856
Eviction Rate	0.502	0.132	-0.078	0.725
Median Home Value	-0.665	0.010	0.000	0.558

Interventions Category

The interventions category includes independent variables that reflect government policies and the relative extent of government efforts to address poverty, the need for affordable housing, and homelessness. Poverty is included in the factor analysis to demonstrate its relationships to variables in this category.

Table 11: Initial Factor Analysis of Intervention Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	9
Rotation: (unrotated)	Number of params	=	90

Beware: solution is a Heywood case (i.e., invalid or boundary values of uniqueness)

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	3.636	1.671	0.389	0.389
Factor 2	1.965	0.643	0.210	0.599
Factor 3	1.322	0.197	0.142	0.741
Factor 4	1.125	0.216	0.120	0.861
Factor 5	0.909	0.448	0.097	0.958
Factor 6	0.460	0.327	0.049	1.008
Factor 7	0.133	0.082	0.014	1.022
Factor 8	0.051	0.051	0.006	1.027
Factor 9	0.000	0.000	0.000	1.027
Factor 10	0.000	0.014	0.000	1.027
Factor 11	-0.014	0.024	-0.002	1.026
Factor 12	-0.038	0.032	-0.004	1.022
Factor 13	-0.070	0.065	-0.007	1.014
Factor 14	-0.135	.	-0.014	1.000

LR test: independent vs. saturated: chi2(91) = . Prob>chi2 = .

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Poverty Rate	0.664	-0.404	-0.187	-0.312	-0.166	-0.097
Charitable Donations	-0.154	0.296	0.191	0.355	0.172	-0.051
Food Stamps	0.695	-0.340	-0.181	-0.415	-0.197	0.013
Public Housing	0.940	-0.031	0.101	0.206	0.254	0.015
Housing Choice	0.813	0.041	0.059	0.201	0.296	-0.442
Non-Housing Choice	0.861	-0.088	0.119	0.169	0.166	0.416
Rent Control	0.051	0.135	0.118	0.268	0.016	0.028
Counties Per CoC	0.022	-0.029	0.072	0.033	-0.086	0.005
Perm Support Housing	0.394	0.777	-0.297	0.081	-0.376	-0.059
Emergency Shelter	-0.008	-0.636	0.630	0.277	-0.340	0.012
Transitional Housing	-0.371	-0.516	-0.621	0.135	0.437	0.050
Rapid Rehousing	-0.086	0.312	0.534	-0.666	0.408	0.007
HMIS	0.069	0.122	-0.065	0.018	0.102	0.178
CoC Funding per Homeless	0.307	0.427	-0.103	-0.015	-0.040	0.203

Variable	Factor 7	Factor 8	Factor 9	Uniqueness
Poverty Rate	-0.133	0.059	0.000	0.205

Variable	Factor 7	Factor 8	Factor 9	Uniqueness
Charitable Donations	-0.142	-0.020	0.000	0.673
Food Stamps	0.032	-0.011	0.000	0.157
Public Housing	-0.002	-0.017	0.000	-0.001
Housing Choice	0.107	-0.003	0.000	0.000
Non-Housing Choice	-0.098	-0.027	0.000	-0.003
Rent Control	-0.060	0.135	0.000	0.870
Counties Per CoC	-0.009	-0.152	0.000	0.962
Perm Support Housing	-0.059	-0.007	0.001	-0.002
Emergency Shelter	0.081	0.011	0.001	-0.001
Transitional Housing	0.009	-0.007	0.001	-0.001
Rapid Rehousing	-0.024	0.007	0.001	0.000
HMIS	0.132	0.071	0.000	0.911
CoC Funding per Homeless	0.203	-0.004	0.000	0.629

Food Stamps and Public Housing (with its components) are strongly related in Factor 1 along with poverty. Eligibility for Food Stamps and Public Housing depend on Poverty and they are therefore endogenous to Poverty (U.S. Department of Agriculture, 2019; U.S. Department of Housing and Urban Development, 2020a). Previous studies included food stamps and public housing, such as Byrne et al. (2012) and Nisar et al. (2019). These studies found positive associations between public benefits and homelessness, but these findings give a possibly false impression that increased utilization of benefits would increase homelessness, when they probably only reflect the indirect impact of poverty. It is possible that a study could find significant differences between benefit utilization and poverty, perhaps in a study over a longer time period. However, such differences did not appear in this dissertation. This topic is included in the section on opportunities for future research. Food Stamps and all public housing variables are removed.

Permanent Supportive Housing, Emergency Shelter, Transitional Housing, and Rapid Rehousing share a common denominator as components of the CoC housing inventory. Emergency Shelter has the strongest correlation to homelessness. Among the remaining housing inventory variables, Rapid Rehousing has the weakest relationship to Emergency Shelter, as seen in factors 2 and 3 of the pattern matrix above. Emergency Shelter and Rapid Rehousing are retained, while Permanent Supportive Housing and Transitional Housing are removed. Conducting a new factor analysis confirms that the retained variables have uniqueness scores greater than 0.73, as shown in Table 12 below.

Table 12: Final Factor Analysis of Intervention Variables

Factor analysis/correlation	Number of obs	=	624
Method: principal factors	Retained factors	=	4
Rotation: (unrotated)	Number of params	=	26

Factor	Eigen value	Difference	Proportion	Cumulative
Factor 1	0.710	0.210	0.974	0.974
Factor 2	0.499	0.347	0.685	1.659
Factor 3	0.152	0.142	0.209	1.868
Factor 4	0.010	0.061	0.014	1.882
Factor 5	-0.051	0.056	-0.070	1.812
Factor 6	-0.107	0.128	-0.147	1.664
Factor 7	-0.235	0.014	-0.322	1.342
Factor 8	-0.249	.	-0.342	1.000

LR test: independent vs. saturated: chi2(28) = 249.36 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Poverty Rate	-0.439	-0.297	0.059	-0.008	0.716
Charitable Donations	0.377	0.355	0.016	-0.002	0.732
Rent Control	0.123	0.187	0.233	-0.015	0.896
Counties Per CoC	-0.085	0.095	0.010	0.097	0.974
Emergency Shelter	-0.400	0.331	0.040	0.000	0.729
Rapid Rehousing	0.252	-0.083	-0.237	0.002	0.873
HMIS	0.203	-0.158	0.116	-0.004	0.920
CoC Funding per Homeless	0.296	-0.316	0.150	0.026	0.790

CHAPTER V

FINDINGS

This chapter describes the outcome of the regression models including multiple variations of the models for both Category One Homelessness and school-reported Homelessness.

Category One Homelessness

An initial model includes all of the dependent variables that were selected based on the correlation matrix and factor analysis. The overall R-squared score for the model is 0.4981, as shown in Table 13 below. The “Between” R-squared is 0.5363, indicating that the variables account for over fifty-three percent of the variation between CoCs the model, whereas the “Within” R-squared is only 0.1243, indicating that the independent variables account for only twelve percent of the average variation over time. In a longitudinal study, one would normally hope that the “within” R-squared would be higher, since it would mean that changes over time in the independent variables are proven to correspond to changes in the dependent variables. The low “within” R-squared is not surprising since this study was constrained by a relatively short period of three observations, and the changes in independent variables are often modest and may be lower than the probable error in many cases. However, this helps to limit expectations of relationships that may appear stronger without the reduction in overall R-squared due to the low "within" R-squared. Therefore, the longitudinal dimension is useful in demonstrating that some variable relationships are not as strong as a purely cross-sectional study might suggest.

In this initial model, seven variables are significant at the level of 0.05 or better. Hispanic Population, Median Income, Homeownership, Rapid Rehousing, CoC Funding per Homeless, and Drug/ Alcohol Induced Deaths have negative associations with the homeless rate. Median Home Value has a positive association with the homeless rate. Median Income and Median Home Value are both highly significant (P>[z] of <0.001) and easily comparable since they have the same unit of measurement: for every thousand dollars of median home price, the log of homelessness increases by 0.002; for every thousand dollars of median income, the log of homeless rate decreases by .019.

Table 13: Initial Longitudinal Regression of Category One Homelessness

Random-effects GLS regression
Group variable: CoC / Multi-CoC County

R-sq: within	0.124	Number of obs	624
between	0.536	Number of groups	208
overall	0.498		

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Population	-0.003	0.003
Population Density	<0.001	<0.001
New Residents	-0.011	0.012
African-American	-0.003	0.003
Hispanic *	-0.008	0.003
January Min Temp	0.005	0.004
East Coast	-0.055	0.075
Median Income ***	-0.019	0.004
Gini Index	0.007	0.009
Unemployment	0.012	0.009

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Accomm/ Food Service	0.016	0.015
Rental Vacancy Rate	-0.009	0.007
Median Home Value ***	0.002	<0.001
Rent-Income Ratio	0.003	0.004
Home Ownership **	-0.016	0.005
Eviction Rate	0.005	0.010
Charitable Giving	-0.075	0.073
Rent Control	-0.062	0.100
Counties Per CoC	-0.005	0.039
Emergency Shelter	0.001	0.002
Rapid Rehousing **	-0.005	0.002
HMIS Participation Rate	-0.001	<0.001
CoC Funding per Homeless **	-0.022	0.007
Drug / Alcohol Deaths *	-0.003	0.001
Constant (Intercept) ***	4.157	0.649

* p<0.05, ** p<0.01, *** p<0.001

A Breusch-Pagan Lagrange Multiplier (LM) test for random effects rejects the null hypothesis that OLS residuals do not contain individual specific error components, which validates that a longitudinal random effects panel model is more appropriate than a simple OLS regression. The P-value of the Chi-squared test statistic is less than 0.001.

Refinement

In order to refine the model, variables are removed in stepwise regression using backwards removal – (lowest Z value first). The order of removal is detailed below with a scree plot in Figure 5 to illustrate the effect of each removal on the R-Squared characteristic. As variables are removed, the R-squared decreases in some cases, as one would normally expect for a multivariate regression. R-squared increases when certain variables are removed, an effect of the multi-dimensional nature of random effects linear models.

Table 14: Stepwise Removal

Variables	R-squared	Wald Chi2	Lowest Z score(removed)	Effect on R-squared
24	0.4981	270.28	Counties Per CoC (-0.12)	0.0003
23	0.4984	271.41	Eviction Rate (0.49)	0.0014
22	0.4998	271.12	Rent Control (-0.64)	-0.0015
21	0.4983	271.09	GRAPI (0.60)	-0.0003
20	0.498	271.28	African American (-0.68)	-0.0009
19	0.4971	271.19	Gini Indiex (0.67)	-0.0011
18	0.496	270.89	Emergency Shelter (0.65)	-0.0038
17	0.4922	268.92	East Coast (-0.94)	0.0027
16	0.4949	268.78	Population (-0.84)	0.0006
15	0.4955	269.41	New Residents (-0.76)	-0.0004
14	0.4951	269.53	January Minimum Temperature (0.91)	0.0039
13	0.499	268.33	Populatio Density (0.96)	0.0036
12	0.5026	267.19	Charitable Contributions (-0.86)	-0.0011
11	0.5015	266.91	HMIS Usage (-1.26)	0.001
10	0.5025	265.84	Accommodations / Food Service (1.34)	-0.001
9	0.5015	264.23	Rental Vacancy Rate (-1.15)	-0.0019
8	0.4996	263.09	Unemployment (1.32)	-0.0054
7	0.4942	260.53	Hispanic Population (-2.08)	-0.0202
6	0.474	252.1	Drug/ Alcohol Induced Deaths (-2.07)	0.0127
5	0.4867	242.58	All IVs have P>|z| of 0.000	n/a

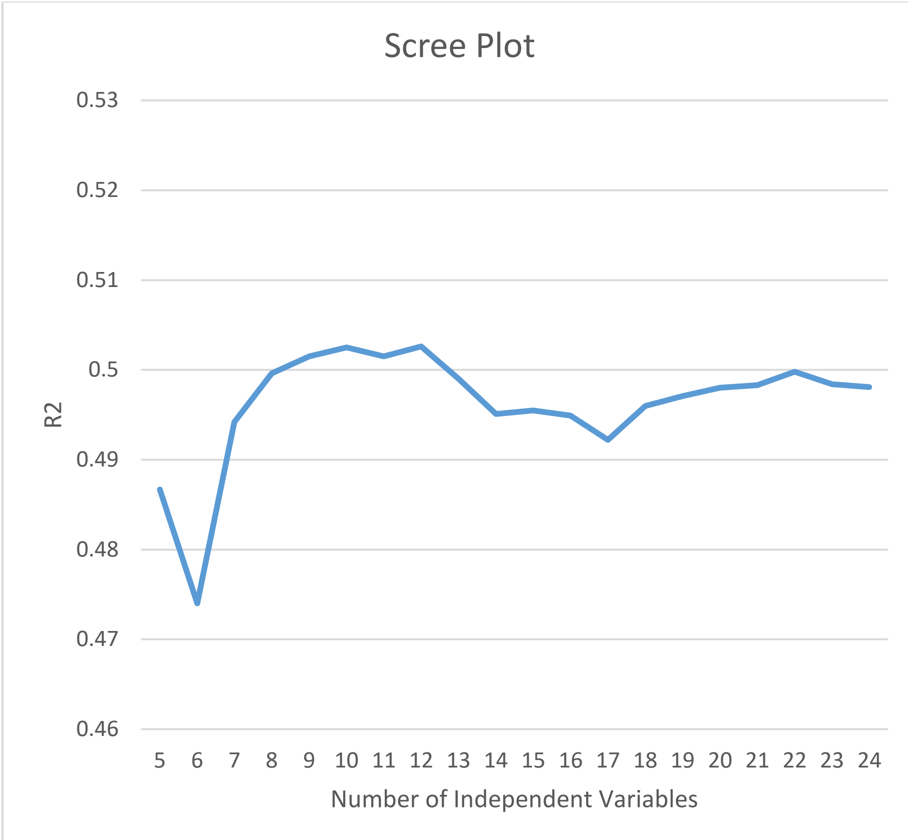

Figure 5: Scree Plot

Parsimonious Model

Stepwise regression reveals the following parsimonious model of five variables. The parsimonious model provides a more elegant solution with only a minor reduction in predictive power. The overall R-squared for the parsimonious model is 0.4867 versus 0.4981, a reduction of slightly more than one percent. One of the goals of this dissertation is to provide a practical tool for planners to forecast homeless rates. The parsimonious tool requires a user to research trends in five variables rather than twenty-four. Furthermore, all of the independent variables in the parsimonious model are highly significant, which makes its policy implications more credible.

Table 15: Parsimonious Model of Category One Homelessness

Random-effects GLS regression
Group variable: CoC / Multi-CoC County

R-sq: within	0.090	Number of obs	624
between	0.528	Number of groups	208
overall	0.487		

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.024	0.003
Median Home Value ***	0.003	<0.001
Home Ownership ***	-0.013	0.004
Rapid Rehousing ***	-0.006	0.001
CoC Funding per Homeless ***	-0.027	0.006
Constant (Intercept) ***	4.535	0.216

* p<0.05, ** p<0.01, *** p<0.001

Alternate Gini Model

An alternate regression equation demonstrates the role of the Gini Index, a measure of income inequality, in Category One homelessness. The parsimonious model above was created through a systematic process of elimination that yields a combination of variables that are significant while retaining a relatively high R-squared to maximize the predictive usefulness of the model. One side-effect of this combination of variables is that it obscures the effect of income inequality. If the Gini Index is included but Home Ownership is removed, the Gini Index is demonstrated to have a significant positive association with homelessness at P>[z] of 0.047. If Gini Index is added but both homeownership and median income are removed, Gini Index has a more significant positive association with homelessness at P>[z] of less than 0.001 as shown in Table 16 below. The R-squared of this model is 0.2613 meaning that it is less useful as a forecasting tool than the parsimonious model at 0.4867. However, the relationship of income inequality to Category One homelessness is worth consideration to examine the causes of homelessness from a different perspective for broader understanding.

Table 16: Alternate Gini Model of Category One Homelessness

Random-effects GLS regression

Group variable: CoC / Multi-CoC County

R-sq: within	0.077	Number of obs	624
between	0.294	Number of groups	208
overall	0.261		

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Gini Index ***	0.037	0.008
Median Home Value **	<0.001	<0.001
Rapid Rehousing ***	-0.008	0.001
CoC Funding per Homeless ***	-0.631	0.180
Constant (Intercept) *	1.021	0.395

* p<0.05, ** p<0.01, *** p<0.001

Non-Longitudinal Model of Category One Homelessness

The variables of the parsimonious model are reproduced in a conventional linear ordinary least squares regression as shown in Table 17. The primary purpose of this step is to enable the model to be indexed by state in the following step, in order to observe the effect of state-specific effects. This is a pooled cross-sectional model since it still includes multiple observations from each CoC. The parsimonious model has a similar coefficient of determination (R-squared) in both methods of regression (0.4867 vs 0.4971, a difference of 0.0104). The Rapid Rehousing variable loses significance (P>[Z] of 0.071) in the conventional model without a longitudinal dimension.

Table 17: Non-longitudinal Model of Category One Homelessness

Ordinary Least Squares Regression

Group variable: CoC / Multi-CoC County

R-squared	0.077	Number of obs	624
Adjusted R-Squared	0.294	F (5, 618)	122.20
		Prob > F	<0.000

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.027	0.002
Median Home Value ***	0.003	<0.001
Home Ownership ***	-0.015	0.003

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Rapid Rehousing	-0.004	0.002
CoC Funding per Homeless ***	-0.050	0.005
Constant (Intercept) ***	4.794	0.151

* p<0.05, ** p<0.01, *** p<0.001

Category One Homelessness Indexed by State

The following version of the conventional parsimonious model (pooled cross sectional ordinary least squares) in Table 18 is indexed by state. Indexing by state helps to reveal differences between local areas that are not explained by the variables in the parsimonious model. The baseline state is Kentucky, because its coefficient is closest to the mean coefficient. Washington DC is the only state or territory level jurisdiction to have a coefficient greater than one, positive or negative. The Adjusted R-squared for the indexed model is 0.5928 compared to 0.4931, indicating that approximately 0.098 (9.8%) of the difference between observations can be explained by unknown variables at the state level.

Table 18: Category One Model Indexed by State

Ordinary Least Squares Regression

Group variable: CoC / Multi-CoC County

R-squared	0.621	Number of obs	624
Adjusted R-Squared	0.593	F (43, 580)	22.09
		Prob > F	<0.000

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.026	0.003
Median Home Value ***	0.003	<0.001
Home Ownership ***	-0.014	0.003
Rapid Rehousing **	-0.005	0.002
CoC Funding per Homeless ***	-0.054	0.006
State		
Alaska **	0.825	0.306

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Alabama **	-0.747	0.216
Arizona	-0.301	0.248
California	-0.218	0.190
Colorado	-0.054	0.304
Connecticut	-0.036	0.253
District of Columbia **	1.067	0.312
Delaware	-0.263	0.307
Florida	-0.304	0.189
Georgia	-0.386	0.208
Hawaii	0.156	0.316
Iowa	0.209	0.304
Idaho	-0.142	0.305
Illinois *	-0.422	0.194
Indiana	-0.420	0.303
Kansas *	-0.471	0.227
Louisiana	-0.243	0.305
Massachusetts	0.182	0.199
Maryland	-0.041	0.202
Michigan	-0.304	0.189
Minnesota	0.139	0.228
Missouri	-0.329	0.226
North Carolina **	-0.546	0.194
Nebraska	0.075	0.248
New Hampshire	0.260	0.305
New Jersey *	-0.429	0.189
Nevada	-0.077	0.248
New York	0.180	0.201
Ohio	-0.158	0.199
Oklahoma **	-0.659	0.248
Oregon	-0.002	0.211
Pennsylvania	-0.272	0.191
Tennessee	-0.248	0.215
Texas	-0.406	0.207
Utah	0.042	0.304
Virginia *	-0.456	0.214
Washington	0.104	0.210
Wisconsin	-0.372	0.226
Constant (Intercept) ***	5.100	0.225

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Outliers

Since the dependent variable of homeless rate is skewed and heteroskedastic, a model without outliers is used to ensure that the inclusion of outliers does not distort the relationships of the independent variables as predictors of homelessness for more typical CoCs. To consider the effect of outliers, this step removes observations that are more than three standard deviations from the mean homeless rate. These twenty observations are above 69.26321 homeless per 10,000. No observations are three standard deviations below the mean due to skew. A list of outlier observations is provided below in Table 19.

Table 19: Outlier Observations

Continuum of Care	Year	Homeless rate
Boston CoC	2014	79
	2016	80
	2018	78
District of Columbia CoC	2014	120
	2016	124
	2018	99
Imperial County CoC	2018	82
New York City CoC	2014	81
	2016	86
	2018	91
Pasco County CoC	2014	71
San Francisco CoC	2014	77
	2016	81
	2018	78
San Luis Obispo County CoC	2014	86
Santa Rosa, Petaluma/Sonoma County CoC	2014	86
Springfield/Hampden County CoC	2018	72
Watsonville/Santa Cruz City & County CoC	2014	131
	2016	71
	2018	84

The exclusion of outliers does not seem to have any important effect on the model of Category One homelessness. The overall R-squared of the parsimonious model is lower at 0.4111. Variables in the parsimonious model without outliers remain significant and have similar coefficients. The output of the parsimonious model without outliers is shown below in Table 20.

Table 20: Category One Parsimonious Model without Outliers

Random-effects GLS regression

Group variable: CoC / Multi-CoC County

R-sq: within	0.118	Number of obs	604
between	0.447	Number of groups	203
overall	0.411		

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.023	0.003
Median Home Value ***	0.002	<0.001
Home Ownership **	-0.011	0.004
Rapid Rehousing ***	-0.005	0.001
CoC Funding per Homeless ***	-0.026	0.006
Constant (Intercept) ***	4.383	0.218

* p<0.05, ** p<0.01, *** p<0.001

Without the outlier observations, the more extensive model of Category One has more changes. The overall R-squared is decreased from 0.4982 to 0.4442. The independent variable of drug /acohol induced deaths loses significance. The coefficient of the non-significant variable of population density which was positive with outliers becomes negative without. The more extensive model of Category One Homelessness without outlier observations is shown in Table 21 below.

Table 21: Category One Full Model without Outliers

Random-effects GLS regression

Group variable: CoC / Multi-CoC County

R-sq: within	0.1499	Number of obs	624
between	0.536	Number of groups	208

overall	0.498

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Population	<0.001	0.004
Population Density	<0.001	<0.001
New Residents	-0.014	0.011
African-American	-0.004	0.003
Hispanic **	-0.010	0.003
January Min Temp	0.005	0.004
East Coast	-0.044	0.073
Median Income ***	-0.017	0.004
Gini Index	0.003	0.009
Unemployment	0.015	0.009
Accomm/ Food Service	0.011	0.015
Rental Vacancy Rate	-0.004	0.006
Median Home Value ***	0.002	<0.001
Rent-Income Ratio	0.004	0.004
Home Ownership ***	-0.022	0.005
Eviction Rate	0.007	0.010
Charitable Giving	-0.070	0.072
Rent Control	-0.064	0.097
Counties Per CoC	-0.013	0.038
Emergency Shelter	0.002	0.002
Rapid Rehousing **	-0.004	0.001
HMIS Participation Rate	<0.001	<0.001
CoC Funding per Homeless **	-0.019	0.007
Drug / Alcohol Deaths	-0.002	0.001
Constant (Intercept) ***	4.539	0.622

School Defined Homelessness

To analyze school-determined homelessness, the same process described above for Category One homelessness was repeated, using factor analysis to reduce the likelihood of multicollinearity between similar variables. Notably, in the Housing category median rent was retained instead of median home value, since median rent has a higher correlation to school-reported homelessness. The model for school-reported homelessness has less predictive value than the model for Category One homelessness. The R-squared for the model of school-reported homelessness is only 0.358, predicting less than thirty-six percent of the variation between CoC areas and over time. The outcome of this process is the model shown in Table 22 below:

Table 22: Initial Model for School Homelessness

Random-effects GLS regression

Group variable: CoC / Multi-CoC County

R-sq: within	0.085	Number of obs	624
between	0.378	Number of groups	208
overall	0.358		

Log of School Homeless Rate	Coef.	Std. Err.
Population	0.001	0.004
Population Density	0.000	0.000
New Residents	0.017	0.012
African-American	0.001	0.004
Hispanic **	0.012	0.004
January Min Temp	0.006	0.004
East Coast ***	-0.462	0.092
Median Income	-0.009	0.005
Gini Index *	-0.023	0.009
Unemployment	-0.009	0.009
Accomm/ Food Service	0.015	0.018
Rental Vacancy Rate	-0.001	0.007
Median Home Value	0.136	0.266
Rent-Income Ratio	-0.001	0.004
Home Ownership	-0.004	0.006
Eviction Rate	0.013	0.011
Charitable Giving *	0.141	0.075
Rent Control *	-0.299	0.113
Counties Per CoC	0.002	0.049
Emergency Shelter	-0.0009	0.002
Rapid Rehousing	-0.002	0.001
HMIS Participation Rate	-0.0003	0.001
CoC Funding per Homeless	<0.001	0.007
Drug / Alcohol Deaths ***	0.008	0.001
Constant (Intercept) ***	4.729	0.688

Parsimonious Model of school-reported Homelessness

Following the same pattern that was used for Category One homelessness, stepwise removal refines the model until only significant independent variables remain. The resulting parsimonious model includes four variables that predict school-reported homelessness: Median Income, Median Rent, Rent Control, and Drug/ Alcohol Induced Deaths. The model R-squared is a modest 0.177.

Table 23: Parsimonious Model of School Homelessness

Random-effects GLS regression

Group variable: CoC / Multi-CoC County

R-sq: within	0.045	Number of obs	624
between	0.188	Number of groups	208
overall	0.177		

Log of School Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.013	0.003
Median Rent **	0.626	0.207
Rent Control ***	-0.476	0.111
Drug / Alcohol Deaths ***	0.007	0.001
Constant (Intercept) ***	3.458	0.138

Non-Longitudinal Model of school-reported Homelessness

Following the same process used for Category One Homelessness, the school-reported homelessness model is converted into a conventional non-longitudinal OLS regression. The results are shown below. The R-squared for the non-longitudinal OLS regression is higher than the panel data regression.

Three of the independent variables remain highly significant, but the variable of Drug/ Alcohol Induced Deaths loses its significance, with a T-value of only -0.72 in the non-longitudinal model. The reduction in significance in Drug/ Alcohol Induced Deaths is reminiscent of the Rapid rehousing variable when it was converted to a non-longitudinal model for Category One homelessness. Like rapid rehousing, Drug/ Alcohol Induced Deaths changed significantly over time (a correlation of 0.3881 with the year variable), so it seems reasonable that Drug/ Alcohol Induced Deaths should lose significance in a model where time is not considered.

Table 24: Non-longitudinal model of school homelessness

Ordinary Least Squares Regression

Group variable: CoC / Multi-CoC County

R-squared	0.222	Number of obs	624
Adjusted R-Squared	0.217	F (4, 619)	44.06
		Prob > F	<0.000

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.026	0.003
Median Rent ***	1.173	0.166
Rent Control ***	-0.647	0.083
Drug / Alcohol Deaths	-0.002	0.002
Constant (Intercept) ***	3.940	0.133

* p<0.05, ** p<0.01, *** p<0.001

School-reported Homelessness Indexed by State

One of the purposes of converting the model to a non-longitudinal form is to enable the model to be indexed by state. Indexing by state reveals the relative importance of state-level differences between communities. States are indexed with Florida as the baseline, as Florida's coefficient was closest to the mean.

The regression indexed by state has an R-squared of 0.5641, 0.3425 higher than the non-indexed regression of 0.2216. In other words, state-level differences account for thirty-four percent of the differences among observations. State-level differences explain a larger portion of the variation than is explained by the independent variables in the model.

Table 25: School homelessness model indexed by state

Ordinary Least Squares Regression

Group variable: CoC / Multi-CoC County

R-squared	0.564	Number of obs	624
Adjusted R-Squared	0.533	F (42, 581)	17.90
		Prob > F	<0.000

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.012	0.003
Median Rent	0.033	0.197
Rent Control	-0.191	0.107
Drug / Alcohol Deaths **	0.006	0.002
State		
Alaska ***	1.109	0.297
Alabama	-0.257	0.164
Arizona	-0.096	0.213
California ***	0.701	0.092
Colorado	-0.146	0.293
Connecticut ***	-1.167	0.217
District of Columbia *	0.744	0.314
Delaware	0.118	0.294
Georgia	-0.174	0.144
Hawaii	-0.126	0.301
Iowa	0.052	0.300
Idaho	0.013	0.296
Illinois	0.025	0.123
Indiana	0.149	0.294
Kansas	0.104	0.189
Kentucky	0.222	0.219
Louisiana **	-0.857	0.294
Massachusetts	-0.097	0.127
Maryland	-0.215	0.137
Michigan	-0.101	0.112
Minnesota	0.142	0.187
Missouri ***	0.726	0.182
North Carolina *	-0.291	0.121
Nebraska **	-0.590	0.221
New Hampshire	0.104	0.300
New Jersey ***	-0.903	0.150
Nevada **	0.618	0.213
New York	0.182	0.145

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Ohio **	-0.416	0.136
Oklahoma	-0.286	0.217
Oregon ***	0.595	0.145
Pennsylvania ***	-0.645	0.115
Tennessee *	-0.418	0.161
Texas	0.217	0.147
Utah	0.536	0.297
Virginia	-0.209	0.155
Washington **	0.436	0.147
Wisconsin *	0.392	0.183
Constant (Intercept) ***	4.045	0.144

* p<0.05, ** p<0.01, *** p<0.001

Interpolated Data

In order to determine whether interpolation may have distorted the outcome, it was necessary to see whether interpolation is a significant variable. A variable named "C3Imputed" was created, with a value of 1 for observations with imputed (interpolated) school-reported homeless rates, and a value of 0 if not imputed. When the regression was run with C3Imputed as an additional variable, C3Imputed was significant with a P>[t] of 0.001. However, the distribution of CoCs with interpolated school homeless data was not random. They were clustered in specific Northern and Western states that have more flexible policies for establishing school system boundaries. A table of states by CoCs with interpolated school system data is provided below.

Table 26: States with Interpolated School Homeless Data

State	Total CoCs	CoCs Interpolated	Percent of CoCs Interpolated
California	28	6	21%
Hawaii	1	1	100%
Idaho	1	1	100%
Illinois	10	5	50%
Kansas	3	2	67%

State	Total CoCs	CoCs Interpolated	Percent of CoCs Interpolated
Massachusetts	8	1	13%
Michigan	15	8	53%
Minnesota	3	2	67%
Missouri	3	1	33%
Nebraska	2	1	50%
New Hampshire	1	1	100%
New York	7	3	43%
Ohio	8	2	25%
Oregon	5	3	60%
Pennsylvania	14	2	14%
Texas	5	1	20%
Washington	2	1	50%
Wisconsin	3	2	67%

Therefore the significance of the C3Imputed variable is likely to reflect the differences of the states with interpolated-data COCs. When the regression was recalculated with the C3Imputed variable but indexed by state, the C3Imputed variable lost significance, indicating that the CoCs with interpolated school homeless data were not significantly different than non-interpolated CoCs in the same states.

Table 27: Test of Interpolated School Homeless Data

Ordinary Least Squares Regression

Group variable: CoC / Multi-CoC County

R-squared	0.565	Number of obs	624
Adjusted R-Squared	0.532	F (43, 580)	17.90
		Prob > F	<0.000

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
Median Income ***	-0.012	0.003
Median Rent	0.020	0.198
Rent Control	-0.195	0.107
Drug / Alcohol Deaths **	0.006	0.002
C3Imputed	-0.042	0.061
State		
Alaska ***	1.111	0.297
Alabama	-0.260	0.164
Arizona	-0.097	0.213

Log of Cat 1 Homeless Rate	Coef.	Std. Err.
California ***	0.714	0.094
Colorado	-0.146	0.294
Connecticut ***	-1.164	0.218
District of Columbia *	0.753	0.314
Delaware	0.118	0.294
Georgia	-0.175	0.144
Hawaii	-0.077	0.309
Iowa	0.049	0.300
Idaho	0.053	0.301
Illinois	0.044	0.126
Indiana	0.148	0.294
Kansas	0.129	0.193
Kentucky	0.220	0.220
Louisiana **	-0.857	0.294
Massachusetts	-0.090	0.127
Maryland	-0.211	0.137
Michigan	-0.081	0.116
Minnesota	0.169	0.191
Missouri ***	0.739	0.183
North Carolina *	-0.293	0.121
Nebraska *	-0.573	0.223
New Hampshire	0.148	0.307
New Jersey ***	-0.897	0.150
Nevada **	0.618	0.213
New York	0.203	0.148
Ohio **	-0.408	0.137
Oklahoma	-0.289	0.217
Oregon ***	0.620	0.150
Pennsylvania ***	-0.640	0.115
Tennessee *	-0.419	0.161
Texas	0.224	0.147
Utah	0.535	0.297
Virginia	-0.204	0.155
Washington **	0.445	0.147
Wisconsin *	0.418	0.187
Constant (Intercept) ***	4.059	0.146

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

CHAPTER VI

DISCUSSION OF FINDINGS

As described in the introduction, this dissertation has two primary purposes. The first is to provide a practical tool that will enable local planners to anticipate changes in the homeless populations of their communities in order to allocate resources more effectively. The second purpose is to contribute to the theoretical debate about the causes of homelessness.

The outcome of this research yielded a useful model for predicting changes in Category One homelessness in a community, and shed light on several issues in the theoretical debate over homelessness. The findings of this dissertation support the arguments that government interventions can be successful in reducing homelessness and that homelessness is increased by a shortage of affordable housing. Furthermore, in the most expensive communities there is a higher ratio of extreme Category One homelessness relative to the milder form of school-reported homelessness.

Practical Model

For Category One homelessness, this dissertation provides a parsimonious model that can predict the Category One homeless population of a continuum of care with reasonable accuracy. As a straightforward linear model, it can be calculated with relative ease by multiplying the value of each variable by its coefficient, adding the constant, and then calculating the exponent. The parsimonious model yields predicted homeless rates per ten thousands with a median absolute difference of 3.702 between predicted and actual values, and a mean absolute difference of 6.879. The mean difference is higher than the median due to the skewing effect of outliers and heteroscedasticity.

One might reasonably question the usefulness of this model for prediction based on whether the input data for the practical model can be realistically obtained in time to calculate a change in the rate of homelessness before it happens. Certainly, the official census data from the prior year will not be available until after the point-in-time count for the dependent year has been conducted. However, local planners can observe longer term trends and economic changes to estimate their effects on the homeless population. For example, the Coronavirus pandemic struck as I was finishing this dissertation, impacting the economy (Long & Fowers, 2020). What would be the change to the local rate of homelessness in Louisville, Kentucky if unemployment rose to the predicted twenty percent? (Lee, 2020). Louisville's current homeless rate was 12 per 10,000, and the unemployment rate was 3.9 percent. In the full model of Category One homelessness, the coefficient for unemployment is 0.012. Multiplying a predicted increase of 16.9 percent unemployment by 0.012 and adding it to 2.485, the natural log of 12, results in a natural log of 2.688, the exponent of which is a homeless rate of 14.7. If the Louisville homeless rate increased from 12 to 14.7 per ten thousand with a population slightly over 771,000, then the homeless population of would increase by approximately 208 people. This would be useful information for the city government and local continuum of care to plan the number of additional emergency shelter beds and rehousing resources that would be needed.

This dissertation also provides a predictive model for school-reported homeless rates that shows significant relationships for several independent variables, but the equation accounts for less than a quarter of the overall variation in school-reported homeless rates. The school-reported homelessness model provides some insights into the conditions that contribute to the broader forms of homelessness, but it has less predictive power for use as a practical tool for planning.

Implications of the Category One Homelessness Models

The GLS random effects linear models yield five significant predictors of Category One homelessness: median income, median home value, home ownership, rapid rehousing, and continuum of care funding. Each of these variables is considered below.

Median Income. Higher median income predicts lower rates of Category One homelessness. Many of the higher income CoCs have high rates of homelessness, but their high homelessness can be explained by other independent variables such as median home value, which are also positively correlated with median income. Median income has only an inconsequential correlation of -0.049 with homelessness, but once the regression equation separates the impact of median income from that of housing costs, the effect of median income is revealed. Ji (2006), Raphael (2010), and Byrne et al. (2012) did not consider median income, but all found a strong association between the closely related variable of poverty and homelessness. It seems reasonable that homelessness is lower in communities with lower poverty and higher median income, all other things being equal, but as the following variable of median home value illustrates, all things are rarely equal.

Median Home Value. Median home value has a strong 0.7451 correlation with median income but has the opposite effect on homelessness. As incomes rise, home values tend to rise with them. Whether home values rise faster or slower than incomes will determine whether homelessness increases or decreases. Numerous previous studies have found associations between housing costs and Category One homelessness but have operationalized housing costs using median rent rather than median home value (as discussed in the median rent section for school-reported homelessness below). It is interesting that this dissertation found median home value to be a more significant homelessness predictor than rent, since one might assume that lower income people are at greater risk of homelessness and also more likely to rent instead of own their homes. Median home value may be a better predictor because it better reflects the overall underlying housing market, upon which rent levels also depend.

Homeownership. In simplest terms, more people owning homes means that fewer people will be homeless. Homeownership reflects affordability and is thus partly a composite of income and home values, but including homeownership along with income and home values improves the model's predictive value. There must therefore be aspects of homeownership in a community that are not entirely dependent on incomes and home values. This could be a reflection of other housing costs beyond home value, such as utility costs and property taxes. The difference in homeownership could also be a proxy measure of deliberate interventions to encourage homeownership or to enable homeowners to retain their homes. The negative relationship of homeownership to homelessness confirms findings of Byrne et al. (2012) and Nisar et al. (2019).

Rapid Rehousing. Category One homeless rates are lower in communities that devote a larger share of their resources towards rapid rehousing programs. This finding was anticipated in the dissertation proposal and is addressed below under Hypothesis Four.

CoC Funding Rate. Category One Homeless rates are lower in communities that received more funding to reduce homelessness relative to the sizes of their homeless populations. The significance of this variable demonstrates that government intervention can make a difference and that policies matter. A greater government investment in addressing homelessness can reduce the number of homeless. CoCs that are more competitive in meeting HUD standards tend to have lower rates of homelessness.

One could reasonably suspect this variable of endogeneity, since the dependent variable of homelessness is the denominator of the ratio. However, the homeless number used to calculate the CoC funding rate is from two years prior to the dependent variable. If homelessness funding were awarded based on population, then as the denominator of homelessness decreased, so the ratio of funding to homelessness would increase. CoC funding is not, however, awarded based on the size of a city's population. It is competitively awarded, partly based on need but partly on the CoCs performance and compliance with HUD priorities (U.S. Department of Housing and Urban Development, 2019b). If CoC funding were entirely based on need, then all CoCs would have the same value for CoC funding per homeless. The difference in this value must then reflect the other considerations for funding: performance and compliance with HUD priorities. Higher funding per homeless thus becomes a proxy measure for the efficacy of a CoC's interventions.

Funding also increases the resources to enable a CoC to further reduce homelessness; though this is not without controversy. This dissertation's finding that greater proportional CoC funding predicts lower rates of homelessness confirms the conclusions of Moulton (2013), but directly contradicts the conclusions of Early (1998) and Lucas (2017). These studies operationalized variables differently and used different time periods and datasets than this dissertation. Moulton's primary conclusion linked new CoC project funding to reduced chronic homelessness. While Moulton also found an association between new project funding and lower total homelessness, it was not statistically significant. Early (1998) found a positive correlation between the number of homeless and service "quality" as measured by spending per shelter bed. Lucas included multiple sources of federal funding and calculated federal funding relative to total population rather than to the homeless population.

Implications of the School-Reported Homelessness Models

The R-squared of the models to predict school-reported homelessness are lower than the models for Category One homelessness, but the school defined models still reveal four significant variables that help to explain the variations in homelessness among communities: median income, median rent, rent control, and Drug/ Alcohol Induced Deaths. Each is considered below.

Median Income. Median income has a significant effect on both Category One and school-reported homelessness, although the effect of income on school-reported homelessness is lower, with a coefficient of.007 on the log of the school-reported homeless rate for every thousand dollars of income, compared to a coefficient of.02 on the log of the Category One homeless rate.

Median Rent. Whereas median home value is a better predictor of Category One homelessness, median rent is a better predictor of school-reported homelessness. Both home value and rent are reflections of housing costs. School-reported homelessness, as with Category One homelessness, depends on housing affordability: the difference between income and housing costs. In both cases, the regression equations separate the relationships of income and housing costs to reveal how they combine to determine homelessness. The positive relationship of median rent to homelessness confirms findings of Raphael (2010), Byrne et al. (2012), and Nisar et al. (2019).

Rent Control. There is a demonstrable relationship between the presence of rent control and lower school-reported homelessness. As discussed in the literature review, the impact of rent control on homelessness was the focus of the first study to compare cities' homeless populations: Tucker's 1987 article in *National Review*. Tucker blamed rent control for increased homelessness, a claim disputed by Quigley (1990) and

Appelbaum et al. (1991). If Tucker's theory were correct, then communities with rent control would have higher homelessness than other communities with the same median rent, as reflected in a positive coefficient for the rent control variable. Tucker's theory would be refuted if the rent control variable did not have statistical significance. Instead the model reveals that communities with rent control ordinances have lower school-reported homeless rates than communities without rent control, even if they had the same median rent. Not only does this refute Tucker's original claim, it might indicate that rent control ordinances are a proxy measure for local governments' willingness to use their power in other ways to reduce poverty and homelessness.

Drug/ Alcohol Induced Deaths. Drug/ Alcohol Induced Deaths are indicative of the extent of substance abuse in a community. Substance abuse has long been associated with homelessness, although the causal relationships are debatable. Does substance abuse lead to homelessness, or vice versa, or are both homelessness and substance abuse caused by other problems? (Johnson et al., 1997; Johnson & Chamberlain, 2008). Whether substance abuse contributes to homelessness or reflects it, this study finds that Drug/ Alcohol Induced Deaths help to predict the extent of homelessness in the following year. The rate of Drug/ Alcohol Induced Deaths was a significant predictor in all of the models for school defined homelessness. The rate of Drug/ Alcohol Induced Deaths was also a significant but negative predictor of Category One homelessness in the initial model, although it did not survive the refinement process for inclusion in the parsimonious model. Its elimination during refinement in combination with other variables perhaps indicates that substance abuse cannot be neatly untangled from other societal problems.

Hypotheses

This section addresses each of the original research questions posed in the initial dissertation proposal.

HYPOTHESIS ONE: A city's availability of affordable housing corresponds to a larger ratio of the school-reported homeless population to the Category One homeless population

This dissertation demonstrates that the ratio of Category One homelessness to school-reported homelessness is higher in less-affordable cities. In most cities, the school-reported homeless rate is higher than the Category One homeless rate. As cities get more expensive, the ratio of school-reported to Category One homelessness narrows. In the most expensive cities, the Category One homeless outnumber the school-reported homeless, as shown in Figure 33. In more expensive cities, lower-income families can only afford small housing units, and tend to be too overcrowded to allow "Category Three" homeless friends or family to stay with them. In more expensive cities, many of those who would otherwise "double up" must either move away or be forced into more extreme Category One homelessness. The relationship between housing price and overcrowding is shown in Figure 34.

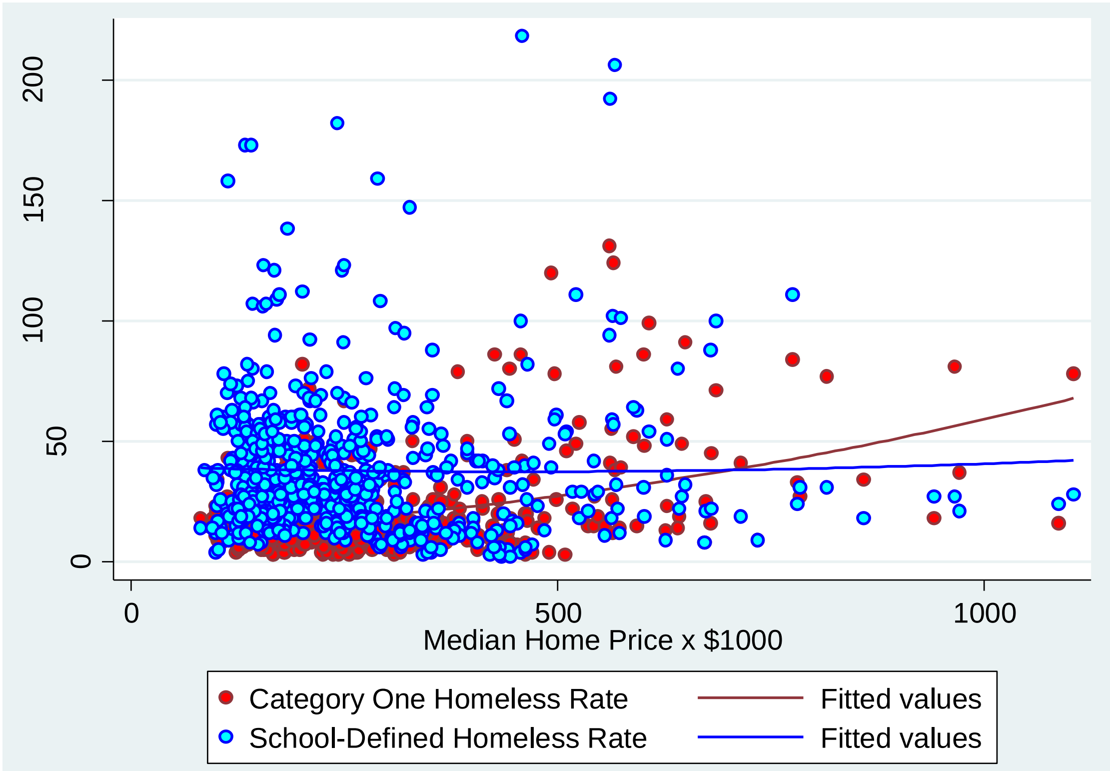

Figure 6: Scatterplot: Median Home Price v Homeless rate

Figure 7: Median Home Price v Overcrowding

HYPOTHESIS TWO: A city's percentage of employment in accommodations/food service corresponds to its Category One homeless population.

The determination of Hypothesis Two is inconclusive. Accommodations/food service has a correlation of 0.1548 with Category One homelessness. According to the initial model, each percentage point of employment in accommodations/food service increases the natural log of the rate of Category One homelessness by.0165. However, the p-value of the relationship is an insignificant 0.283. It seemed plausible that a larger share of the poorest and most unstable employment sector would contribute to homelessness, but the data in this dissertation are unable to validate this claim definitively. The effect of a higher share of employment in the accommodations/food service sector on homelessness may occur indirectly by lowering a community's median income.

HYPOTHESIS THREE: A city's percentage of HMIS (Homeless Management Information System) participation has a negative correlation to the size of its Category One homeless participation

HUD strongly encourages homeless providers to share data using Homeless Management Information Systems ("HMIS"), arguing that it helps to coordinate resources to serve the homeless more effectively. It therefore seemed a reasonable hypothesis to test whether data demonstrate that more widespread use of HMIS predicts lower rates of homelessness. However, the outcome of this hypothesis is inconclusive. HMIS has an insignificant -0.007 correlation to Category One homelessness. When considered along with the other variables in the initial longitudinal model, each percentage point of HMIS usage in a CoC has a -.001209 coefficient with the rate of Category One homelessness.

The p-score is 0.164, not a conclusive level of significance. HMIS usage does not survive the refinement process for inclusion in the parsimonious model. The model's overall R-squared improves by 0.001 when HMIS is removed. If HMIS usage has an effect on homeless rates, it may be reflected indirectly through the variable of CoC funding.

HYPOTHESIS FOUR: A city's higher ratio of rapid-rehousing beds (relative to shelter or permanent supportive housing beds) corresponds to a lower Category One homeless rate.

An important finding of this study is that more rapid rehousing is a predictor of lower homelessness. Specifically, each percentage point of total CoC-funded beds designated as rapid rehousing predicts lower homelessness with a coefficient of 0.005 to the log of the Category One homeless rate per ten thousand residents (coefficient of 0.006 in the parsimonious model).

One explanation for the success of "Housing First" is based on Maslow's famous hierarchy of needs, according to which a person's more basic needs must normally be met before it will be possible to motivate them to meet higher needs (Maslow, 1943). The previous linear model required participants to comply with behavioral requirements based on higher needs before it would provide them with the more basic need of reliable shelter. This expectation defies the logic of Maslow's hierarchy. "Individuals who are homeless face inordinate stress simply tending to the demands of daily survival in an inhospitable world. In this state, seeking treatment is not among their priorities" (Tsemberis 2004, 191). The Housing First model meets the basic needs of participants first. "Their security assured, they become ready to address higher-order needs such as treatment, employment, or family reunification" (ibid, 192).

In addition to its novel approach, Rapid Rehousing also reduces the number of homeless through a trick of classification. Residents of homeless shelters or transitional housing (provider-owned) units are classified as homeless and counted in the PIT until they exit their programs and no longer receive assistance. Rapid rehousing clients, on the other hand, are no longer classified as homeless and are dropped from the homeless population count immediately upon joining the program, even though they continue to receive assistance. Rapid rehousing participants have housing units with leases in their own names, and therefore are considered no longer homeless. Rapid rehousing tenants are therefore equivalent to lease holders who receive Section 8 or other rental subsidies but are not counted as homeless (U.S. Department of Housing & Urban Development, 2013). As Mary Frances Schafer, the CoC coordinator for Louisville Kentucky, explained: "What is the easiest way to reduce the weeds in your garden? By changing your definition of a weed." (2020).

Homeless Migration

Many believe that homeless people migrate to warmer cities or to cities where the homeless receive better services, as expressed by consultant Robert Marbut in a report to the County of Sarasota, Florida: "Communities with beaches, palm trees and golf courses will always attract homeless individuals because of the nice climate. Then if the community is enabling, homeless individuals will continue to stay on the streets and in encampments" (2013, p.10). President Trump appointed Marbut Director of the U.S.

Interagency Council on Homelessness in 2019 (Capps, 2019). In many communities, there is a popular belief that they are a "Mecca" or "magnet" for the homeless due to their climate, generosity, or both (Greenstone, 2019; Griffin & Boyd, 215; Kaufman, 2003; Ow, 2020; Walters, 2006).

This claim warrants consideration. If true, then efforts to reduce homelessness at the local level would be less effective and possibly counter-productive from the jurisdiction's perspective. Relocation of the homeless to warmer CoCs would distort the effects of policies: CoCs in harsh climates would see lower homelessness regardless of other variables, yet the same economic or homelessness policies in mild weather CoCs would inevitably appear to cause higher homelessness. Relocation of the homeless to CoCs with better homeless services would have an even worse effect: more effective policies for assisting the homeless would attract homeless from outside, frustrating any local efforts. The results of this study indicate that this claim is unlikely.

Climate, operationalized as mean January Low Temperature, may have a minor effect on the homeless rate, but it is not conclusive. A warmer January has a modest correlation of 0.2266 with higher homelessness when considered without context. However, warmer areas tend to have higher home prices relative to incomes and other variables associated with higher homelessness. These variables explain most of the variation between warmer and cooler areas. In the initial model of Category One homelessness, each Fahrenheit degree of average January minimum temperature has a.005069 coefficient to increase the log of the homeless rate, with a nearly significant p-score of 0.163. In other words, a CoC that is close to the mean homeless rate of 19 per

10,000 will have one additional homeless person per ten thousand residents for every ten degrees of Fahrenheit. However, removing January Minimum Temperature from the model increases the model's overall R-squared by.0039, so it does not survive the process of stepwise refinement and is eliminated from the parsimonious model.

As an alternative test to consider whether, or to what extent, some homeless people might relocate to warmer climates, we can compare the model's prediction to the geographically isolated CoCs of Anchorage, with a harsh climate, and Honolulu, with a mild climate. The model predicts that Anchorage would have homeless rates of 13, 14, and 15 per 10,000 in 2014, 2016, and 2018 respectively. The actual rates are 34, 37, and 37 per 10,000, 21-23 per 10,000 higher than the model predicts. One could argue that rates are higher than predicted in Anchorage because it is more difficult for homeless people to migrate to warmer areas. If this were true, we would expect homeless rates in Honolulu to be lower than similarly warm areas, since it is difficult for homeless people to migrate to Honolulu from cooler areas. However homeless rates in Honolulu are also higher than expected based on the model. The model predicts homeless rates of 35, 41, and 37 per 10,000 in 2014, 2016, and 2018 but actual rates were 48, 49, and 45 per 10,000; 7-12 higher than predicted. The contrasting examples of Honolulu and Anchorage are inconsistent in suggesting an association between climate and homelessness.

The findings of this dissertation also refute the popular claim that homeless people tend to relocate to communities with better services, where it is easier to remain homeless. For a homeless person to prefer a community where it is comfortable to be homeless, they must intend to remain homeless. Yet less than twenty percent of the homeless population is chronically homeless. Over eighty percent are homeless for a relatively short period before regaining some form of housing. When all variables of the model are considered, CoCs that receive more funding per homeless person tend to have lower rates of homelessness. If homeless people relocated to cities with better resources, then the amount of funding relative to homeless populations would tend to equalize over time. Therefore if homeless people relocate to communities with higher relative homeless funding, those destination communities must be reducing their homeless populations faster than they attract homeless people from outside.

There is reason to believe that homeless people relocate to other areas. Over six percent of Americans in general relocate from one community to another annually, according to the American Community Survey (Table CP02) and the homeless sometimes relocate as well. A 2016 study of homeless veteran migration by Metraux, Treglia, and O'Toole found that "…while migration among homeless veterans is somewhat higher than among the general population, the large majority stayed within the bounds of the VISN [administrative region] in which they became homeless" (p.1215). The findings of this dissertation do not support the claim that the homeless tend to relocate to areas where it is more comfortable to be homeless with a milder climate or better services. Instead, they may relocate to find work, to seek housing with friends or family, or for other reasons (Rahimian et al., 1992; Tompkins, 2003).

Summary of Conclusions

I believe the most important insight gained from this research is an appreciation that the problem of homelessness includes not only the more extreme forms of HUD Category One such as sleeping on the street or in homeless shelters as recorded by the annual Point-in-Time Homeless Census, but also the less visible forms of marginal housing that constitute HUD Category Three such as staying with friends or family or living in hotels as captured in school-reported homelessness.

The interactions between these forms of homelessness can be complex and may frustrate efforts to address Category One homelessness in a vacuum. For example, O'Flaherty (1996) and Ellikson (1990) found that more shelter beds did not equally reduce the number of unsheltered homeless, and theorized that shelter beds drew some people from conventional housing. This theory seems more reasonable if they were drawn from Category Three homelessness rather than conventional housing. People living in Category Three homeless may be eager to stop living in hotels or imposing on friends or family, but not at the price of sleeping outdoors. Similarly Corinth (2017) concluded that ten permanent supportive housing beds were needed to reduce the Category One homeless population by one. This makes more sense if one considers that Category Three homeless as well as Category One homeless people may be in the pipeline to enter the permanent supportive housing program. The Category Three population may take slots in shelters or rehousing programs, seeming to frustrate progress in reducing Category One homelessness.

On a larger scale, Category Three hides much of the homeless population that would otherwise have no choice but to fall into Category One. As this dissertation demonstrates, the ratio of Category Three to Category One in a community depends on affordability. In the most expensive communities, housing units are more crowded and there is less opportunity for the homeless to double up, compounding the rate of Category One homelessness. Category Three homelessness is more difficult to define and quantify, as exemplified by the lower coefficients of determination in this dissertation's models for school-reported homelessness. Though it is less clearly delineated or visible, Category Three homelessness is nevertheless real and must be considered by homeless services planners in order to address the overall circumstances of homelessness.

In addition, this dissertation reinforces the consensus of those earlier scholars that this dissertation labelled "skeptical of market" in opposition to those labelled as "skeptical of government." This dissertation refutes the popular belief that the homeless tend to migrate to communities that have milder climates and better services. Like the other "skeptical of market" studies, this dissertation finds that a majority of the variation in Category One homeless among cities depends on housing affordability and on the relative effectiveness of government programs to address homelessness.

Policy Implications

But which government programs are likely to be effective? The regression model in this dissertation validates HUD's advocacy of rapid rehousing as an effective tool to reduce Category One homelessness. The model also demonstrates that CoCs that are more effective in competing for HUD funding also tend to reduce the number of Category One homeless in their communities, which would seem to support the continuum of care as an organizational structure to provide homeless services. In addition, the findings of this dissertation reinforce the argument that various forms of rent control are generally effective in reducing the rate of school-defined homelessness. This dissertation does not provide a thorough comparison of various policies to address homelessness, but the findings indicate that rapid rehousing, a competitive CoC, and rent control polices correspond to lower rates of homelessness.

While the “skeptical of government” scholars have disagreed with these conclusions, hopefully this study can add to the growing consensus that housing affordability and effective government interventions are important to address homelessness. Almost half of the variation in homeless rates between communities remains unaccounted for, leaving room for future research.

CHAPTER VII

OPPORTUNITIES FOR FUTURE RESEARCH

Two of the primary findings of this dissertation confirm the conclusions of previous authors: variations in local homelessness depend primarily on the availability of affordable housing, and effective community interventions can reduce the size of a homeless population. Perhaps these conclusions will soon acquire a firm consensus among scholars. Nevertheless, there are many other aspects of community-level homelessness that deserve further exploration.

Longer Observation Period

The dataset for this dissertation includes a fairly short time period of three observations over five years. This short timeframe was the only period for which school-reported homelessness data were readily available. A longer observation period would be preferable. In many cases, the incremental changes to variables during the period of observation were small, particularly relative to the survey margins of error. Over the relatively short period of this study, it was not possible to discern the impact of slight changes to the utilization of benefits relative to poverty, for example. Furthermore, 2013-2018 was a period of steady economic growth. A longer period that included earlier or later observations during economic recessions might yield different results.

Healthcare

This dissertation did not include any variables that reflected differences in local accessibility of health insurance or quality of healthcare. Scholars have argued that health issues, including mental health, contribute to homelessness as causes of homelessness and as constraints that keep people homeless (Bax & Middleton, 2019; Clifford et al., 2019; Markowitz, 2006; Schanzer et al., 2007). A study that added a variable to operationalize the effect of local healthcare access could help quantify the relative impact on local homeless populations.

Land Use Regulation

This study intended to include the WRLURI measure of land use regulation (Wharton Residential Land Use Regulation Index), but at the time of this study it was not available for most jurisdictions in this study's data set for the period of observation. If characteristics of land use regulation could be operationalized with more recent data for a broader array of communities, one could quantify the impact of land use regulation on housing availability and homelessness.

Crime Free Multi-Housing

Crime-Free Multi-Housing is the brand name for programs that involve coordination between police and landlords to facilitate the removal of criminal tenants by either arrest or eviction. Crime Free Multi-Housing programs have become popular in recent decades (Smith, 2020). These programs are promoted by the International Crime Free Association, Inc., which claims that Crime Free Multi-Housing Programs have been adopted in 2,000 cities (International Crime Free Association, 2020). Some allege that crime free multi-housing policies are counter-productive and could contribute to homelessness (Archer, 2019; Janzer, 2020, Michaels, 2019; Smith, 2020). If so, research that included data on crime-free multi-housing could demonstrate that government interventions can be harmful to the rate of homelessness as well as helpful. I might have included this variable in my study, but I became aware of the topic too late in the dissertation writing process.

Further Comparisons of Category One and School-Defined Homelessness

Since the introduction of the HUD Point-in-Time survey, it appears that no other authors have compared Category One homeless rates to measures of marginal homelessness such as the school-defined homeless rate. The findings of this dissertation indicate that Category One homelessness and school-defined homelessness are not found in the same proportion in all communities. In more affordable communities there tends to be a higher proportion of school-defined homelessness, which includes families living in hotels, doubled up with other families, and in other forms of unstable housing. In less affordable communities these options for housed-homelessness are less available and so the Category One homeless rate is proportionately higher. This dissertation suggests that additional useful insights may be gained by further exploring the interactions between extreme homelessness and the broader form of homelessness.

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APPENDIX A: CHANGES FROM PROPOSAL

During my research, I was compelled to make several changes to my original proposal. This section itemizes the differences between my proposal and final dissertation.

<u>Period of observations</u>

I proposed to include observations from the years 2007-2008, 2012-2013, and 2017-2018. School-reported homeless data were not publicly available for years prior to 2012, and I was not able to obtain them. Consequently, I changed the years of observation to 2013-2014, 2015-2016, and 2017-2018.

<u>Statistical Model</u>

In the proposal, I planned to use a generalized estimating equation, a type of longitudinal model using panel data. I discovered that a generalized estimating equation does not provide an easily understood measure of model fit such as a coefficient of determination. I followed the recommendation of my dissertation chair, Dr. Ruther, to employ a different longitudinal panel model, the generalized-least squares random effects longitudinal regression.

<u>WRLURI Removed</u>

I proposed to consider the Wharton Residential Land Use Regulation Index (WRLURI), which Raphael (2010) found to be a significant predictor of homelessness. I discovered that WRLURI data were not available for most of the COC areas in my data set for the period of observation, so I was compelled to drop the WRLURI from the independent variables.

Drug/ Alcohol Induced Deaths Added

In the course of my research, I discovered that county-level data on Drug/ Alcohol Induced Deaths were available for the time period of my study. Since previous studies of community-level homeless populations have considered measures of drug use as predictors (Burt, 1992; Culhane et al., 2011; Troutman et al., 1999), I added it and discovered that it was relevant. This addition fit the intent expressed in my proposal to include as many variables as possible from the list of those considered by earlier studies of the topic.

APPENDIX B: DATA SET

The units of analysis in the data set each comprise one or more counties and/or one or more HUD continuums of care (CoCs). This list documents which US communities are included in the data set and demonstrates how counties and/or CoCs are organized into units of analysis. CoC names are assigned by HUD. County Names are as portrayed by the Census Bureau.

In cases where multiple CoCs shared counties and were aggregated for the study, the unit of analysis is named for the largest city or county. In cases where CoCs merged, the unit of analysis name is the HUD designated CoC number for the merged CoC.

Table 28: Units of Analysis

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
AK-500	AK-500	Anchorage CoC	2020	Anchorage Municipality, Alaska
AL-500	AL-500	Birmingham/Jefferson, St. Clair, Shelby Counties CoC	1073	Jefferson County, Alabama
			1117	Shelby County, Alabama
			1115	St. Clair County, Alabama
AL-501	AL-501	Mobile City & County/Baldwin County CoC	1003	Baldwin County, Alabama
			1097	Mobile County, Alabama
AL-503	AL-503	Huntsville/North Alabama CoC	1083	Limestone County, Alabama
			1089	Madison County, Alabama
			1103	Morgan County, Alabama
AL-506	AL-506	Tuscaloosa City & County CoC	1125	Tuscaloosa County, Alabama
AZ-501	AZ-501	Tucson/Pima County CoC	4019	Pima County, Arizona
AZ-502	AZ-502	Phoenix, Mesa/Maricopa County CoC	4013	Maricopa County, Arizona
CA-500	CA-500	San Jose/Santa Clara City & County CoC	6085	Santa Clara County, California

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
CA-501	CA-501	San Francisco CoC	6075	San Francisco County, California
CA-502	CA-502	Oakland, Berkeley/Alameda County CoC	6001	Alameda County, California
CA-503	CA-503	Sacramento City & County CoC	6067	Sacramento County, California
CA-504	CA-504	Santa Rosa, Petaluma/Sonoma County CoC	6097	Sonoma County, California
CA-505	CA-505	Richmond/Contra Costa County CoC	6013	Contra Costa County, California
CA-508	CA-508	Watsonville/Santa Cruz City & County CoC	6087	Santa Cruz County, California
CA-510	CA-510	Turlock, Modesto/Stanislaus County CoC	6099	Stanislaus County, California
CA-511	CA-511	Stockton/San Joaquin County CoC	6077	San Joaquin County, California
CA-512	CA-512	Daly City/San Mateo County CoC	6081	San Mateo County, California
CA-513	CA-513	Visalia/Kings, Tulare Counties CoC	6031	Kings County, California
			6107	Tulare County, California
CA-514	CA-514	Fresno City & County/Madera County CoC	6019	Fresno County, California
			6039	Madera County, California
CA-515	CA-515	Roseville, Rocklin/Placer, Nevada Counties CoC	6057	Nevada County, California
			6061	Placer County, California
CA-517	CA-517	Napa City & County CoC	6055	Napa County, California
CA-518	CA-518	Vallejo/Solano County CoC	6095	Solano County, California
CA-521	CA-521	Davis, Woodland/Yolo County CoC	6113	Yolo County, California
CA-524	CA-524	Yuba City & County/Sutter County CoC	6101	Sutter County, California
			6115	Yuba County, California
CA-525	CA-525	El Dorado County CoC	6017	El Dorado County, California
CA-601	CA-601	San Diego City and County CoC	6073	San Diego County, California
CA-602	CA-602	Santa Ana, Anaheim/Orange County CoC	6059	Orange County, California
CA-603	CA-603	Santa Maria/Santa Barbara County CoC	6083	Santa Barbara County, California
CA-604	CA-604	Bakersfield/Kern County CoC	6029	Kern County, California
CA-608	CA-608	Riverside City & County CoC	6065	Riverside County, California
CA-609	CA-609	San Bernardino City & County CoC	6071	San Bernardino County, California
CA-611	CA-611	Oxnard, San Buenaventura/Ventura County CoC	6111	Ventura County, California
CA-613	CA-613	Imperial County CoC	6025	Imperial County, California

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
CA-614	CA-614	San Luis Obispo County CoC	6079	San Luis Obispo County, California
CA-Los Angeles	CA-600	Los Angeles City & County CoC	6037	Los Angeles County, California
	CA-606	Long Beach CoC		
	CA-607	Pasadena CoC		
	CA-612	Glendale CoC		
CO-504	CO-504	Colorado Springs/El Paso County CoC	8041	El Paso County, Colorado
CT-503	CT-503	Bridgeport, Stamford, Norwalk/Fairfield County CoC	9001	Fairfield County, Connecticut
	CT-506	Norwalk/Fairfield County CoC		
	CT-508	Stamford/ Greenwich CoC		
CT-505	CT-502	Hartford CoC	9003	Hartford County, Connecticut
	CT-505	Connecticut Balance of State CoC	9005	Litchfield County, Connecticut
			9007	Middlesex County, Connecticut
	CT-512	City of Waterbury CoC	9009	New Haven County, Connecticut
	CT-505	Connecticut Balance of State CoC	9011	New London County, Connecticut
			9013	Tolland County, Connecticut
			9015	Windham County, Connecticut
DC-500	DC-500	District of Columbia CoC	11001	District of Columbia, District of Columbia
DE-500	DE-500	Delaware Statewide CoC	10001	Kent County, Delaware
			10003	New Castle County, Delaware
			10005	Sussex County, Delaware
FL-501	FL-501	Tampa/Hillsborough County CoC	12057	Hillsborough County, Florida
FL-502	FL-502	St. Petersburg, Clearwater, Largo/Pinellas County CoC	12103	Pinellas County, Florida
FL-503	FL-503	Lakeland, Winterhaven/Polk County CoC	12105	Polk County, Florida
FL-504	FL-504	Daytona Beach, Daytona/Volusia, Flagler Counties CoC	12035	Flagler County, Florida
			12127	Volusia County, Florida
FL-507	FL-507	Orlando/Orange, Osceola, Seminole Counties CoC	12095	Orange County, Florida
			12097	Osceola County, Florida
			12117	Seminole County, Florida
FL-509	FL-509	Fort Pierce/St. Lucie, Indian River, Martin Counties CoC	12061	Indian River County, Florida
			12085	Martin County, Florida
			12111	St. Lucie County, Florida
FL-510	FL-510		12019	Clay County, Florida

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
		Jacksonville-Duval, Clay Counties CoC	12031	Duval County, Florida
			12089	Nassau County, Florida
FL-511	FL-511	Pensacola/Escambia, Santa Rosa Counties CoC	12033	Escambia County, Florida
			12113	Santa Rosa County, Florida
FL-512	FL-512	St. Johns County CoC	12109	St. Johns County, Florida
FL-513	FL-513	Palm Bay, Melbourne/Brevard County CoC	12009	Brevard County, Florida
FL-514	FL-514	Ocala/Marion County CoC	12083	Marion County, Florida
FL-519	FL-519	Pasco County CoC	12101	Pasco County, Florida
FL-520	FL-520	Citrus, Hernando, Lake, Sumter Counties CoC	12017	Citrus County, Florida
			12053	Hernando County, Florida
			12069	Lake County, Florida
			12119	Sumter County, Florida
FL-600	FL-600	Miami-Dade County CoC	12086	Miami-Dade County, Florida
FL-601	FL-601	Ft Lauderdale/Broward County CoC	12011	Broward County, Florida
FL-602	FL-602	Punta Gorda/Charlotte County CoC	12015	Charlotte County, Florida
FL-603	FL-603	Ft Myers, Cape Coral/Lee County CoC	12071	Lee County, Florida
FL-605	FL-605	West Palm Beach/Palm Beach County CoC	12099	Palm Beach County, Florida
FL-606	FL-606	Naples/Collier County CoC	12021	Collier County, Florida
GA-503	GA-503	Athens-Clarke County CoC	13059	Clarke County, Georgia
GA-504	GA-504	Augusta-Richmond County CoC	13245	Richmond County, Georgia
GA-506	GA-506	Marietta/Cobb County CoC	13067	Cobb County, Georgia
GA-507	GA-507	Savannah/Chatham County CoC	13051	Chatham County, Georgia
GA-Atlanta	GA-508	DeKalb County CoC	13089	DeKalb County, Georgia
	GA-500	Atlanta CoC	13121	Fulton County, Georgia
	GA-502	Fulton County CoC		
HI-501	HI-501	Honolulu City and County CoC	15003	Honolulu County, Hawaii
IA-502	IA-502	Des Moines/Polk County CoC	19153	Polk County, Iowa
ID-500	ID-500	Boise/Ada County CoC	16001	Ada County, Idaho
IL-502	IL-502	Waukegan, North Chicago/Lake County CoC	17097	Lake County, Illinois
IL-503	IL-503	Champaign, Urbana, Rantoul/Champaign County CoC	17019	Champaign County, Illinois
IL-504	IL-504	Madison County CoC	17119	Madison County, Illinois
IL-508	IL-508	East St. Louis, Belleville/St. Clair County CoC	17163	St. Clair County, Illinois

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
IL-509	IL-509	DeKalb City & County CoC	17037	DeKalb County, Illinois
IL-513	IL-513	Springfield/Sangamon County CoC	17167	Sangamon County, Illinois
IL-514	IL-514	Dupage County CoC	17043	DuPage County, Illinois
IL-516	IL-516	Decatur/Macon County CoC	17115	Macon County, Illinois
IL-517	IL-517	Aurora, Elgin/Kane County CoC	17089	Kane County, Illinois
IL-Chicago	IL-510	Chicago CoC	17031	Cook County, Illinois
	IL-511	Cook County CoC		
IN-503	IN-503	Indianapolis CoC	18097	Marion County, Indiana
KS-502	KS-502	Wichita/Sedgwick County CoC	20173	Sedgwick County, Kansas
KS-503	KS-503	Topeka/Shawnee County CoC	20177	Shawnee County, Kansas
KS-505	KS-505	Overland Park, Shawnee/Johnson County CoC	20091	Johnson County, Kansas
KY-501	KY-501	Louisville-Jefferson County CoC	21111	Jefferson County, Kentucky
KY-502	KY-502	Lexington-Fayette County CoC	21067	Fayette County, Kentucky
LA-503	LA-503	New Orleans/Jefferson Parish CoC	22051	Jefferson Parish, Louisiana
			22071	Orleans Parish, Louisiana
MA-500	MA-500	Boston CoC	25025	Suffolk County, Massachusetts
MA-503	MA-503	Cape Cod Islands CoC	25001	Barnstable County, Massachusetts
MA-504	MA-504	Springfield/Hampden County CoC	25013	Hampden County, Massachusetts
MA-506	MA-506	Worcester City & County CoC	25027	Worcester County, Massachusetts
MA-507	MA-507	Pittsfield/Berkshire, Franklin, Hampshire Counties CoC	25003	Berkshire County, Massachusetts
			25011	Franklin County, Massachusetts
			25015	Hampshire County, Massachusetts
MA-511	MA-511	Quincy, Brockton, Weymouth, Plymouth City and County CoC	25021	Norfolk County, Massachusetts
			25023	Plymouth County, Massachusetts
MA-Bristol	MA-505	New Bedford CoC	25005	Bristol County, Massachusetts
	MA-515	Fall River CoC		
	MA-519	Attleboro, Taunton/Bristol County CoC		
MA-Essex	MA-502	Lynn CoC	25009	Essex County, Massachusetts
	MA-510	Gloucester, Haverhill, Salem/Essex County CoC		

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
	MA-508	Lowell CoC	25017	Middlesex County, Massachusetts
	MA-509	Cambridge CoC		
	MA-517	Somerville CoC		
MD-500	MD-500	Cumberland/Allegany County CoC	24001	Allegany County, Maryland
MD-501	MD-501	Baltimore CoC	24510	Baltimore city, Maryland
MD-502	MD-502	Harford County CoC	24025	Harford County, Maryland
MD-503	MD-503	Annapolis/Anne Arundel County CoC	24003	Anne Arundel County, Maryland
MD-504	MD-504	Howard County CoC	24027	Howard County, Maryland
MD-508	MD-508	Charles, Calvert, St. Mary's Counties CoC	24009	Calvert County, Maryland
			24017	Charles County, Maryland
			24037	St. Mary's County, Maryland
MD-600	MD-600	Prince George's County CoC	24033	Prince George's County, Maryland
MI-503	MI-503	St. Clair Shores, Warren/Macomb County CoC	26099	Macomb County, Michigan
MI-504	MI-504	Pontiac, Royal Oak/Oakland County CoC	26125	Oakland County, Michigan
MI-505	MI-505	Flint/Genesee County CoC	26049	Genesee County, Michigan
MI-506	MI-506	Grand Rapids, Wyoming/Kent County CoC	26081	Kent County, Michigan
MI-507	MI-507	Portage, Kalamazoo City & County CoC	26077	Kalamazoo County, Michigan
MI-508	MI-508	Lansing, East Lansing/Ingham County CoC	26065	Ingham County, Michigan
MI-509	MI-509	Washtenaw County CoC	26161	Washtenaw County, Michigan
MI-510	MI-510	Saginaw City & County CoC	26145	Saginaw County, Michigan
MI-514	MI-514	Battle Creek/Calhoun County CoC	26025	Calhoun County, Michigan
MI-515	MI-515	Monroe City & County CoC	26115	Monroe County, Michigan
MI-516	MI-516	Norton Shores, Muskegon City & County CoC	26121	Muskegon County, Michigan
MI-518	MI-518	Livingston County CoC	26093	Livingston County, Michigan
MI-519	MI-519	Holland/Ottawa County CoC	26139	Ottawa County, Michigan
MI-523	MI-523	Eaton County CoC	26045	Eaton County, Michigan
MI-Detroit	MI-501	Detroit CoC	26163	Wayne County, Michigan
	MI-502	Dearborn, Dearborn Heights, Westland/Wayne County CoC		
MN-500	MN-500	Minneapolis/Hennepin County CoC	27053	Hennepin County, Minnesota
MN-501	MN-501	St. Paul/Ramsey County CoC	27123	Ramsey County, Minnesota

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
MN-503	MN-503	Dakota, Anoka, Washington,Â Scott, Carver Counties CoC	27003	Anoka County, Minnesota
			27019	Carver County, Minnesota
			27037	Dakota County, Minnesota
			27139	Scott County, Minnesota
			27163	Washington County, Minnesota
MO-500	MO-500	St. Louis County CoC	29189	St. Louis County, Missouri
MO-501	MO-501	St. Louis City CoC	29510	St. Louis city, Missouri
MO-604	MO-604	Kansas City, Independence, Lee's Summit/Jackson, Wyandotte Counties, MO & KS	29095	Jackson County, Missouri
			29047	Clay County, Missouri
			29165	Platte County, Missouri
			29037	Cass County, Missouri
			20209	Wyandotte County, Kansas
NC-500	NC-500	Winston-Salem/Forsyth County CoC	37067	Forsyth County, North Carolina
NC-501	NC-501	Asheville/Buncombe County CoC	37021	Buncombe County, North Carolina
NC-502	NC-502	Durham City & County CoC	37063	Durham County, North Carolina
NC-504	NC-504	Greensboro, High Point CoC	37081	Guilford County, North Carolina
NC-505	NC-505	Charlotte/Mecklenburg County CoC	37119	Mecklenburg County, North Carolina
NC-507	NC-507	Raleigh/Wake County CoC	37183	Wake County, North Carolina
NC-509	NC-509	Gastonia/Cleveland, Gaston, Lincoln Counties CoC	37045	Cleveland County, North Carolina
			37071	Gaston County, North Carolina
			37109	Lincoln County, North Carolina
NC-511	NC-511	Fayetteville/Cumberland County CoC	37051	Cumberland County, North Carolina
NC-513	NC-513	Chapel Hill/Orange County CoC	37135	Orange County, North Carolina
NE-501	NE-501	Omaha, Council Bluffs CoC	31055	Douglas County, Nebraska
			19155	Pottawattamie County, Iowa
			31153	Sarpy County, Nebraska
NE-502	NE-502	Lincoln CoC	31109	Lancaster County, Nebraska
NH-Hillsborough	NH-501	Manchester CoC	33011	Hillsborough County, New Hampshire
	NH-502	Nashua/Hillsborough County CoC		
NJ-500	NJ-500	Atlantic City & County CoC	34001	Atlantic County, New Jersey
NJ-501	NJ-501	Bergen County CoC	34003	Bergen County, New Jersey
NJ-502	NJ-502	Burlington County CoC	34005	Burlington County, New Jersey
NJ-503	NJ-503		34007	Camden County, New Jersey

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
		Camden City & County/Gloucester, Cape May, Cumberland Counties CoC	34009	Cape May County, New Jersey
			34011	Cumberland County, New Jersey
			34015	Gloucester County, New Jersey
NJ-504	NJ-504	Newark/Essex County CoC	34013	Essex County, New Jersey
NJ-506	NJ-506	Jersey City, Bayonne/Hudson County CoC	34017	Hudson County, New Jersey
NJ-507	NJ-507	New Brunswick/Middlesex County CoC	34023	Middlesex County, New Jersey
NJ-508	NJ-508	Monmouth County CoC	34025	Monmouth County, New Jersey
NJ-509	NJ-509	Morris County CoC	34027	Morris County, New Jersey
NJ-510	NJ-510	Lakewood Township/Ocean County CoC	34029	Ocean County, New Jersey
NJ-511	NJ-511	Paterson/Passaic County CoC	34031	Passaic County, New Jersey
NJ-513	NJ-513	Somerset County CoC	34035	Somerset County, New Jersey
NJ-514	NJ-514	Trenton/Mercer County CoC	34021	Mercer County, New Jersey
NJ-515	NJ-515	Elizabeth/Union County CoC	34039	Union County, New Jersey
NJ-516	NJ-516	Warren, Sussex, Hunterdon Counties CoC	34019	Hunterdon County, New Jersey
			34037	Sussex County, New Jersey
			34041	Warren County, New Jersey
NV-500	NV-500	Las Vegas/Clark County CoC	32003	Clark County, Nevada
NV-501	NV-501	Reno, Sparks/Washoe County CoC	32031	Washoe County, Nevada
NY-503	NY-503	Albany City & County CoC	36001	Albany County, New York
NY-505	NY-505	Syracuse, Auburn/Onondaga, Oswego, Cayuga Counties CoC	36011	Cayuga County, New York
			36067	Onondaga County, New York
			36075	Oswego County, New York
NY-507	NY-507	Schenectady City & County CoC	36093	Schenectady County, New York
NY-600	NY-600	New York City CoC	36005	Bronx County, New York
			36047	Kings County, New York
			36061	New York County, New York
			36081	Queens County, New York
			36085	Richmond County, New York
NY-601	NY-601	Poughkeepsie/Dutchess County CoC	36027	Dutchess County, New York
NY-602	NY-602	Newburgh, Middletown/Orange County CoC	36071	Orange County, New York

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
NY-604	NY-604	Yonkers, Mount Vernon/Westchester County CoC	36119	Westchester County, New York
OH-500	OH-500	Cincinnati/Hamilton County CoC	39061	Hamilton County, Ohio
OH-501	OH-501	Toledo/Lucas County CoC	39095	Lucas County, Ohio
OH-502	OH-502	Cleveland/Cuyahoga County CoC	39035	Cuyahoga County, Ohio
OH-503	OH-503	Columbus/Franklin County CoC	39049	Franklin County, Ohio
OH-504	OH-504	Youngstown/Mahoning County CoC	39099	Mahoning County, Ohio
OH-505	OH-505	Dayton, Kettering/Montgomery County CoC	39113	Montgomery County, Ohio
OH-506	OH-506	Akron/Summit County CoC	39153	Summit County, Ohio
OH-508	OH-508	Canton, Massillon, Alliance/Stark County CoC	39151	Stark County, Ohio
OK-501	OK-501	Tulsa City & County CoC	40143	Tulsa County, Oklahoma
OK-504	OK-504	Norman/Cleveland County CoC	40027	Cleveland County, Oklahoma
OR-500	OR-500	Eugene, Springfield/Lane County CoC	41039	Lane County, Oregon
OR-501	OR-501	Portland, Gresham/Multnomah County CoC	41051	Multnomah County, Oregon
OR-502	OR-502	Medford, Ashland/Jackson County CoC	41029	Jackson County, Oregon
OR-506	OR-506	Hillsboro, Beaverton/Washington County CoC	41067	Washington County, Oregon
OR-507	OR-507	Clackamas County CoC	41005	Clackamas County, Oregon
PA-500	PA-500	Philadelphia CoC	42101	Philadelphia County, Pennsylvania
PA-501	PA-501	Harrisburg/Dauphin County CoC	42043	Dauphin County, Pennsylvania
PA-502	PA-502	Upper Darby, Chester, Haverford/Delaware County CoC	42045	Delaware County, Pennsylvania
PA-503	PA-503	Wilkes-Barre, Hazleton/Luzerne County CoC	42079	Luzerne County, Pennsylvania
PA-504	PA-504	Lower Merion, Norristown, Abington/Montgomery County CoC	42091	Montgomery County, Pennsylvania
PA-505	PA-505	Chester County CoC	42029	Chester County, Pennsylvania
PA-506	PA-506	Reading/Berks County CoC	42011	Berks County, Pennsylvania
PA-508	PA-508	Scranton/Lackawanna County CoC	42069	Lackawanna County, Pennsylvania
PA-510	PA-510	Lancaster City & County CoC	42071	Lancaster County, Pennsylvania
PA-511	PA-511	Bristol, Bensalem/Bucks County CoC	42017	Bucks County, Pennsylvania
PA-512	PA-512	York City & County CoC	42133	York County, Pennsylvania

Unit of Analysis	CoC number	CoC Name	County FIPS	County Name
PA-600	PA-600	Pittsburgh, McKeesport, Penn Hills/Allegheny County CoC	42003	Allegheny County, Pennsylvania
PA-603	PA-603	Beaver County CoC	42007	Beaver County, Pennsylvania
PA-605	PA-605	Erie City & County CoC	42049	Erie County, Pennsylvania
TN-501	TN-501	Memphis/Shelby County CoC	47157	Shelby County, Tennessee
TN-502	TN-502	Knoxville/Knox County CoC	47093	Knox County, Tennessee
TN-504	TN-504	Nashville-Davidson County CoC	47037	Davidson County, Tennessee
TN-510	TN-510	Murfreesboro/Rutherford County CoC	47149	Rutherford County, Tennessee
TX-500	TX-500	San Antonio/Bexar County CoC	48029	Bexar County, Texas
TX-503	TX-503	Austin/Travis County CoC	48453	Travis County, Texas
TX-600	TX-600	Dallas City & County, Irving CoC	48085	Collin County, Texas
			48113	Dallas County, Texas
TX-601	TX-601	Fort Worth, Arlington/Tarrant County CoC	48367	Parker County, Texas
			48439	Tarrant County, Texas
TX-603	TX-603	El Paso City & County CoC	48141	El Paso County, Texas
UT-500	UT-500	Salt Lake City & County CoC	49035	Salt Lake County, Utah
VA-503	VA-503	Virginia Beach CoC	51810	Virginia Beach city, Virginia
VA-507	VA-507	Portsmouth CoC	51740	Portsmouth city, Virginia
VA-600	VA-600	Arlington County CoC	51013	Arlington County, Virginia
VA-602	VA-602	Loudoun County CoC	51107	Loudoun County, Virginia
VA-603	VA-603	Alexandria CoC	51510	Alexandria city, Virginia
WA-500	WA-500	Seattle/King County CoC	53033	King County, Washington
WA-502	WA-502	Spokane City & County CoC	53063	Spokane County, Washington
WA-503	WA-503	Tacoma, Lakewood/Pierce County CoC	53053	Pierce County, Washington
WA-504	WA-504	Everett/Snohomish County CoC	53061	Snohomish County, Washington
WA-508	WA-508	Vancouver/Clark County CoC	53011	Clark County, Washington
WI-501	WI-501	Milwaukee City & County CoC	55079	Milwaukee County, Wisconsin
WI-502	WI-502	Racine City & County CoC	55101	Racine County, Wisconsin
WI-503	WI-503	Madison/Dane County CoC	55025	Dane County, Wisconsin

APPENDIX C: EXCLUDED CONTINUUMS OF CARE

The following continuum of care areas were excluded from analysis because they included counties with populations below 65,000.

Table 29: CoCs Excluded Due to Counties with Low Population

CoC	CoC Name	Category
AL-504	Montgomery/Montgomery, Elmore Counties CoC	other urban
AR-500	Little Rock/Central Arkansas CoC	other urban
AR-501	Fayetteville/Northwest Arkansas CoC	other urban
CO-503	Metropolitan Denver CoC	Major cities
FL-505	Fort Walton Beach/Okaloosa, Walton Counties CoC	suburban
FL-506	Tallahassee/Leon County CoC	other urban
GA-505	Columbus-Muscogee/Russell County CoC	other urban
IA-500	Sioux City/Dakota, Woodbury Counties CoC	other urban
IL-501	Rockford/Winnebago, Boone Counties CoC	suburban
IL-506	Will, Kendall, Grundy County CoC	suburban
IL-507	Peoria, Pekin/Fulton, Tazewell, Peoria, Woodford Counties CoC	suburban
LA-502	Shreveport, Bossier/Northwest Louisiana CoC	other urban
LA-506	Slidell/Southeast Louisiana CoC	suburban
LA-509	Louisiana Balance of State CoC	suburban
MA-516	Massachusetts Balance of State CoC	suburban
MO-503	St. Charles City & County, Lincoln, Warren Counties CoC	suburban
MO-600	Springfield/Greene, Christian, Webster Counties CoC	other urban
MO-603	St. Joseph/Andrew, Buchanan, DeKalb Counties CoC	other urban
MS-500	Jackson/Rankin, Madison Counties CoC	suburban
NC-506	Wilmington/Brunswick, New Hanover, Pender Counties CoC	suburban
NY-508	Buffalo, Niagara Falls/Erie, Niagara, Orleans, Genesee, Wyoming Counties CoC	suburban

CoC	CoC Name	Category
NY-523	Glens Falls, Saratoga Springs/Saratoga, Washington, Warren, Hamilton Counties CoC	suburban
RI-500	Rhode Island Statewide CoC	suburban
SC-500	Charleston/Low Country CoC	suburban
SC-501	Greenville, Anderson, Spartanburg/Upstate CoC	suburban
SC-502	Columbia/Midlands CoC	suburban
TX-701	Bryan, College Station/Brazos Valley CoC	other urban
UT-503	Utah Balance of State CoC	suburban
UT-504	Provo/Mountainland CoC	suburban
VA-500	Richmond/Henrico, Chesterfield, Hanover Counties CoC	suburban
VA-501	Norfolk/Chesapeake, Suffolk, Isle of Wight, Southampton Counties CoC	suburban
VA-502	Roanoke City & County, Salem CoC	suburban
VA-505	Newport News, Hampton/Virginia Peninsula CoC	other urban
VA-514	Fredericksburg/Spotsylvania, Stafford Counties CoC	suburban
WV-503	Charleston/Kanawha, Putnam, Boone, Clay Counties CoC	suburban

The following continuum of care areas were excluded from analysis for other reasons, specified below:

Table 30: Other CoCs Excluded from Data Set

CoC	CoC Name	Category	Reason for Exclusion
CA-507	Marin County CoC	suburban	No eviction data
CA-520	Merced City & County CoC	suburban	Added county during period of analysis
FL-500	Sarasota, Bradenton/Manatee, Sarasota Counties CoC	suburban	Missing from HUD shapefile
IL-500	McHenry County CoC	Suburban	Missing from HUD shapefile
MD-505	Baltimore County CoC	suburban	No eviction data
MD-506	Carroll County CoC	suburban	No eviction data
MD-507	Cecil County CoC	suburban	No eviction data
MD-509	Frederick City & County CoC	suburban	No eviction data

CoC	CoC Name	Category	Reason for Exclusion
MD-512	Hagerstown/Washington County CoC	suburban	No eviction data
MD-601	Montgomery County CoC	suburban	No eviction data
NJ-512	Salem County CoC	suburban	No HUD data for 2016
NM-500	Albuquerque	major cities	Municipality only
NY-500	Rochester, Irondequoit, Greece/Monroe County CoC	suburban	No eviction data
NY-512	Troy/Rensselaer County CoC	suburban	No eviction data
NY-603	Nassau, Suffolk Counties CoC	suburban	No eviction data
NY-606	Rockland County CoC	suburban	No eviction data
OK-502	Oklahoma City CoC	Major cities	Municipality only
TX-611	Amarillo CoC	Other urban	Municipality only
TX-700	Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery, Counties CoC	Major cities	Added county during period of analysis
VA-601	Fairfax County CoC	Suburban	Bureau of Labor Statistics data missing
VA-604	Prince William County CoC	Suburban	Bureau of Labor Statistics data missing
VT-501	Burlington/Chittenden County CoC	other urban	No eviction data

APPENDIX D: DATA SOURCES

Dependent Variables

Category One Homeless Rate: The Category One homeless population reported in the annual Point-in-Time homeless census ("PIT") as "Overall Homeless," divided by the total population of the CoC reporting area according to the U.S. Census Bureau. The PIT homeless count for January of each year is divided by the ACS population estimate for the previous year: 2014/2013, 2016/2015, 2018/2017. Data source: PIT data for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Population data downloaded from the US Census at the American Factfinder Website, ACS 1-year estimates for 2013, 2015, and 2017, Table CP02. Stata variable name: HLESSRATE.

School-reported Homeless Children Rate: The population of homeless children reported in school districts within the CoC divided by the total population of the CoC reporting area according to the U.S. Census Bureau. The homeless children count for each school year is divided by the ACS population estimate for the initial year: 2013-2014 homeless children /2013 CoC population; 2015-2016/2015, 2017-2018/2017. Data source: Homeless children data for 2013-2014, 2015-2016, and 2017-2018 downloaded from the Department of Education website EdFacts website at https://www2.ed.gov/about/inits/ed/edfacts/data-files/school-status-data.html.

Population data downloaded from the US Census at the American Factfinder Website, ACS 1-year estimates for 2013, 2015, and 2017, Table CP02. The total school defined homeless rate is portrayed with the Stata variable name: C3TOTALRATE.

Independent Variables

Population: The total population of the CoC area expressed in hundreds of thousands. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP02 downloaded from the American Factfinder website. Stata variable name: "Population."

Population Density: The population variable divided by the area variable. Stata variable name: "PopDensity."

Area: The land area of the CoC in square miles. Data source: US Census Table GCT-PH1 Population, Housing Units, Area, and Density for 2010 downloaded from the American Factfinder website.

New Residents: Total percentage of residents that moved from a different county, state, or country in the past year. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table S0201 downloaded from the American Factfinder website. Stata variable name: "NewResidents."

Percent African-American: Percentage of the population in the CoC area that selected the race "African-American/Black." Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP05 downloaded from the American Factfinder website. Stata variable name: "Afam."

Percent Hispanic: Percentage of the population in the CoC area that selected the ethnicity “Hispanic.” Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP05 downloaded from the American Factfinder website. Stata variable name: “Hispanic.”

January Low Temperature: The average January low temperature for years 1979-2011 for counties in the CoC area, expressed in Fahrenheit. Data source: “North America Land Data Assimilation System (NLDAS) Daily Air Temperatures and Heat Index (1979-2011)” data table by county downloaded from the Centers for Disease Control and Prevention website. This is a fixed variable – it does not change over the period of observation. Stata variable name: “January Minimum Temperature.”

East Coast: Whether the CoC is located in a state on the East Coast (adjacent to the Atlantic Ocean plus Pennsylvania). CoCs that meet the criteria have a value of 1; others have a value of 0. Stata variable name: “East Coast.”

West Coast: Whether the CoC is in a state on the East Coast (adjacent to the Pacific Ocean including Alaska and Hawaii). CoCs that meet the criteria have a value of 1; others have a value of 0. This is a static variable – it does not change over the observation period. Stata variable name: “West Coast.”

Median Income: Median household income in the past twelve months, in thousands of 2017 inflation adjusted dollars. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP03 downloaded from the American Factfinder website. Stata variable name: “MedInc.”

Gini Index: A popular measure of income inequality, named for the author Corrado Gini, ranging from zero to one. A higher score indicates greater income inequality (Giorgi & Gigliarano, 2017). Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table B19083 downloaded from the American Factfinder website. Stata variable name: “Gini.”

Poverty Rate: Percentage of the population in the CoC area with income below the poverty level. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP03 downloaded from the American Factfinder website. Other studies have included poverty but did not find a significant association. Stata variable name: “Poverty.”

Unemployment Rate: Percentage of the population in the CoC area that is unemployed. Data source: U.S. Bureau for Labor Statistics Labor Force Data by County for 2013, 2015, and 2017, Table S2301. Stata variable name: “Unemployment.”

Employment in Accommodations and Food Service: Percentage of the workforce employed in the accommodations and food service sector by County for 2013, 2015, and 2017. Data source: Regional Data CAEMP25N “Total Full-Time and Part-Time Employment by NAICS Industry” downloaded from the Bureau of Economic Analysis website. Stata variable name: “AccFoodSvc.”

Drug / Alcohol Induced Deaths: The death rate due to drug / alcohol induced causes per ten thousand residents by County for 2013, 2015, and 2017. Data source: Centers For Disease Control and Prevention website, Underlying Cause of Death data request by County for drug/alcohol induced causes. Stata variable name: “DrugDeaths.”

Rental Vacancy Rate: Percentage of rental units that are unoccupied. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “RentVacancy.”

Median Home Value: The median home price in thousands of 2017 inflation adjusted dollars. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “MedHome.”

Median Rent: The median rent in thousands of 2017 inflation adjusted dollars. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “MedRent.”

Lower Quartile Rent: The maximum rent paid by the bottom 25% of the renting population, in hundreds of 2017 inflation adjusted dollars. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “LowQuartRent.”

Homeownership: Percentage of housing units that are occupied by owners. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “Homeownershp.”

Rent-Income Ratio: Median Gross Rent as a Percentage of Household Income (GRAPI). Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. Stata variable name: “Grapi.”

Overcrowding: Percentage of housing units with more than 1.5 occupants per room. Data source: US Census ACS 5-year estimates for 2013, 2015, and 2017, Table DP04 downloaded from the American Factfinder website. Stata variable name: “Overcrowded.”

Eviction Rate. The number of evictions per year divided by the number of renters, expressed in percentage points. Data Source: Eviction Lab project data for 2013, 2015, and 2017. Where eviction lab project data are missing for some years and/or some counties in a CoC, they were imputed from other years and/or other counties. Stata variable name: “EvictRate.”

Eviction Filing Rate. The number of eviction filings per year divided by the number of renters, expressed in percentage points. Data Source: Eviction Lab project data for 2013, 2015, and 2017. Where eviction lab project data are missing for some years and/or some counties in a CoC, they were imputed from other years and/or other counties. Stata variable name: “EvictFileRate.”

Charitable Giving: Total itemized deductions by taxpayers in the CoC area divided by population, expressed in 2017 inflation-adjusted dollars. Data Source: Total itemized deductions (variable A04470) in County Income Data for 2012, 2014, and 2016 downloaded from SOI Tax Stats County Data on the IRS website. Stata variable name: “Charitable.”

Food Stamps: The percentage of households in poverty receiving cash assistance or food stamps in the previous 12 months. Data source: US Census ACS 1-year estimates for 2013, 2015, and 2017, Table S2201 downloaded from the American Factfinder website. Stata variable name: “FoodStamps.”

Public Housing: Percentage of housing units that are provided by the local housing authority and funded by HUD. This includes housing units that are owned by the housing authority plus “housing choice” programs that subsidize the rent of privately owned apartments leased by subsidized tenants. Data source: Public housing units downloaded from HUD Office of Policy Development and Research website at https://www.huduser.gov/portal/datasets/assthsg.html. Total housing units from US Census ACS 1-year estimates for 2013, 2015, and 2017, Table CP04 downloaded from the American Factfinder website. The total rate of all public housing is represented by the Stata variable name: “PubHousing.” The rate of housing choice subsidized units is represented by the Stata variable name “HChoice.” The rate of all other forms of public housing, including housing authority-owned units and site-based public housing, is represented by the Stata variable name: “NonHChoice.” “PubHousing” is the sum of “HChoice” and “NonHChoice.”

Rent Control: Whether the primary municipal government of the CoC area has statutes or ordinances that limit rent increases or limit grounds for eviction as a Yes (1) or No (0) variable. If a CoC includes multiple counties, the rent control value is the number of counties with rent control divided by the total number of counties. Data source: Table of cities with rent control by state as of 2014 retrieved from Landlord.com, adjusted based on an internet search for jurisdictions that implemented or repealed rent control measures during the period of observation. Stata variable name: “RentControl.”

Counties Per CoC: The number of counties in the Unit of Analysis divided by the number of CoCs. The purpose of this variable is to determine if the rate of homelessness is associated with the scale of COCs: whether they are multi-county regional COCs, single-county CoCs, or multiple CoCs aggregated within counties. Stata variable name: "CtiesPerCoC."

Permanent Supportive Housing: The percentage of CoC-funded beds that are in permanent supportive housing. Data Source: Housing Inventory Count (HIC) for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Stata variable name: "Permanent Supportive Housing."

Emergency Shelter: The percentage of CoC-funded beds that are in emergency shelters. Data Source: Housing Inventory Count (HIC) for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Stata variable name: "Emergency Shelter."

Transitional Housing: Percentage of CoC-funded housing units that are classified as transitional housing. Data Source: Housing Inventory Count (HIC) for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Stata variable name: "Transitional Housing."

Rapid Rehousing: Percentage of CoC-funded housing units that are classified as rapid rehousing. Data Source: Housing Inventory Count (HIC) for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Stata variable name: "Rapid Rehousing."

HMIS Participation Rate: The percentage of homeless service agencies that participate in the CoCs shared Homeless Management Information System. Data Source: Housing Inventory Count (HIC) for 2014, 2016, and 2018 downloaded from the Department of Housing and Urban Development website. Stata variable name: “Hmis.”

Continuum of Care Funding: The amount of funding in dollars awarded to the CoC by HUD in 2012, 2014, and 2016 (two years prior to the dependent variable in the same observation), downloaded from the HUD Exchange website “Awards and Allocations” page. The CoC funding variable is taken from two years prior to the dependent variable in order to be consistent with the other funding variable of charitable donations. More importantly, since funding is expended in the year after it is awarded, the two-year delay provides time for the funding to be implemented and have an effect. CoC funding relative to the total population has the Stata variable name “CoCPerCap.” CoC funding relative to the homeless population has the Stata variable name “CoCPherHless” and is expressed in increments of thousands of dollars.

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