ABSTRACT

Title of Dissertation: MODELING THE RELATIONSHIP BETWEEN THE HOUSING FIRST APPROACH AND HOMELESSNESS

David Boston, Doctor of Philosophy, 2020

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A growing body of evidence from individual-level studies demonstrating that the Housing First approach is effective at keeping those experiencing homelessness in stable housing has led to the approach being championed by many leading experts, especially as a way to address chronic homelessness (O'Flaherty, 2019). This helps us understand the relationship between Housing First and an individual's homelessness, but we know very little about the relationship between implementation of a Housing First approach and overall homelessness rates in a community.

In a 2019 survey of homelessness research published by the *Journal of Housing Economics*, Brendan O'Flaherty wrote:

> *"What has been missing in studies of Housing First are estimates of aggregate impact: does operating a Housing First program actually reduce the total amount of homelessness in a community?"*

Through this study, I sought to understand if Continuums of Care (CoC) that have adopted a Housing First approach by dedicating a higher proportion of their resources towards permanent housing units are associated with a lower proportion of people experiencing homelessness between the years 2009 and 2017 than CoCs dedicating a higher proportion of their resources towards emergency shelter and other short-term solutions. Additionally, I sought to understand how that relationship between the implementation of a Housing First approach and homelessness rates change as the values of median rent, unemployment, and other covariates typically associated with homelessness rates change. I hypothesized that CoCs adopting a Housing First approach, as defined in the context of this study, would experience lower homelessness rates.

The hypothesis that homelessness rates would decrease as the Housing First index increases was supported by the results, but the relationship is more complex than hypothesized. The relationship between Housing First and homelessness rates was quadratic in nature and influenced by an interaction effect with housing tenure. Jurisdictions that adopted a Housing First approach generally experienced lower homelessness rates, except where a vast majority of households are owner-occupied.

MODELING THE RELATIONSHIP BETWEEN THE HOUSING FIRST APPROACH AND HOMELESSNESS

by

David Boston

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I, David Boston, confirm that the work presented in this dissertation is my own. Where information has been derived from other sources, I confirm that this has been indicated in the dissertation.

Preface

To paraphrase the ethical principles of the American Planning Association (APA), we in the planning community must continuously pursue and faithfully serve the public interest by striving to expand choice and opportunity for all persons, recognizing a special responsibility to plan for the needs of disadvantaged groups and persons (1992). To strive to better understand why people experience homelessness is striving to uphold our profession's ethical principles, because this allows us to better plan for some of the most disadvantaged people in our communities. It is my hope that the contributions of this study are beyond academic in nature, and that the results of this work may benefit practitioners who work in the realm of planning, housing, and development, and those who work with people experiencing homelessness.

Dedication

I dedicate this research to my grandmother, Patricia Given, who made me the person I am today. You taught me to speak up, lend my voice to the voiceless, strive to be clever, and not give up a good fight.

I also dedicate this research to anyone struggling with homelessness. You are seen and this struggle will not define you.

Acknowledgements

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Table of Contents

List of Tables

List of Figures

List of Equations

List of Abbreviations

ACS: American Community Survey

AFDC: Aid to Families with Dependent Children

AIC: Akaike's Information Criterion

ANOVA: analysis of variance

APA: American Planning Association

CoC: Continuum of Care

ESRI: Environmental Systems Research Institute

FIPS: Federal Information Processing Standard

GIS: geographic information system

GLM: general linear model

HAP: Homeless Assistance Program

HEARTH: Homeless Emergency and Rapid Transition to Housing Program

HF: Housing First

HIC: Housing Inventory Count

HMIS: Homelessness Management Information System

HPRP: Homelessness Prevention and Rapid Re-housing Program

HUD: United States Department of Housing and Urban Development

IQR: interquartile range

IRS: Internal Revenue Service

LMM: linear mixed models

nClimDiv: National Climate Divisional Database

NCSHA: National Council of State Housing Agencies

NGO: nongovernmental organization

NOAA: National Oceanic and Atmospheric Administration

NOFA: Super Notice of Fund Availability

NYHS: New York Housing Study

PIT: Point-in-Time

RCT: randomized controlled trial

REML: restricted maximum likelihood

RM ANOVA: repeated measures analysis of variance

RRHD: Rapid Re-housing for Homeless Families Demonstration

S+C: Shelter Plus Care Program

SAMHSA: Substance Abuse and Mental Health Services Administration

SHP: Supportive Housing Program

SPSS: Statistical Package for the Social Sciences

SRO: single-room occupancy

SSI: Social Security Income

TF: treatment first

TIGER: Topologically Integrated Geographic Encoding and Referencing

USICH: United States Interagency Council on Homelessness

VARCOMP: variance components

Chapter 1: Introduction

The Housing First (HF) model of addressing homelessness was developed by Sam Tsemberis, a psychologist in New York, who started a program to move people experiencing homelessness with severe disabling conditions directly into permanent housing with wrap-around services instead of a shelter or hospital ward (Padgett, Henwood, & Tsemberis, 2016). Tsemberis and other researchers have studied the results of the HF approach versus traditional Treatment First (TF) approaches, in which participants must graduate from shelter to transitional housing and then eventually to housing of their own, in a series of randomized controlled trials (RCT) studying individuals' ability to remaining housed in each program. A review of 12 such RCTs found that in 11 of the 12 RCTs, Housing First produced greater housing retention than the TF approach (Kertesz & Johnson, 2017).

This growing body of evidence from individual-level studies demonstrating that the Housing First approach is effective at keeping those experiencing homelessness in stable housing has led to the approach being championed by many leading experts, especially as a way to address chronic homelessness (O'Flaherty, 2019). Beginning in 2013, the United States Department of Housing and Urban Development began encouraging local agencies applying for federal funds to demonstrate that they plan to address homelessness in their communities using a Housing First approach (HUD, 2013). However, not all scholars or service providers are convinced that the Housing First model is the best way to reduce homelessness. This study seeks to determine the efficacy of the Housing First approach in reducing homelessness rates by answering the following research question to help move us closer to resolving this debate.

1.1: Research Question

Are Continuums of Care (CoC) that have adopted a Housing First approach by dedicating a higher proportion of their resources towards permanent housing and support services associated with a lower proportion of people experiencing homelessness between the years 2009 and 2017 than CoCs that dedicate a higher proportion of their resources towards emergency shelter and other short-term solutions? Additionally, how does that relationship between the implementation of a Housing First approach and homelessness rates change as the values of median rent, unemployment, and other covariates typically associated with homelessness rates change?

1.2: Debate

In an examination of Housing First research conducted in the United States and Australia published by the *Australian Economic Review*, Kertesz and Johnson (2017) found that despite credible housing outcomes in longitudinal studies, some claims made on behalf of the Housing First approach remained controversial. Some of those controversies include how effective supportive services provided as part of a Housing First approach are for treating poor physical and mental health, or how cost-effective the Housing First approach is in comparison to the traditional Treatment First approach (Kertesz & Johnson, 2017).

However, the question of whether Housing First is an effective approach to ending homelessness at an individual level is largely settled. Many researchers conducting longitudinal studies comparing housing retention rates in Housing First programs versus Treatment First programs have found housing retention rates to be higher among participants of a Housing First program. Mares and Rosenheck (2007), Pearson, Montgomery, and Locke (2009), and Stergiopoulos et al. (2015) conducted longitudinal studies including multiple cities and found housing retention rates to be higher among Housing First participants in each city. Tsemberis, Kent, and Respress (2012), Stefancic et al. (2013), and Collins, Malone, and Clifasefi (2013) all found housing retention rates to be higher among participants in Housing First programs in single jurisdictions as well.

The debate on Housing First as a solution to homelessness has been light, and that's because this research is addressing a gap in the existing literature that has not seen much attention as opposed to answering a question that is central to a longstanding debate. Most longitudinal studies of the effectiveness of the Housing First approach have consistently shown that people experiencing homelessness who participate in a Housing First program are much more likely to retain their housing than a person experiencing homelessness participating in a program that follows a traditional treatment-first approach, so there isn't much room for debate there. A small number of opponents look at the issue from a different perspective. Benston (2015) points out that problems with the existing body of research, such as varying measurements of attrition, lack of detail on housing conditions and supportive services, selection bias among both participants and administrators, and lack of standardized program models and definitions limit internal validity, the ability to generalize findings, and efforts to replicate research conditions. Essentially, Benston (2015) and Kertesz and Johnson (2017) argue that the results of existing studies are unique to their environments.

1.3: Contribution of this Study

However, just because this research isn't answering a longstanding question in the field subject to fierce debate does not mean that it is unimportant. HUD is pushing implementation of the Housing First approach across the country by giving some level of funding preference to Continuums of Care, or CoCs, that demonstrate a commitment to Housing First. And to some degree, it's working. I found in this research that CoCs are slowly moving towards a Housing First model to a greater degree each year.

I am a member of the CoC where I live. The CoC's resources for combatting homelessness are scarce and some service agency representatives are concerned that spending money on permanent supportive housing and rapid rehousing to implement a Housing First approach will help a very small fraction of people compared to the number of people who could be helped if the money was spread across less expensive options. A longitudinal study does not take money into account. It does not take overall homelessness levels into account. Some people worry that a Housing First approach means that a few people are helped very effectively at the expense of homelessness rising in the CoC as a result of the lack of other services the CoC could not afford. The research community in this field have a moral imperative to develop an evidence-based approach to ending homelessness, and researchers must look at the relationship between Housing First and homelessness rates to develop that approach.

In a 2019 survey of homelessness research published by the *Journal of Housing Economics* focusing primarily, but not exclusively, on research conducted in the United States, Brendan O'Flaherty wrote:

> *"What has been missing in studies of Housing First are estimates of aggregate impact: does operating a Housing First program actually reduce the total amount of homelessness in a community?"*

This study will address this knowledge gap in the field of homelessness research by investigating the relationship between implementation of a Housing First approach at the Continuum of Care (CoC) level and homelessness rates in communities across the United States using a linear mixed models panel analysis. Past research on the efficacy of the Housing First approach has consisted of longitudinal studies of specific groups of participants experiencing chronic homelessness in a particular place or handful of places to compare housing retention rates of those in a Housing First program to those enrolled in a Treatment First program[1]. These studies of Housing First have not looked at the relationship between Housing First and homelessness rates or studied homelessness nationwide using CoC boundaries or data. On the other hand, models studying the relationship between

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[1] Longitudinal studies of this nature have been conducted by Tsemberis and Eisenberg (2000); Culhane, Metraux, and Hadley (2002); Gulcur, Stefancic, Shinn, Tsemberis, and Fischer (2003); Tsemberis, Gulcur, and Nakae (2004); Mares and Rosenheck (2007); Stefancic and Tsemberis (2007); Culhane and Metraux (2008); Pearson et al. (2009); Sadowski, Kee, VanderWeele, and Buchanan (2009); Tsemberis (2010); Stefancic et al. (2013); Stergiopoulos et al. (2015); and Aubry et al. (2016).

homelessness and the variables associated with homelessness using CoC data and boundaries have not included a measurement of Housing First or conducted a panel analysis to account for interaction effects and within-subject correlations over time. This study is an attempt to bridge the gap between longitudinal research on Housing First and modeling research on the determinants of homelessness, and to move each body of research a couple steps forward by incorporating new variables and methods.

By studying the relationship between Housing First and homelessness, this research will address some, though admittedly not all, of the criticisms levied against past longitudinal research. Since homelessness and the implementation of Housing First is done at the CoC level instead of the individual household or even program level, the level of detail of a longitudinal study is lost. Validity remains similarly limited by the quality of available data, because each local CoC is responsible for conducting their own point-in-time (PIT) count of people experiencing homelessness, and the people conducting these PIT counts are often untrained volunteers. This method does obviously eliminate the risk of selection bias, because a randomized controlled trial is not being conducted. This study also uses a standard definition of Housing First and homelessness across all CoCs, so this type of method gives future researchers the ability to replicate research conditions and generalize results very easily.

By studying variables associated with homelessness using a linear mixed models panel analysis, the analysis is able to analyze interaction effects and control for within-subject correlations over time. Interaction effects look at how the relationship between a primary independent variable and a dependent variable change in association with changes in a control or interaction variable. Past models studying variables associated with homelessness rates have been multivariate regression analyses only capable of measuring direct effects of variables while controlling for others, so incorporating interaction effects helps one to develop a more comprehensive and nuanced understanding of how these factors are associated with homelessness rates. The inclusion of these interaction effects turned out to be crucial, because the relationship between Housing First and homelessness rates was shown to be much more nuanced and complex than I had hypothesized.

The other benefit associated with panel analyses is that they control for within-subject correlations over time, whereas multivariate regression models like those used in past analyses assume that the error terms are not correlated across observations. When one has multiple observations within the same CoC over the course of several years, however, it is very likely that the error terms of those observations in the same CoC are correlated with one another.

This study will also include variables that have not been used in past models studying variables associated with homelessness, such as a measure of CoC funding rates, inclusionary zoning/housing policies, eviction filing rates, income inequality using CoC data, and a measurement of the degree to which a CoC has implemented a Housing First approach. The CoCs are the primary bodies responsible for coordinating the full range of homelessness services in a geographic area (HUD, 2018a), including the distribution of HUD funds, so it is important that we develop a better understanding of the effectiveness of these funds and the CoCs facilitating their use.

To measure the degree to which a CoC has implemented a Housing First approach, a Housing First index will be created. Investigating the fidelity of each permanent housing program in the country to ensure that it is following a Housing First model is not possible, so the scale of this research necessitates an adjustment to the definition of Housing First for use in the index. Definitions of Housing First used by O'Flaherty (2019) or Katz, Zerger, and Hwang (2017) refer exclusively to the use of permanent supportive housing, which is long-term housing provided for individuals with disabilities experiencing homelessness or families experiencing homelessness in which one member of the household has a disability and supportive services that are designed to meet the needs of the program participants.

This study uses HUD's (2019b) slightly broader definition of Housing First, which includes two components: (1) individuals are rapidly placed and stabilized in permanent housing without any preconditions regarding income, work effort, sobriety or any other factor, and (2) once in housing, individuals never face requirements to participate in services as a condition of retaining their housing. While the Housing First approach has been particularly more effective than the Treatment First approach in addressing the needs of people experiencing chronic homelessness who require permanent supportive housing, this definition is broad enough to include the use of rapid re-housing and other permanent housing solutions. As O'Flaherty (2019) discussed, an estimate regarding the relationship between Housing First and homelessness in a community is missing from the existing literature, so an index by which to measure the degree to which Housing First is being implemented in a community has not been created before. With no previous examples to build from, this study is making a first attempt at creating a Housing First index with the hope that future research will improve upon this design. In this study, the degree to which a CoC is implementing a Housing First approach is calculated using data from the Housing Inventory Count (HIC), which is submitted by CoCs to HUD each year.

Equation 1: Housing First index

$$hf = \frac{\left(\frac{\tau}{2}\right) + \rho + \varphi + \phi}{\beta}$$

The Housing First index is equal to the sum of the number of transitional housing beds (τ) divided by two, the number of rapid re-housing beds (ρ), the number of permanent supportive housing beds (φ), and the number of other permanent housing beds (ϕ) divided by the total number of beds (β) in the CoC, which also includes emergency shelter and safe haven beds. This results in an index score between 0 and 1 where a higher value indicates more reliance on permanent housing strategies and a stronger alignment with the Housing First approach. This index does not measure the fidelity of each permanent housing program with the Housing First model, so this index does not really tell me if the permanent housing solutions used in the CoC provides people experiencing homelessness with a home without barriers to entry. Data regarding the fidelity of each program in the United States to the Housing First model do not yet exist and collecting such data would require an incredible amount of resources. This index instead attempts to serve as a proxy measurement of implementation of the Housing First approach by measuring the degree to which a CoC prioritizes permanent housing solutions over transitional or temporary shelter solutions. The assumption behind this approach being that CoCs will not be able to prioritize permanent housing solutions that do not follow a Housing First approach without pushing many people back into temporary shelter or onto the streets because participants were not able to obtain or remain in permanent housing units with high barriers to entry or strict requirements to remain in their homes. Therefore, if a large portion of a CoC's beds are in permanent housing units and the CoC is able to fill those beds, this study assumes that a significant number of those permanent housing units must be provided through a program following the Housing First model.

This research will use a study period of 2009 to 2017, because the United States Census Bureau's American Community Survey (ACS) five-year estimate data are used for many of the variables in this study. The ACS was started in 2005, so ACS five-year estimates are available starting in 2009. At the time of data collection and model construction, 2017 data were the latest available for most of the variables used in this study.

Chapter 2: Progress Understanding and Ending Homelessness

The U.S. Department of Housing and Urban Development (HUD, 2018a) generally defines a homeless individual or family as one "who lacks a fixed, regular, and adequate nighttime residence." The many people who have dedicated their lives to the pursuit of understanding and ending homelessness know the implications that hide behind a rather sterile definition. Homelessness is a state of being that changes the way a person sees and experiences the world. The world becomes a more dangerous and uncertain place (Huey, 2010; B. A. Lee & Schreck, 2005), and most of the people you interact with are unkind and judgmental (Anderson, Snow, & Cress, 1994; Roschelle & Kaufman, 2004). Holding on to your possessions is difficult (B. A. Lee & Schreck, 2005). Finding food to eat is difficult (Bowen & Irish, 2018). Finding a safe and warm place to sleep is difficult (Bao, Whitbeck, & Hoyt, 2000; Huey, 2010). Many people live without a car, go long periods of time without a shower, and survive without a network of friends and family (Meanwell, 2012).

Despite all of this, many people do get back on their feet. Not only that, but homelessness had been steadily declining since 2007 until the number plateaued (and slightly increased) in the two years after 2016 (HUD, 2018a). This dissertation seeks to help determine what strategies to alleviate the crisis of homelessness were driving that reduction in homelessness rates so that we can continue to invest in strategies that work in the future.

2.1: Housing First

The Housing First (HF) strategy is to give people experiencing homelessness immediate access to housing and support services. The traditional or Treatment First (TF) approach to homelessness alleviation is to feed and shelter people while treating them for their various addictions, mental illnesses, or other personal characteristics deemed to be a barrier to them living in permanent housing before moving them through the system. Service providers using the TF approach viewed Housing First with great skepticism, and advocates of the HF approach were quick to try to support their idea with data.

2.1.1: Development of the Housing First approach

Psychologist Sam Tsemberis and others developed the Housing First approach and founded Pathways to Housing, Inc. in 1992 based on the idea that attempts to treat poor mental health are much more effective when a person has a safe and private place to call home. Shortly after the founding of Pathways, a study was conducted through a collaboration between Pathways to Housing, New York City's Human Resources Administration, and New York State's Nathan Kline Institute. Researchers compiled data for several thousand people experiencing homelessness who were participating in traditional continuum of care programs or the Pathways to Housing program over a five-year period. They analyzed rates at which people remained sheltered or housed, controlling for differences in client characteristics before program entry. In a comparison between traditional programs and the Housing First approach, the results showed that 88 percent of Housing First participants remained housed compared to 47 percent of traditional program participants (Tsemberis & Eisenberg, 2000).

In 1996, the federal Substance Abuse and Mental Health Services Administration (SAMHSA) issued a request for proposals for grant funding to study mental illness and homelessness. SAMHSA awarded six grants and required that all recipients of funding use a common set of outcome measures so that results could be compared across the various study areas. Pathways to Housing was awarded one of the grants, and was the only program testing HF (Padgett et al., 2016).

The project began in 1997 was called the New York Housing Study (NYHS). The longitudinal study followed participants for two years and lasted for about four years total. Participants were recruited between 1997 and 1999 and were required to have spent 15 of the last 30 days unsheltered, have a history of homelessness over the past six months, and have a psychiatric diagnosis of severe mental illness. About 90 percent of the 225 people enrolled in the study also struggled with substance abuse (Padgett et al., 2016). Of the 225 people enrolled, 99 of them were randomly assigned to the HF group and 126 of them were randomly assigned to the control group, which was a TF program that provided “treatment as usual.” People in the HF group were immediately placed in a small studio or one-bedroom apartment in an affordable area. Participants were required to pay 30 percent of their income, which many times was Social Security Income (SSI) benefits, toward their rent. They were also required to allow the support services team to visit their apartment on a weekly basis. In the control group, participants were placed in a group home, shelter, or single-room occupancy (SRO) building with shared sleeping, cooking, and bathing facilities.

Participants were expected to remain drug and alcohol free, stick to curfews, and follow other rules typical of a TF program in the hopes that they may ultimately be rewarded with a home (Padgett et al., 2016).

The results of the NYHS showed that participants in the HF group spent approximately 80 percent of their time in stable housing compared to 30 percent of the TF group participants after two years. The study also had a high participant retention rate of 94 percent after 12 months and 87 percent by the conclusion of the study, giving researchers a relatively large sample size to analyze for a longitudinal study of this length and detail (Tsemberis et al., 2004). The NYHS also found that HF group participants spent less time hospitalized for psychiatric problems, and that housing people struggling with drug or alcohol abuse problems in a private apartment may be more effective at reducing rates of substance abuse than an abstinence program in a group setting, where disruptive behaviors are more likely to impinge on others (Gulcur et al., 2003).

2.1.2: Debate regarding the efficacy of Housing First

After the NYHS, other research efforts attempted to gauge the efficacy of the Housing First approach by conducting longitudinal studies on people experiencing homelessness and comparing the housing retention rate of people in Housing First programs versus the housing retention rate of people in traditional or treatment-first programs. The results of these studies have generally provided overwhelming support for the Housing First approach. In 2004, the United States Interagency Council on Homelessness (USICH) provided grant funding for projects intended to address chronic homelessness in eleven cities. Seven of those eleven cities used the HF model. After 12 months, the housing retention rate among the HF project participants in those seven cities was 85 percent (Mares & Rosenheck, 2007). A similar three-city, 12-month study by HUD achieved an 84 percent housing retention rate (Pearson et al., 2009). Studies in Washington, DC (Tsemberis et al., 2012); the State of Vermont (Stefancic et al., 2013); and Seattle, Washington (Collins et al., 2013) all found similar results with housing retention rates of 84 percent, 85 percent, and 77 percent, respectively. A study in four Canadian cities (Vancouver, Winnipeg, Toronto, and Montreal) supported American results as well. Among 1,198 participants, the study found that people housed using a Housing First program were housed 63 to 77 percent of the time in the two-year study period, while those in the control group were housed only 24 to 39 percent of the time (Stergiopoulos et al., 2015).

However, some scholars have pointed out that there are scientific limitations to the results of longitudinal studies regarding the efficacy of Housing First conducted thus far. Benston (2015) argues that researchers have used various methods of measuring attrition, making comparisons difficult. In a review of 12 longitudinal studies, seven reported attrition as the percentage of participants housed at the end of the study, two reported attrition as the percentage of participants completing follow-up interviews, two reported attrition as the proportion of time spent homeless, and one reported days spent homeless. Additionally, all of the studies reporting attrition included participants who had dropped out of the study in their statistical calculations through methods of inputting missing data on the basis of assumed values, weighting adjustments for nonrespondents, and analyzing relationships between baseline scores and participant characteristics for those who stayed in the study and those who dropped out (Benston, 2015). High attrition rates cause a decrease of statistical power in the model, and all of these methods of dealing with attrition rely on unstable assumptions about chance events that if wrong could lead to inaccurate or misleading conclusions (Ribisl et al., 1996).

A lack of detail on housing conditions and supportive services, selection bias among both participants and administrators, and lack of standardized program models and definitions limit internal validity, the ability to generalize findings, and efforts to replicate research conditions. Essentially, Benston (2015) and Kertesz and Johnson (2017) argue that the results of existing studies are unique to their environments.

Some researchers have also found that using a Housing First approach is cost-effective compared to other homelessness alleviation strategies. Culhane et al. (2002) analyzed administrative data for several thousand people experiencing homelessness with severe mental illness in New York City who were placed in housing between 1989 and 1997 and a control group of people with severe mental illness experiencing homelessness who were not placed in housing tracked over the same time period. Their findings indicated that the average annual cost of shelter use, hospitalization, and incarceration for a person experiencing homelessness with severe mental illness was $40,451.[2] This number was reduced by an average of $16,281 per year when the person was placed in a home, and the average cost of a home was $17,277 (Culhane et al., 2002). This did not result in a comprehensive cost-savings, but putting people

[2] Their findings also indicated that approximately 10 percent of people experiencing homelessness were responsible for 50 percent of service costs (in shelters, hospitals, and jails). This subgroup was labeled the "chronically homeless" (Padgett et al., 2016).

in housing did result in a reduction in homelessness for only an overall $996 per unit per year in New York City.

2.2: Measures of Homelessness

About a decade before the Housing First approach was developed, with the rise of visible, chronic homelessness and the "worst housing crisis since the Great Depression" (Appelbaum, Dolny, Dreier, & Gilderbloom, 1991) in the 1980s, researchers began attempting to measure the size and composition of the homeless population. Since then, four major sources of homelessness data have been used to study the homeless population of the United States: (1) a 1984 HUD homelessness estimate; (2) the 1987 sheltered population survey conducted by Martha Burt and others with the Urban Institute for cities with populations of at least 100,000; (3) the 1990 Census S-Night (Shelter and Street-Night) Enumeration of people experiencing both sheltered and unsheltered homelessness in five cities (New York, Los Angeles, Chicago, New Orleans, and Phoenix); and (4) HUD point-in-time (PIT) count data gathered in the last week of January from 2007 to the present.

2.2.1: 1984 HUD estimate

In 1984, HUD published one of the first nationwide assessments of the population experiencing homelessness. HUD determined that there were approximately 250,000 to 350,000 people experiencing homelessness throughout the country on an average night (HUD, 1984). To arrive at that number, researchers used four different methods: (1) estimates from local studies; (2) 500 key informant interviews in 60 metropolitan areas; (3) surveys of 184 shelter operators in 60 metropolitan areas; and (4) estimates of ratios of sheltered and unsheltered populations (Honig & Filer, 1993).[3]

The HUD estimate was provided almost immediately after the visible population of people experiencing homelessness exploded during the 1981-1982 recession (Burt, 1992). Some of the earliest studies that found quantitative evidence of a relationship between housing costs and homelessness were based on the estimates of the population experiencing homelessness from the 1984 HUD study (Bohanon, 1991; Elliot & Krivo, 1991; Honig & Filer, 1993).

2.2.2: 1987 Burt sheltered population survey

In a study commissioned by HUD, the Urban Institute surveyed local officials in all cities with a population of at least 100,000 in 1986. This sample included 147 central cities and 35 suburban jurisdictions. The principal investigator, Martha Burt, used Comprehensive Homeless Assistance Plans that local officials were required to submit to HUD to develop a nationwide list of shelter providers in major cities. Burt surveyed nongovernmental organizations (NGOs) and homeless service coordinators to identify additional shelter providers in each city (Quigley et al., 2001). The survey used a probability sample of service-using homeless individuals and estimated a total of 500,000-600,000 on any given night in March 1987 (Burt, 1992; Burt & Cohen, 1989).

[3] The results of this count were used in combination with 1980 decennial census data for some of the first analyses of the variables associated with homelessness (Appelbaum et al., 1991; Bohanon, 1991; Elliot & Krivo, 1991; Honig & Filer, 1993; Quigley & Portney, 1990), summarized and discussed in more detail in sections 1.4 and 1.5 below.

Two obvious methodological problems with using shelter bed capacity to study variables associated with homelessness are that not all people experiencing homelessness stay in emergency shelters and using shelter bed capacity measures a response to homelessness rather than homelessness itself. Although a street-to-shelter ratio was used in an attempt to estimate a full count, that ratio is not constant across metropolitan areas (Quigley et al., 2001).

O'Flaherty (1996) brought up two different scenarios in which the results of the Burt survey could be misleading. One scenario being that if homeless services are normal goods, wealthier cities will allocate more funds for homeless shelters, thus introducing a spurious positive correlation between this measure of homelessness and mean household income. Alternatively, wealthier areas may devote fewer resources to homeless shelters or oppose the opening of shelters through local land-use controls so as not to attract the users of such services. If rents are higher in wealthier areas, this activity would weaken the relationship between homelessness, as measured by shelter capacity, and local rents.

The results of the Burt survey were released close to the release of the Census 1990 S-night enumeration results, which was thereafter the preferred source of homelessness data among researchers. While the Burt survey was referenced in many academic works, data from the Burt survey were not used as the dependent variable for homelessness in any major quantitative efforts to determine the variables most strongly associated with homelessness.

2.2.3: Census 1990 S-night enumeration

As part of the 1990 Census, the U.S. Census Bureau conducted a one-night count of people experiencing homelessness in urban places with populations of at least 50,000. The "S-night" (street and shelter night) enumeration was conducted on March 20–21, 1990, and consisted of three components. From 6 p.m. to midnight, enumerators counted everyone sleeping or staying at a predesignated list of shelters that was intended to be a complete list of all known shelters (Write & Devine, 1992). Between 2 a.m. and 4 a.m., enumerators attempted to count everyone experiencing homelessness on the streets at locations designated by local officials as known congregating areas. Enumerators counted everyone they saw except for people in uniform and people engaging in obvious money-making activities other than panhandling. Enumerators did not talk to any of the people they counted. (Early & Olsen, 2002). Between 4 a.m. and 8 a.m., enumerators attempted to count all individuals exiting pre-designated abandoned buildings (Write & Devine, 1992).

Researchers have criticized the way the S-night counts were conducted and the accuracy of the resulting data. One common criticism is that a point-in-time count is not a representation of the number of people experiencing homelessness in a particular year, but rather a count of the number of people experiencing homelessness on a single day in that particular year. Additionally, enumerators of the S-night count were instructed to not enter abandoned buildings, but only to wait outside until 8 a.m. and count those who left, therefore anyone experiencing homelessness staying in one of those abandoned buildings who left after 8 a.m. were not counted (Grimes & Chressanthis, 1997).

The S-night enumeration likely underestimated the number of people experiencing homelessness (Grimes & Chressanthis, 1997; Hudson, 1993; Quigley et al., 2001). To evaluate the S-night count, the Census Bureau sponsored research in five cities in which evaluators were deployed undercover to impersonate people experiencing homelessness at the listed street locations for enumerations. Evaluators observed the behavior of enumerators to monitor whether they showed up and followed directions, estimated the number of people experiencing homelessness at listed street locations, and reported whether they themselves had been counted. The proportion of counted "decoys" provides a rough estimate of the degree of undercounting at listed street locations across these five cities. The actual degree of undercounting is likely higher to the degree that people experiencing homelessness were in places other than the listed street and shelter locations used in each city. The percentages of decoys explicitly indicating that they had not been counted was 10% in New Orleans, 10% in Phoenix, 13% in Los Angeles, 20% in New York, and 25% in Chicago (Martin, 1992).

Evaluations of the enumeration efforts found that enumerators in Chicago simply dropped off census forms at the largest shelter, and only people staying in the shelter who expressed interest in filling out a form were provided a form by shelter staff. Otherwise, people in the largest shelter in Chicago were not counted (Edin, 1992). Evaluations of the count also revealed that many enumerators either failed to visit many of the sites and shelters or did not follow the predetermined protocol in counting the number of people at the location (Quigley et al., 2001). In Chicago, the police department generated locations for enumerators to count unsheltered people experiencing homelessness without consulting anyone in the city's social services network (Edin, 1992). Reasons cited for low-quality enumeration in the S-night count include poor training (Hopper, 1992), poorly-defined geographies and incorrect addresses (Edin, 1992), and enumerator concerns for their personal safety (Quigley et al., 2001).

The Census Bureau estimated a 1990 population of people experiencing homelessness of 230,000 based on the S-night enumeration, but the consensus among researchers was that the population of people experiencing homelessness in 1990 was between 550,000 and 600,000 (Quigley et al., 2001).

2.2.4: HUD Continuums of Care

Since 1994, HUD has provided support under the Super Notice of Fund Availability (NOFA) program to assist people experiencing homelessness achieve self-sufficiency and permanent housing. Eligible counties seeking funding were required to submit a "continuum of care" plan to HUD. These plans justified community requests for funding under a variety of federal programs, such as the Supportive Housing Program (SHP) and the Shelter Plus Care Program (S+C). HUD guidelines for completion of these continuum of care plans encouraged consistency among estimate methodologies and data schemas (Quigley et al., 2001; HUD, 1994). HUD's official definition of a CoC plan was the following (HUD, 1999):

A Continuum of Care Plan is a community plan to organize and deliver housing and services to meet the specific needs of people who are homeless as they move to stable housing and maximum self-sufficiency. It includes action steps to end homelessness and prevent a return to homelessness.

Beginning in 2005, HUD mandated that jurisdictions conduct a point-in-time (PIT) count at least once every two years in the last week of January to receive federal aid for homelessness programs (Schwartz, 2010). Before CoC plans began incorporating PIT counts into the requirements for federal aid, people experiencing homelessness were not counted in the decennial Census, the American Community Survey, the Current Population Survey, the American Housing Survey, or any other national quantitative dataset of the population or households (Schwartz, 2010).

Division B of the Act to Prevent Mortgage Foreclosures and Enhance Mortgage Credit Availability, called the Homeless Emergency Assistance and Rapid Transition to Housing Act of 2009 (HEARTH Act), amended the McKinney-Vento Homeless Assistance Act and established the Continuum of Care (CoC) Program by consolidating and amending the SHP, S+C, & Section 8/SRO programs. The purpose of consolidating these programs into the CoC Program was to improve efficiency and enhance the response coordination of these programs to better meet the needs of homeless individuals and families (HUD, 2011). President Obama signed the HEARTH Act into law in 2009, and HUD published the CoC Program Interim Rule in 2012 to formally implement the CoC Program.

The CoC Program is designed to promote community-wide commitment to the goal of ending homelessness, quickly re-house individuals and families experiencing homelessness, provide those individuals and families with access to supportive services and programs to keep them in housing, and to optimize self-sufficiency among program participants (HUD, 2014a). The CoC program was designed to prioritize strategies like permanent supportive housing and rapid re-housing that results from the New York Housing Study (NYHS), the Rapid Re-housing for Homeless Families Demonstration (RRHD) program, and the Homelessness Prevention and Rapid Re-housing Program (HPRP) showed to be effective at ending homelessness for program participants (Burt et al., 2016; Finkel et al., 2016; Padgett et al., 2016).

For purposes of distributing federal aid and conducting regional counts, most of the nation is split into CoC areas. In almost all cases, a CoC area comprises a county or group of counties and CoC boundaries are drawn along county lines. HUD encourages coordination and cooperation among jurisdictions to create comprehensive packages of services and solutions to homelessness, and CoC applications that demonstrate good coordination are more competitive (HUD, 2012). Participating in a CoC is voluntary, and jurisdictions that are not interested in applying for federal funds are not required to participate in a CoC or conduct PIT counts.

One of the primary responsibilities of the CoC Board[4] is to understand the extent and nature of homelessness in the geographic area that the CoC services, partly by conducting annual or biennial point-in-time (PIT) and annual housing inventory counts (HIC) through the homelessness management information system (HMIS). Each CoC develops a methodology that best fits their geographic area in accordance with HUD's minimum standards for conducting the PIT count. CoCs may either

[4] The CoC Board is the entity established by the CoC to act on its behalf. The CoC's Board must be representative of the CoC and must include at least one homeless or previously homeless individual. The responsibilities of the Board depend on how much authority is delegated to the Board by the CoC, in accordance with the CoC's governance charter (HUD, 2014a).

conduct a complete census or one or more sampling and extrapolation methods. HUD evaluates the nature and basis for estimation and extrapolation of CoCs sheltered and/or unsheltered counts in the annual CoC Program Competition (HUD, 2014b).

A criticism of the S-Night enumeration that also applies to the CoC PIT count is that a point-in-time count is not a representation of the number of people experiencing homelessness in a particular year, but rather a count of the number of people experiencing homelessness on a single day in that particular year (Grimes & Chressanthis, 1997). Additionally, enumerators for PIT counts are typically teams of CoC agency representatives and community volunteers, so levels of volunteer participation and training can significantly affect the quality or completeness of a count, and there may be inconsistencies in the way that communities measure homelessness over time (Hanratty, 2017).

Overall, the PIT count data are the best available data for the number of people experiencing homelessness, and researchers have found PIT count data to be an improvement over past sources of homelessness data. Byrne et al. found that the explanatory power of their homelessness model increased from 35 percent to 58 percent compared to Lee et al.'s model and attributed that increase to the higher quality of CoC data (2013).

2.3: Determinants of Homelessness

Research on structural determinants of homelessness emerged in the 1990s as a response to studies focused on the personal characteristics of those experiencing homelessness. In the context of homelessness research, individual-level variables measure characteristics of people experiencing homelessness, such as their age, race, whether they abuse drugs or experience a mental illness, etc. Structural variables measure characteristics of the communities in which people experience homelessness.

These early studies were primarily conducted by researchers in the medical and social services fields. By their nature, individual-level studies focused on characteristics and conditions of individuals and households, and were based on theoretical models that conceptualized homelessness as a result of individual-level factors as varied as adverse childhood experiences, disability, mental illness, substance abuse disorders, lack of social or human capital, a history of institutional involvement, and exogenous health and income shocks (Byrne et al., 2013). These researchers studied only personal characteristics of those already experiencing homelessness and some found that their hypothesized causes of homelessness explained only a small proportion of the variance in the length of time a person experienced homelessness (Calsyn & Roades, 1994), while others resulted in findings that mental illness was the primary determinant of homelessness and that emergency shelters were replacing institutions that had previously been dedicated to people with mental health conditions (Bassuk, Rubin, & Lauriat, 1984; Jones, 1983). Other researchers, like Freeman and Hall (1987), argued that deinstitutionalization cannot be cited as a significant direct cause of homelessness because deinstitutionalization began in the late 1950s and early 1960s, while homelessness did not begin to spike until the 1980s, roughly 20 years later.

Quigley et al. (2001) explain that the tendency to downplay housing availability as an explanation for homelessness appears to be justified by the traits of the people experiencing homelessness. Research describes a group suffering disproportionately from mental illness, drug and alcohol addiction, and extreme social isolation. Nearly one-third of people experiencing homelessness suffer from mental illness and one-half abuse drugs or alcohol. Three-quarters of the homeless have been institutionalized (Burt & Cohen, 1989; Shlay & Rossi, 1992). Given this confluence of personal problems and the relatively low incidence of homelessness, several authors have dismissed the explanations of homelessness that focus on housing market conditions (Jencks, 1994).

Point-prevalence estimates fail to account for turnover among the homeless and thus understate the likelihood of experiencing a homelessness spell. Culhane et al. (1994) show that, although on any day 0.1% of the population of New York City is homeless, 1% of the population experiences homelessness over the course of a year, and larger percentages of people experience homelessness when measured over longer periods. Moreover, turnover among the homeless suggests that point-prevalence samples are disproportionately composed of individuals suffering long spells. Phelan and Link (1999) demonstrate that this composition bias overstates the prevalence of personal problems and social isolation among people experiencing homelessness, those overemphasizing those factors' importance as an explanation for homelessness.

One of the earliest economic theories attempting to explain how homelessness was primarily a structural problem was laid out by Cecil Bohanon (1991), depicted in panels A-D of Figure 1.

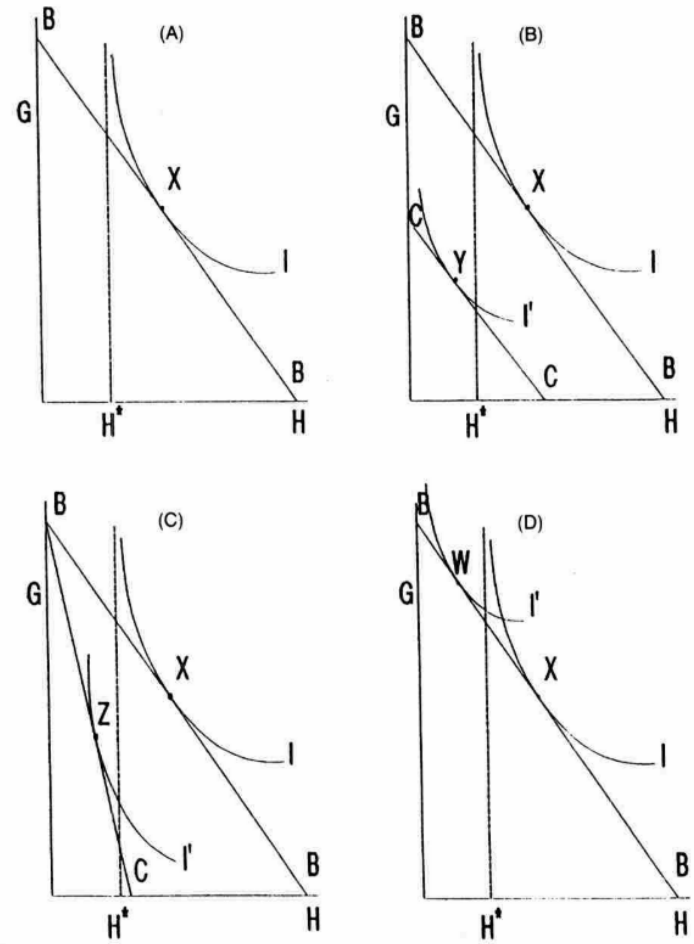

Figure 1: Bohanon's economic theory of homelessness

In all four panels, the horizontal H axis represents housing consumed where a quantity of housing less than H* depicts homelessness, the vertical G axis represents all other goods consumed, the line BB represents the budget constraint of a household living below the poverty threshold, I represents the indifference curve (or the limits within which spending could change without a corresponding change in quality of life), and point X represents the quantity of housing consumed by a household living in poverty that is not considered to be experiencing homelessness.

Panel A represents a household living below the poverty line before any changes that may cause the household to begin experiencing homelessness, which could include a decrease in income (represented in panel B), an increase in the cost of housing (represented in panel C), or a change in household spending priorities (represented in panel D). In panels B, C, and D, a new point Y, Z, or W, respectively, represents the quantity of housing consumed by a household living in poverty after a change resulted in a situation in which a household could logically choose homelessness without experiencing a decrease in their quality of life, represented by a new indifference curve, I'. Albeit simplified, this theoretical framework provides a foundation for understanding structural determinants of homelessness.

Like Bohanon and many researchers who conducted studies prior to this one, this study is written from the perspective that there will always be people in our communities with personal problems that affect their ability to be self-sufficient, and research on determinants of homelessness has moved towards a general consensus that individual and structural explanations are not mutually exclusive (Byrne et al., 2013; Culhane, Lee, & Wachter, 1996; O'Flaherty, 2004), but structural conditions determine whether or not those most vulnerable members of our society fall into homelessness. Below are descriptions of the most commonly studied structural determinants of homelessness with arguments as to why they could potentially affect homelessness rates and past findings.[5] These variables are all included in the panel analysis conducted for this study.

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[5] One variable that was frequently studied in the early 1990s and not included in this analysis is rent control. William Tucker (1987) wrote an article for The National Review (a conservative political magazine), and various spinoffs of the article began circulating through the media. Several scholars included rent control as a variable in models analyzing the relationship between homelessness and associated variables to test the validity of the claim and the found the claim that rent control causes increases in homelessness to be false almost to the point of fraudulent (Appelbaum et al., 1991; Bohanon, 1991; Honig & Filer, 1993; Quigley & Portney, 1990).

2.3.1: Housing affordability

In a response to Randall Filer's (1990) claim in an article of the Wall Street Journal that "we know almost nothing about the connection between homelessness and housing markets. There is no reliable evidence that homelessness is more extensive in cities with tight housing markets," Bohanon (1991) conducted a cross-sectional multivariate regression analysis using HUD 1984 sheltered population data and 1980 Census data and found that median rent, the most common measurement of housing affordability, was the leading factor associated with homelessness rates with statistical significance at the one percent level.

In the early 1980s, the rent-to-income ratio rose so sharply that by 1983, 22 percent of renters paid 50 percent or more of their income towards rent. In addition, declining federal support for public housing construction, growing waiting lists for public housing, increasing home ownership costs, more frequent displacement and abandonment of residential buildings, and widespread demolition of single-room occupancy hotels have all operated to decrease the supply of low-cost housing, especially among the very lowest priced units (Hartman, 1986; Hopper & Hamberg, 1986; Rossi & Wright, 1987). Consequently, some individuals are unable to find alternative living arrangements short of emergency shelters or the streets (Elliot & Krivo, 1991).

It cost a young family with children 23 percent of their income to take out a mortgage on an average-priced house in 1973, and by 1988 the same scenario would cost over half of a young family's income (Children's Defense Fund, 1988). In 1988, the average single-parent household with a head under the age of 25 paid 81 percent of its income on housing alone (Children's Defense Fund, 1988). Between 1970 and 1983 rents tripled, while renters' income only doubled. As a result, the average rent-income ratio grew from roughly one-quarter to one-third, and by 1985 close to one out of every four renters paid over half of their income for housing costs. Among households living below the poverty line, roughly 45 percent paid more than 70 percent of their income on housing in 1985, 65 percent paid more than half, and 85 percent spent more than 30 percent of their income on housing (Appelbaum et al., 1991).

Without available or affordable housing, some people will live with relatives or friends, thereby increasing the level of household doubling-up (Mutchler & Krivo, 1989). Other people, especially those with weaker or less resourceful social networks (Rossi, 1989), will not find a home at all (Elliot & Krivo, 1991).

Using data as early as the 1984 HUD survey of opinions used for the agency's national estimate of homeless, Elliot and Krivo (1991) found that the supply of low-rent housing was one of the two strongest predictors of homelessness, along with per capita expenditures on mental health care.[6] Bohanon (1991) found that median rent was the leading variable associated with homelessness rates with statistical significance at the one percent level. Honig and Filer (1993) found a strong

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[6] The data source for per capita expenditures on mental health care used by Elliot and Krivo has since been discontinued. The National Association of State Mental Health Program Directors provided data on mental health expenditures by state mental health agencies at the state level. I was unable to find a suitable alternative for use in this analysis. Grimes and Chressanthis (1997) believe they found that rent control has a highly significant, albeit small, positive impact on homelessness by making rent control an endogenous variable instead of an exogenous variable, as it was treated in past studies. However, they failed to address the likelihood that the supposed significance of predicted rates of rent control was merely masking the significant impact of variables used to predict whether or not rent control would be implemented, such as the price of an apartment at the city's 10th percentile of the rent distribution and the percent of the total housing stock which are renter-occupied units.

relationship between measures of housing cost and informed opinion about the incidence of homelessness. Hanratty (2017) found that once area-fixed effects are included, median rent was the only variable that remained positive and significant in its relationship to homelessness. A finding that median rent is statistically significant and positively associated with homelessness is common among scholars studying homelessness (Burt, 1992; Byrne et al., 2013; Early & Olsen, 2002; Fargo, Munley, Byrne, Montgomery, & Culhane, 2013; Grimes & Chressanthis, 1997; Barrett A. Lee, Price-Spratlen, & Kanan, 2003; Quigley & Portney, 1990; Quigley et al., 2001).

I hypothesize that median rent will be statistically significant and positively associated with homelessness rates. This has been a consistent finding in past research, and I expect that a CoC's ability to implement Housing First strategies is dependent on the availability of affordable housing.

2.3.2: Income and poverty

When more people live in poverty, the rate of homelessness may also be higher because more people are forced to choose between paying for housing and meeting other needs such as food, clothing, and medical care. An area's poverty rate has commonly been included in models studying homelessness, but these models have rarely found any statistically significant association between poverty rates and homelessness rates. Other measures of income have sometimes been included in models studying homelessness, and the results regarding the relationship between income and homelessness have been inconsistent.

For example, Burt (1992) found that poverty and income had no statistically significant impact on homelessness rates. Fargo et al. (2013) did not test for poverty, but found that income is statistically significant and negatively associated with homelessness rates. Quigley et al. (2001) found that median household income is statistically significant and positively associated with homelessness rates, but found per capita income and poverty rates to be statistically insignificant.

Quigley et al. (2001) tested a theory that homelessness increases with the degree of income inequality by regressing homelessness on vacancy rates, median rents, the proportion of households with incomes under $15,000, and median household income. Their model used median household income as a measurement of income inequality by holding the proportion of households with incomes under $15,000 constant. The results of their model showed that higher levels of income inequality were associated with higher levels of homelessness. To this author's knowledge, a measure of income inequality has not been used in any models studying homelessness subsequent to Quigley et al.'s 2001 research, and a measure of income inequality will be included in the panel analysis used in this study.

Marta Elliot and Lauren Krivo (1991) studied income indirectly by using a proportion of unskilled jobs as a covariate in their model. They found that unskilled jobs, which often do not provide enough income to support monthly housing costs, may be the only jobs available to individuals experiencing homelessness (Elliot & Krivo, 1991).

An increase in the percentage of people living below the poverty line from 11.4 percent in 1978 to 14.4 percent in 1984 support this argument (Elliot & Krivo, 1991). Reductions in federal means-tested benefit programs, stricter eligibility requirements for disability benefits, and decreases in the real value of income maintenance programs in the early 1980s worsened housing instability for people living below the poverty line (Elliot & Krivo, 1991; Hopper & Hamberg, 1986; Redburn & Buss, 1986; Rossi & Wright, 1987).

Despite these findings, income and poverty were found to be statistically insignificant in their associations with homelessness more often than they were significant (Appelbaum et al., 1991; Burt, 1992; Byrne et al., 2013; Early & Olsen, 2002; Elliot & Krivo, 1991; Grimes & Chressanthis, 1997; Honig & Filer, 1993; Barrett A. Lee et al., 2003; Quigley & Portney, 1990; Quigley et al., 2001). I hypothesize that income will not be statistically significant in this model, but that income inequality will be statistically significant and positively associated with homelessness rates.

2.3.3: Unemployment and underemployment

A 1984 survey of nearly 1,000 homeless persons in Ohio (Roth & Bean, 1986) emphasizes the importance of unemployment as a cause of homelessness wherein 22 percent of respondents listed unemployment as the primary reason for their homelessness. The long-term shift in employment from manufacturing to service industries has increased the proportion of unstable, nonadvancing, low-paying jobs (Elliot & Krivo, 1991). Burt and Cohen (1989) reported that single women, women with children, and single men experiencing homelessness were without a steady job for at least three months for an average of 3.4, 3.8, and 4.2 years respectively. However, among these same single men and women experiencing homelessness, income from working was the most common single source of income, indicating that a notable portion of people experiencing homelessness work in unstable jobs for short periods of time (Elliot & Krivo, 1991).

Scholars are split in determining the influence that unemployment rates have on homelessness. Unemployment was found to be insignificant in several models that tested the impact of unemployment on homelessness rates (Byrne et al., 2013; Early & Olsen, 2002; Elliot & Krivo, 1991; Hanratty, 2017; Barrett A. Lee et al., 2003; Quigley et al., 2001). However, there have been a nearly equivalent number of studies that found unemployment to be positively and significantly associated with the homelessness rate (Appelbaum et al., 1991; Bohanon, 1991; Burt, 1992; Troutman, Jackson, & Ekelund, 1999). In Hanratty's (2017) model, unemployment became significant and positively associated with homelessness when included in a model that used small area estimates of unemployment and vacancy rates. I hypothesize that unemployment will be statistically significant and positively associated with homelessness in this study.

2.3.4: Vacancy

A low residential rental vacancy rate is a signal of a tight housing market, and many prior models studying homelessness have included vacancy rates. In models that include both median rent and vacancy rates as variables possibly associated with homelessness rates, multicollinearity is likely an issue because those two variables are likely to be highly correlated with one another. In the case of a tight housing market, one would expect vacancy rates to be low and median rent to be high, and vice versa in the opposite scenario.

This is likely to be why past findings are split on whether vacancy rates are statistically significant in their association with homelessness. In some studies, the vacancy rate was found to be statistically significant and negatively associated with homelessness, meaning that homelessness is higher in tight housing markets with low vacancy rates (Appelbaum et al., 1991; Quigley & Portney, 1990; Quigley et al., 2001; Troutman et al., 1999). In other studies, the vacancy rate has been found to be statistically insignificant (Burt, 1992). I am not aware of any studies that have found the vacancy rate to be positively associated with homelessness. I hypothesize that the vacancy rate will be statistically insignificant in this model.

2.3.5: Tenure

As housing prices inflate, the transition to home ownership becomes more difficult and competition in the rental market increases, pushing previously affordable rental units out of reach for low-income households at risk of experiencing homelessness (Barrett A. Lee et al., 2003). Like the vacancy rate, there is a possibility of multicollinearity problems between the effect that tenure has on homelessness rates and the effect of housing affordability, since higher proportions of renter-occupied households tend to occur in tight housing markets in which low-income households are less likely to be able to afford the down payment or acquire financing to purchase a home. However, the recent housing crisis has shown that this is not always the case, and it is possible for low-income households to receive financing for homes even as housing values are inflated.

Many past studies have not included tenure as an independent variable in models analyzing the relationship of variables associated with homelessness rates.

However, past research that has included tenure has been split in their results. The majority has found that areas with large proportions of renter-occupied households tend to have higher homelessness rates (Appelbaum et al., 1991; Byrne et al., 2013; Fargo et al., 2013; Hanratty, 2017). At least one study has found that tenure has no statistically significant association with homelessness rates (Barrett A. Lee et al., 2003), although the rate of homeownership was negatively associated with homelessness rates—a result in line with past research. I hypothesize that the proportion of renter-occupied households will be statistically significant and positively associated with homelessness rates in this study.

2.3.6: Race and ethnicity

Several studies and reports have found that black and Hispanic people have been heavily overrepresented among people experiencing homelessness (Burt & Cohen, 1989; Rossi, 1989; Roth, Bean, Lust, & Saveanu, 1985; HUD, 1984; HUD, 2018a). Black households in particular are highly segregated (Massey & Denton, 1993) and often face discrimination in the housing market (Berkovec, Canner, Hannan, & Gabriel, 1997; Galster, 1987; Massey, Rugh, Steil, & Albright, 2016; Munnell, Tootell, Browne, & McEneaney, 1996; Schafer & Ladd, 1981; Wienk, Reid, Simonson, & Eggers, 1979). This discrimination worsened in the lead up to the Great Recession. In the mid-1990s, an estimated 10 to 35 percent of people issued subprime loans were eligible for prime loans (Mahoney & Zorn, 1996). About 10 years later, as we approached the Great Recession, this percentage grew until 62 percent of subprime borrowers, disproportionately black and Hispanic, actually qualified for prime loans in 2006 (Brooks & Simon, 2007).

Massey et al. (2016) analyzed a randomly-selected sample of 220 deposition statements and testimonies from cases where discrimination in the real estate market during the housing boom prior to the Great Recession was alleged and the case went to trial to identify instances of structural or individual discrimination. They found that structural racism was evident in 76 percent of the 220 deposition statements and testimonies, and that individual racism was only evident in 11 percent of the same texts. In the deposition statements analyzed, defendants referred to subprime mortgages as “ghetto loans” and black customers were referred to as “less sophisticated and intelligent,” “easier to manipulate,” “people who don’t pay their bills,” and even “mud people.” Some of the strategies used by lending institutions that were discussed in these cases included cold-calling black potential lenders multiple times per day, deliberate deception and misrepresentation of lending terms, falsification of loan documents, recruiting community leaders to unwittingly build trust for predatory lenders, targeting elderly households for aggressive high-pressure marketing, the organization of sales events for subprime loans labeled “wealth-building seminars,” and the use of a particularly deceptive practice of mailing “live draft checks” to targeted households in black communities (Massey et al., 2016):

> *Wells Fargo would mail checks in the amount of $1,000 or $1,500 to leads. Once these checks were deposited or cashed, they instantly became loans with Wells Fargo at very high interest rates. Individuals who cashed these checks became an instant “lead” target for a home equity refinance loan, which of course would end up placing the borrower’s home at risk.*

During the Great Recession, the level of black-white segregation powerfully predicted the rate of foreclosures (Rugh & Massey, 2010). For example, majority-black Prince George’s County experienced the largest concentration of foreclosures following the Great Recession compared to any other county in Maryland (Boston, 2012). According to an analysis of Home Mortgage Disclosure Act data, this was a trend across the country, as minority and particularly black households were more likely to receive subprime loans than white households in the lead up to the Great Recession (Goldstein & Urevick-Ackelsberg, 2008).

These practices unfairly diminished the wealth of black borrowers and exposed them to elevated risk of foreclosure and repossession, making those households unstably housed and increasing pressure on the rental market in black communities (Massey et al., 2016). In the rental market, evictions are much more common among black households than white households (Desmond, 2016).

Racial discrimination in housing intersects with gender, and there is evidence that black women are affected specifically. In Milwaukee's poorest black neighborhoods, one female renter in 17 was evicted through the court system each year, which was twice as often as men from those neighborhoods and nine times as often as women from the city's poorest white areas. Women from black neighborhoods made up nine percent of Milwaukee's population and 30 percent of its evicted tenants (Desmond, 2016). Desmond summarized the proliferation of evictions being carried out against low-income black women (2016):

If incarceration had come to define the lives of men from impoverished black neighborhoods, eviction was shaping the lives of women. Poor black men were locked up. Poor black women were locked out.

Structural racism has worked its way into social media platforms used for real estate advertising as well. The Department of Housing and Urban Development (HUD) recently charged Facebook with violating the Fair Housing Act and stated that

Facebook is "encouraging, enabling, and causing" housing discrimination through its advertising platform. An article published by CNN cited an investigation reportedly conducted by ProPublica in November 2017 that found discriminatory ads were being published on Facebook and thereby violating the Fair Housing Act. ProPublica was able to purchase dozens of home-rental ads that specifically excluded "African Americans, mothers of high school kids, people interested in wheelchair ramps, Jews, expats from Argentina and Spanish speakers" (Yurieff, 2019). Regarding the case, HUD Secretary Ben Carson said the following in a statement (Yurieff, 2019):

> *Facebook is discriminating against people based upon who they are and where they live. Using a computer to limit a person's housing choices can be just as discriminatory as slamming a door in someone's face.*

Discrimination in the real estate market based on race and ethnicity for both homeowners and renters limits peoples' housing choices and theoretically increases the risk of homelessness for at-risk households who experience either structural or individual discrimination while searching for a home. HUD (2018a) notes that nearly half of all people experiencing homelessness (49% or 270,568 people) identified their race as white, and nearly 6 in 10 people (59%) experiencing unsheltered homelessness were white. While comprising nearly half of the population of people experiencing homelessness, people identifying as white were underrepresented compared to their share of the U.S. population (72 percent). In comparison, almost 40 percent of people experiencing homelessness identified their race as black, while the population of the United States is under 13 percent black (Census, 2013-2017; HUD, 2018a).

Much of the prior research conducted on variables associated with homelessness has not included race or ethnicity as a tested variable, and the research that has included race or ethnicity experienced mixed results. Two known studies found that the relative size of the black population was statistically significant and positively associated with homelessness rates (Elliot & Krivo, 1991; Honig & Filer, 1993). Honig and Filer (1993) found that the relative size of the black population had an especially strong association with the rate at which households doubled-up with family members or friends. Other studies have found no statistically significant association between race or ethnicity and homelessness rates (Byrne et al., 2013; Early & Olsen, 2002; Barrett A. Lee et al., 2003; Troutman et al., 1999). I hypothesize that the percentage of renters identifying as white, non-Hispanic will be statistically significant and negatively associated with homelessness rates.

2.3.7: Climate

Theoretical frameworks for understanding structural determinants of homelessness, such as those proposed by Bohanon (1991) and O'Flaherty (1996, 2010, 2012) look at homelessness as, to some extent, a result of a rational economic decision-making process for low-income households between housing and other goods. From this theoretical vantage point, the inclusion of climate in a model studying variables associated with homelessness makes sense, because a household's tolerance for homelessness in favor of other goods may be higher in areas with a temperate climate and low precipitation. It may also be possible that people find temporary housing that is not picked up in the PIT count and that is not normally available to them when the climate is particularly severe, or that some migration of people experiencing chronic homelessness to areas with milder temperatures and less rainfall takes place, which would mean that climate variables may be statistically significant, but not as substantively relevant.

Past research has sometimes found mean temperature to be statistically significant and positively associated with homelessness (Appelbaum et al., 1991; Troutman et al., 1999). Other studies found that higher temperatures are only statistically significant and positively associated with specifically unsheltered homelessness (Corinth & Lucas, 2018; Early & Olsen, 2002). Some studies have found that climatic variables are not associated with homelessness rates in a statistically significant way (Bohanon, 1991). Byrne et al. (2013) determined that it was not feasible to include measures of climate given that CoCs, which formed their unit of analysis, can be large enough that there was significant within-CoC climate variation. This study also uses CoCs as the unit of analysis and will attempt to include temperature and precipitation data using methods described in the next chapter. I hypothesize that climatic variables will be statistically significant, and that temperature will be positively associated with homelessness rates while precipitation is negatively associated with homelessness rates.

2.3.8: Inclusionary zoning

Grounded Solutions Network conducted a national census of local inclusionary housing programs and a national survey of state-level legislation and judicial decisions related to the adoption of inclusionary housing programs to create an inclusionary housing database in 2016. The existence of an inclusionary housing policy mandating or incentivizing the creation of affordable housing may have an impact on homelessness rates, so data from the Grounded Solutions database was included in this study.

2.3.9: Eviction filing rates

A national database of eviction data became available from Princeton University's Eviction Lab in 2018, and past researchers have not yet had the opportunity to study the association between eviction filing rates and homelessness rates at the national level. However, Collinson and Reed (2018) found that evictions cause households in New York City to be more likely to become homeless.

2.3.10: Housing First strategies

Research on the effectiveness of Housing First strategies has been limited thus far to small-scale longitudinal studies in one or several CoC areas. This study will broaden the scope to all CoCs to determine whether those CoCs that are more diligently implementing Housing First strategies such as permanent supportive housing and rapid re-housing are more effective in reducing homelessness than CoCs that rely more on emergency shelters and other high-barrier, short-term, or transitional strategies.

Given past literature's findings that the availability of affordable housing tends to be the most commonly cited statistically significant variable associated with homelessness rates, and the Housing First approach is geared towards finding ways to place people experiencing homelessness in an affordable housing unit permanently, I hypothesize that the implementation of Housing First strategies will have a statistically significant and negative association with homelessness rates.

2.4: Prior Models

Past studies have found that structural socio-economic factors such as rent levels, race, and unemployment contribute to homelessness. Most studies analyzed a cross-section of data from a single year. Quigley et al. (2001) conducted a panel analysis using the Aid to Families with Dependent Children Homeless Assistance Program (AFDC-HAP) eight-year dataset as part of their study, but this analysis was limited to counties in California.

Hanratty (2017) and Corinth (2017) also used a panel analysis like the one used in this study. Hanratty (2017) broadened the scope from California to CoCs across the country, and she studied the effect of right-to-shelter policies. Corinth (2017) studied the relationship between permanent supportive housing and homelessness and found that a significant negative relationship existed, but that the relationship was not very substantive and permanent supportive housing was not responsible for the most recent reductions in homelessness.

This study builds from the progress made by the modeling research of Hanratty (2017) and Corinth (2017) and introduces an index measuring the implementation of Housing First into a modeling study, thereby bridging the gap between longitudinal studies of Housing First and modeling studies on the relationship between homelessness rates and various independent variables. Methodologically, this study also builds from the research of Hanratty (2017) and Corinth (2017) by adding an analysis of interaction effects. This allows one to better understand how a third variable may interact with an independent variable to change the independent variable's relationship with homelessness rates. The results of this analysis will provide a deeper and more nuanced understanding of the relationship that Housing First and other variables have with homelessness in the United States.

For a simplified summary of studies that included models analyzing the relationship between homelessness rates and variables associated with homelessness and that were discussed most frequently in the literature review preceding this section, please see Table 1 below. The table includes each study's authors, data source for homelessness rates, and simplified indications of a small selection of key variables' statistical significance and the variable's positive or negative relationship with homelessness rates. Key variables in Table 1 include rent, vacancy rates, unemployment, poverty levels, housing tenure (positive and negative correlations relate to renter levels), race (positive and negative correlations relate to percent black), and income levels.

Table 1: Prior research of homelessness rates and associated variables

Study	Y Data	Rent	Vac.	Unem.	Pov.	Tenure (renter)	Race (black)	Income
Quigley (1990)	HUD, 1984	+**	-**	N/A	0	N/A	N/A	N/A
Elliot & Krivo (1991)	HUD, 1984	+**	N/A	0	0	N/A	+**	N/A
Appelbaum et al. (1991)	HUD, 1984	0	-*	+**	0	+**	N/A	N/A
Bohanon (1991)	HUD, 1984	+**	N/A	+**	N/A	N/A	N/A	N/A
Burt (1992)	Burt, 1989	+**	0	+**	0	N/A	N/A	0
Honig & Filer (1993)	HUD, 1984	+**	0	N/A	0	N/A	+*	N/A
Grimes & Chressanthis (1997)	Census, 1990	+**	N/A	N/A	0	N/A	N/A	N/A
Troutman et al. (1999)	Census, 1990	0	-**	+**	+*	N/A	0	N/A
Quigley et al. (2001)	Census, 1990	+**	-**	0	0	N/A	N/A	+**
Early & Olsen (2002)	Census, 1990	+**	0	0	0	N/A	0	N/A
Lee et al. (2003)	Census, 1990	+**	0	0	0	0	0	N/A
Byrne et al. (2013)	HUD, 2009	+**	0	0	0	+**	0	N/A
Fargo et al. (2013)	HUD, 2009	+**	N/A	N/A	N/A	+*	N/A	-*
Hanratty (2017)	HUD, 2007-14	+**	0	0	+**	+**	N/A	N/A
Corinth (2017)	HUD, 2007-14	+**	N/A	+**	N/A	N/A	N/A	N/A

**significant at a 5% level; *significant at a 10% level; 0 indicates factor was not significant; N/A indicates factor was not tested, or was only included within a composite variable in which individual significance was not tested

Note: In several cases, studies ran several different models and/or tested multiple methods or subpopulations of people experiencing homelessness as the dependent variable; therefore, the correlations and levels of significance reported in this table will not reflect the complexity and nuance of past studies' results.

Chapter 3: Methodology, Data, and Constructing the Model

To answer this study's research question, a linear mixed models panel analysis is conducted using time-series data between 2009 and 2017. The independent variables include many of the commonly cited variables associated with homelessness discussed in the previous chapter, along with an independent variable measuring the degree to which a CoC's response to homelessness follows the Housing First approach. Determining the degree to which this variable is associated with homelessness rates is the primary focus of this study. The dependent variable will be homelessness rates.

Both direct effects and interaction effects of the implementation of the Housing First approach on homelessness rates while controlling for other variables associated with homelessness will be analyzed as a part of this study. This study will thus (a) analyze whether Housing First is associated with decreases in homelessness rates at the CoC level, and (b) analyze whether Housing First is associated with decreases in homelessness rates at the CoC level under particular types of structural and community conditions, as indicated by the interaction effects of changes in other variables associated with homelessness rates.

This study uses Continuum of Care (CoC) boundaries, as described in section 2.2.4: , as the units of analysis and uses 355 of the 384 CoCs across the country, including the two CoCs in Puerto Rico, to conduct the analyses. The study analyzes data between years 2009 and 2017 using a linear mixed model to determine the variables most significantly associated with homelessness rates and to learn the nature of those relationships.

3.1: Study Variables

The dependent variables used in this study are rates of homelessness and rates of homelessness experienced by different subpopulations. The independent variables are listed in Table 2 below and include a mixture of variables used in past studies and new variables made available thanks to the efforts of researchers creating new sources of data subsequent to much of the prior research being conducted on variables associated with homelessness.

The selection of several variables matches the variables used in prior studies because some prior studies have found those independent variables to be related to homelessness rates in a statistically significant way and because including the same variables allows for the results of this study to be more easily compared to prior studies. Some of these variables include the percentage of renter-occupied households, the unemployment rate, the poverty rate, the vacancy rate, and climate variables. Other variables used in this study have been used less frequently in prior studies and I will briefly explain some of those variable choices.

The racial composition of a community has been studied infrequently in past research, and this study used the percentage of renters who identified as non-Hispanic white as a measure of race instead of a breakdown of racial composition to avoid collinearity issues in the model. Racial segregation or concentration was not considered, because many CoCs are composed of multiple counties and the scale was too large for a measurement of segregation to be meaningful.

Rent burden was used a measure of housing affordability in each CoC, and collinearity concerns are also why other measures of housing affordability were not included. Rent burden was chosen instead of an overall percentage of households burdened with housing costs, because renters are more vulnerable to homelessness if they can no longer afford their home.

Two variables were included in this model because of the availability of new data measuring inclusionary zoning and eviction filing rates from the Grounded Solutions Network and Princeton University's Eviction Lab. Both of these variables have an intuitive link to homelessness rates, but the existence of relationship between either variable and homelessness rates has not been studied.

The Housing First index was included in this study to test the primary research question of this study, which is related to the relationship between the Housing First approach to ending homelessness and homelessness rates in CoCs across the country. The Housing First approach has been studied in longitudinal research, but the index will allow the relationship between Housing First and homelessness rates to be studied as well.

Table 2: Variables used in this model

Name	Type	Description	Notes
hl	y	people per 1,000 experiencing homelessness	
hls	y	people per 1,000 experiencing sheltered homelessness	
hlu	y	people per 1,000 experiencing unsheltered homelessness	
hlf	y	people per 1,000 in families experiencing homelessness	
hlc	y	people per 1,000 experiencing chronic homelessness	
hf	x	Housing First index	
medren	x	median gross rent of renter-occupied housing units	
medval	x	median home value of owner-occupied housing units	
medinc	x	median household income	
renocc	x	percentage of renter-occupied housing units	
renfam	x	percentage of renters in a family with children	no 2009 data
renwhi	x	percentage of renters identifying as white, non-Hispanic	
renedu	x	percentage of renters without a college degree	
unemp	x	unemployment rate	
pov	x	poverty rate	no 2009 data
fund	x	HUD CoC funding in the previous year per person	
evic	x	eviction filing rate	no PR or 2017 data; 17% missing
burd	x	percentage of rent-burdened households	
gini	x	gini index	no 2009 data
vac	x	vacancy rate	
coccat	x	CoC category: balance of state, smaller city or county, or major city	not longitudinal
temp	x	average January temperature	no DC, HI, or PR data
precip	x	total January precipitation	no DC, HI, or PR data
inczon	x	inclusionary zoning policy dummy variable	not longitudinal
Sources: U.S. Census Bureau ACS 5-year estimates; Eviction Lab, Princeton University; HUD PIT count data; HUD allocations and awards data			

3.2: Creation of a Housing First Index

The primary independent variable used in this study is a Housing First index. As O'Flaherty (2019) discussed, an estimate regarding the relationship between Housing First and homelessness in a community is missing from the existing literature, so an index by which to measure the degree to which Housing First is being implemented in a community has not been created before. With no previous examples to build from, this study will create a Housing First index with the hope that future research will improve upon this design. In this study, the degree to which a CoC is implementing a Housing First approach is calculated using data from the Housing Inventory Count (HIC), which is submitted by CoCs to HUD each year.

The index is constructed by using housing inventory count data gathered from HUD Exchange (2018b) and a simple formula:

Equation 2: Housing First index

$$hf = \frac{\left(\frac{\tau}{2}\right) + \rho + \varphi + \phi}{\beta}$$

The Housing First index is equal to the sum of the number of transitional housing beds (τ) divided by two, the number of rapid re-housing beds (ρ), the number of permanent supportive housing beds (φ), and the number of other permanent housing beds (ϕ) divided by the total number of beds (β) in the CoC, which also includes emergency shelter and safe haven beds. This results in an index score between 0 and 1 where a higher value indicates more reliance on permanent housing strategies and a stronger alignment with the Housing First approach. Since the idea of the Housing First approach is to move people experiencing homelessness into a permanent housing unit as quickly as possible to stabilize them and to give them the best chance of retaining their housing, a permanent unit of any kind is worth the most points, emergency shelter options are worth no points, and transitional housing falls somewhere in between, so those beds are worth half points. See a brief definition of Housing First and each category of the housing inventory in the glossary of this study for more information (HUD, 2017b; 2019a).

Of the 3,195 possible index scores for this variable, 3,148 or 98.5% of the total possible scores were calculated. Unlike the point-in-time counts that are required to be conducted once every two years, housing inventory count data come from a CoC's mandatory maintenance of a Homelessness Management Information System (HMIS). Data are required to be collected from service providers and submitted to HUD each year. Although some entries are missing, the amount of data available nonetheless provides a large enough sample size for use in this study, likely thanks to the HMIS requirement.

There were changes to the components of this index score over the duration of the study period. At the beginning of the study period in 2009, the only categories of housing included in the housing inventory count were emergency shelter, transitional housing, safe haven, and permanent supportive housing. In 2013, after HUD had published the CoC Program Interim Rule to formally implement the CoC Program adopted by the HEARTH Act of 2009, rapid re-housing was added to the housing inventory count. In 2014, other permanent housing was added to the housing inventory count as well.

3.3: Conducting the Panel Analyses

Panel analysis is a way to study the relationships between dependent variables and independent variables over both space and time, i.e. the data are both cross-sectional and longitudinal in nature. This study is analyzing the relationships between various types of homelessness and a number of independent variables across a set of 349 CoCs over a span of nine years. The study will use the linear mixed models (LMM) procedure in SPSS to conduct the panel analyses.

3.3.1: Linear mixed models procedure

The linear mixed models (LMM) procedure has several benefits over other types of methods for conducting panel analyses. One such benefit is that the LMM procedure is better able to handle data in an unbalanced design, i.e. a dataset with missing values. In the case of this study, of the 3,141 observations left for analysis after the data were cleaned as described in previous sections, only 1,724 of those observations would be usable in a panel analysis that required a balanced design that excluded cases listwise as opposed to pairwise. In a comparison between a balanced and unbalanced dataset, a general linear model (GLM) procedure will produce different results in terms of its fixed effects estimates and its estimates of covariance parameters, while a variance components (VARCOMP) procedure and LMM procedure can produce the same estimates in an unbalanced design. This is because the LMM and VARCOMP procedures offer maximum likelihood or restricted maximum likelihood methods of estimation, while GLM estimates are based on the method-of-moments approach. LMM is generally preferred because it is asymptotically efficient (minimum variance), whether or not the data are balanced, while GLM only achieves its optimum behavior when the data are balanced (SPSS Inc., 2005). In the case of this study, the ability of the model to handle an unbalanced dataset well is necessary.

In cases where observations are repeated for each subject over time, as is the case in this study, the LMM procedure accounts for the assumption that the error terms within a subject may be correlated, but independent across subjects. The GLM and VARCOMP procedures ignore possible correlations within the data, which may lead to incorrect conclusions regarding the significance of independent variables in the model. Although VARCOMP is a subset of LMM and the two procedures produce the same variance estimates, VARCOMP only fits relatively simple models because no statistics on fixed effects are produced and it can only handle random effects that are independent and identically distributed. For these reasons, LMM is the preferred alternative to GLM and VARCOMP when data are likely correlated because they come from the same subject (SPSS Inc., 2005).

Compared to a repeated measures analysis of variance (RM ANOVA) procedure, the LMM procedure is capable of considering time-dependent or time-varying continuous covariates, while the RM ANOVA procedure is only capable of considering baseline values of continuous covariates. Like GLM, the RM ANOVA procedure is also unable to analyze unbalanced datasets well. A single missing variable value in a case will cause that case to be dropped from the analysis in a process known as listwise, as opposed to pairwise, deletion (West, 2009).

The LMM procedure can uniquely consider random effects to explain random between-subject (CoCs, in the case of this study) variance in trajectories, and to also then analyze several different alternative covariance structures for random effects and compare those covariance structure models to determine the model with best fit to a longitudinal dataset (West, 2009; West, Welch, & Galecki, 2015). I chose to measure fixed effects for every independent variable except for time and place, because I am analyzing the entire population of CoCs and attempting to understand the relationship between the independent variables and homelessness rates in this population. This is different from testing within a sample to extrapolate information about the relationships to apply in a broader context, in which it may be more appropriate to test more of the independent variables' relationship with homelessness rates for random effects. All in all, the LMM procedure is the best method to use in the case of an unbalanced panel dataset in which I expect longitudinal observations in the same CoC to be at least partially dependent on one another due to the conditions and environment in which that CoC is operating.

3.3.2: Methodology for model selection

Müller, Scealy, and Welsh (2013) reviewed a large body of literature on linear mixed models selection and compared four different model selection methods. These methods include using information criteria, shrinkage methods based on penalized loss functions, the Fence procedure, and Bayesian techniques. According to Müller et al. (2013), using information criteria such as Akaike's Information Criterion (AIC) is the preferred method, paired with ensuring that the model is supported by the literature. For this study, the analysis will be run in SPSS using the MIXED procedure, which allows for a report of the AIC and other information criteria in each model run.

To select a final model, first a simple linear or polynomial regression was run, testing each potential covariate's independent relationship with homelessness rates (see Appendix 4: Individual Variable Regressions). Those variables without a statistically significant relationship with homelessness rates and without strong support in the literature suggesting a relationship with homelessness rates were excluded from the linear mixed models. Those variables without a statistically significant relationship in an independent linear or polynomial regression that are strongly supported by the literature may be important in interactions with other variables, which were tested in the linear mixed models. All remaining variables were included in the linear mixed models, and those variables that did not show a statistically significant relationship in their main effects with homelessness rates were removed one at a time in order of their p score values from highest to lowest and tested for interaction effects with all remaining variables before being removed if they were not significant in their interaction effects. Any interactions that showed significance and lowered the AIC were kept in the model even after main effects were removed. The model was continually reduced in this manner until all the variables left in the model were statistically significant.

Once all the model's independent variables were significant, the goal of the model refinement process became lowering the AIC. At that point, all main effect variables that were removed were reintroduced one at a time, and interaction effects between all remaining variables were tested one at a time to see if inclusion of a main effect or interaction variable can further decrease the AIC or change the significance of existing variables. After the reintroduction of main effect variables and the inclusion of interaction effects was tested, this resulting model with the lowest AIC and statistically significant variables was considered the final model from which the bulk of the study's conclusions are drawn.

This method will produce a model that will show which variables had the most statistically significant relationship with homelessness rates, and will help one to understand the relationship or lack of a relationship between implementation of the Housing First approach and homelessness rates in CoCs across the United States.

Chapter 4: Descriptive Statistics

This chapter includes descriptive statistics of some of the primary variables used in the panel analyses to provide a foundational understanding of the values and distributions of each variable before attempting to interpret the results of the panel analyses. Additional descriptive statistical results can be found in the appendices.

4.1: Housing First Index Scores

Despite changes to the way the Housing First index is measured over the study period due to changes in available data from HUD, the average Housing First index score across all CoCs slowly and steadily increased each year of the study period (see Table 3 below). This suggests that this index score is accurately reflecting a trend of service providers transitioning to more of a Housing First approach, and that the addition of more categories in the housing inventory count did not include service providers assisting people experiencing homelessness with permanent housing options that were previously excluded from the housing inventory count, but rather that service providers' permanent housing programs were simply recategorized into more refined categories that more accurately describe the services they provide.

Table 3: Housing First index scores

Year	Housing First index score
2009	0.502
2010	0.510
2011	0.528
2012	0.531
2013	0.543
2014	0.562
2015	0.582
2016	0.609
2017	0.623

This indication that more service providers across the country are moving towards a Housing First model makes it even more important that we study the relationship between the Housing First approach and homelessness rates.

4.2: Means Comparison

Descriptive statistics were run on the variables used in this study to better understand the dataset. [7] To establish a foundation for understanding the variables used in this study and their relationships with homelessness, variable means stratified by the median homelessness rate were calculated and provided in Table 4.

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[7] See Appendix 1 for a complete set of descriptive statistics run for the dataset used in this study, including variables that were not used in the final panel analyses.

4.2.1: Means comparison split by homelessness rates

Table 4: Means of variables stratified by observations with above- and below-median homelessness rates

Variable	Full Sample	Below-Median Homelessness	Above-Median Homelessness
People per 1,000 homeless	1.97 (.036)	0.86 (.008)	3.09 (.059)
Total population (1000s)	729.81 (18.27)	745.20 (23.20)	713.99 (28.36)
% Bachelor's degree or higher	29.13 (.221)	28.69 (.349)	29.59 (.267)
Median household income	55,411 (360)	56,879 (601)	53,903 (384)
Median gross rent	894.72 (5.82)	865.41 (9.25)	924.85 (6.90)
Median home value (1000s)	214.50 (2.36)	190.41 (2.67)	239.26 (3.81)
% Renters	33.92 (.215)	31.01 (.332)	36.90 (.252)
% Renters with children	34.26 (.204)	34.97 (.343)	33.50 (.210)
% Renters, white non-Hispanic	63.79 (.405)	67.20 (.461)	60.28 (.502)
% Renters, no college	45.21 (.243)	47.11 (.408)	43.27 (.408)
Unemployment rate	8.41 (.055)	7.97 (.085)	8.86 (.066)
CoC funding per person	5.16 (.093)	3.72 (.079)	6.62 (.160)
Poverty rate	15.11 (.133)	14.56 (.225)	15.69 (.132)
Eviction filing rate	6.30 (.171)	6.50 (.287)	6.10 (.181)
% Rent-burdened	31.04 (.126)	30.56 (.225)	31.54 (.106)
Gini index	0.46 (.002)	0.45 (.004)	0.46 (.002)
Vacancy rate	12.65 (.126)	12.41 (.176)	12.89 (.182)
Mean temperature in Jan	35.45 (.302)	33.19 (.465)	37.79 (.374)
Total precipitation in Jan	2.96 (.049)	2.79 (.059)	3.14 (.078)
CoC category*	1.96 (.008)	2.08 (.010)	1.84 (.012)
Inclusionary zoning*	0.34 (.008)	0.26 (.011)	0.42 (.012)
Housing First index	0.54 (.003)	0.54 (.004)	0.54 (.004)

Standard errors are in parentheses.
* Non-continuous variable. For CoC categories, 1 indicates a major city, 2 indicates a smaller town or county jurisdiction and 3 indicates a balance-of-state CoC. Inclusionary zoning is a dummy variable in which 1 indicates the adoption of an inclusionary zoning policy in at least one jurisdiction within the CoC and 0 indicates that no inclusionary zoning policies have been adopted within the CoC.

Though the means comparison is not part of the primary analysis and does not control for the effects of any of the independent variables, Table 4 shows no difference between the mean Housing First index scores of observations below or and above the median homelessness rate. Across observations, meaning a single year within a single CoC, where homelessness rates were above or below the median (1.40

people per 1,000 experiencing homelessness) across the study period, the mean Housing First index score was 0.54. This tells me that though Housing First is slowly being adopted by more service providers each year, it is being adopted at the same rate by CoCs with both above median and below median homelessness rates. This could be an early indication that Housing First will not be associated with a decrease in homelessness rates, but this means comparison is simply descriptive and does not control for any other variables or describe a relationship between Housing First and homelessness rates.

Another highlight from the means comparison is that there is a considerable disparity in the mean number of people per 1,000 experiencing homelessness between the two groups. In the below-median homelessness group, the mean homelessness rate is only 0.86 people per 1,000 experiencing homelessness. That number is the above-median homelessness group is almost three and a half times greater at 3.09 people per 1,000 experiencing homelessness. This tells me that there is a high amount of disparity between areas with low homelessness rates and areas with high homelessness rates, and this adds some weight to the differences in means of the other variables. While this table only shows me correlations with no attempt to determine causality, any discernable difference in the means of other variables should be studied very carefully.

In observations with homelessness rates above the median, the means of the median gross rent, median home values, and the percentage of renters in the housing market were all considerably higher, but the median household income was lower and the poverty rate was higher. This shows that in areas with higher homelessness rates, there are more renters, more expensive housing, and lower incomes. These correlations appear to line up with past findings that homelessness is largely a structural economic problem driven at least partially by a lack of affordable housing accessible to the most vulnerable households. The mean values for the percentage of rent-burdened households line up with past findings of that nature as well, being that jurisdictions with above-median homelessness rates have a higher mean percentage of rent-burdened households, although only slightly. Vacancy rates, on the other hand, do not. A slightly higher mean vacancy rate in observations with homelessness rates above the median implies that the housing market is tighter in areas with below-median homelessness rates, though the difference in means for that variable is small (12.41 to 12.89).

Another interesting means comparison is that the percentage of renters who are white, non-Hispanic, is lower in the above-median homelessness group with observations above the median homelessness rate. HUD's tabulations of point-in-time (PIT) count data (2018a) show that while nearly half of all people experiencing homelessness in 2018 (49 percent or 270,568) identified their race as white, and 59 percent of people experiencing unsheltered homelessness identified their race as white, people identifying as white were still underrepresented in the population of people experiencing homelessness compared to their share of the U.S. population, which is 72 percent (HUD, 2018a). This could be indicative of areas with large white, non-Hispanic, populations having more wealth, more accommodating access to services, and stronger safety nets in place, either institutional or social in nature, that prevent vulnerable populations from experiencing homelessness and merits careful study during the primary analyses.

Observations with homelessness rates above the median also had a higher mean temperature in January, when the point-in-time count is conducted. This lines up with some past findings (Appelbaum et al., 1991; Early & Olsen, 2002; Troutman et al., 1999) and suggests that those people experiencing homelessness who have the ability to move from one area of the country to another may move to warmer areas during the winter. It could also be an indication that people experiencing homelessness in colder areas are more likely to seek temporary housing in the last week of January that causes them to be missed during the PIT count, such as doubling up with family or friends, or staying in a motel room.

The mean CoC funding per person and the rate at which CoCs had at least one inclusionary zoning policy in place were also both higher in observations where the homelessness rate was above the median for all CoCs. This may be indicative of responses to homelessness and a lack of affordable housing, respectively, but the differences merit further investigation during the primary analyses of this study.

Other variables that tended to have higher means in the above-median homelessness group included unemployment and precipitation. The unemployment rate has been shown to be positively and significantly associated with homelessness rates in several prior modeling studies (Appelbaum et al., 1991; Bohanon, 1991; Burt, 1992; Corinth, 2017; Troutman et al., 1999), so it is not surprising that the mean unemployment rate is a little higher in CoCs with above-median homelessness rates, where the mean unemployment rate is 8.86, compared to CoCs with below-median homelessness rates where the unemployment rate is 7.97.

Precipitation being higher in CoCs with above-median homelessness rates is not very intuitive, nor does it align with my hypothesis for the relationship between precipitation and homelessness rates. It could be that any changes in precipitation between CoCs with above-median homelessness rates and below-median homelessness rates is purely coincidental. It could also be an indication that precipitation is not significantly related to homelessness, but temperature is positively and significantly associated with homelessness rates, and precipitation is simply higher in CoCs with warmer mean temperatures in January. A simple regression was run to test whether this is true for the data used in this study, and the results are plotted in Figure 2. Though it is obvious from the scatterplot that the relationship between temperature and precipitation is not best described linearly, there is a clear positive slope to the linear fit line in which precipitation goes up by 0.05 inches with each increase in the mean temperature of one degree Fahrenheit.

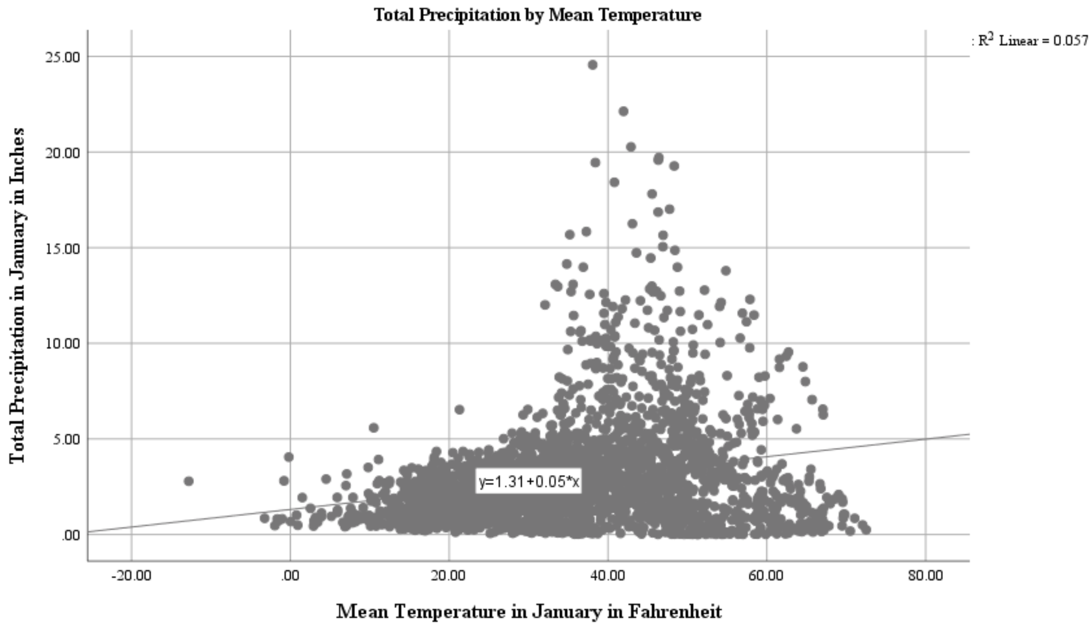

Figure 2: Total precipitation by mean temperature linear regression

The percentage of renters with no college education and the CoC category had lower mean values in CoCs with above-median homelessness rates. This tells me that homelessness rates are higher in CoCs with more educated renters and in major cities. These two variables could certainly be associated with one another and variables like income and median rent, so it will be important to test for multicollinearity when refining the model for use in the panel analysis.

Variables that did not show a noteworthy difference in means between the two groups included total population, the total percentage of people with a bachelor's degree or higher (though this percentage was slightly higher in above-median homelessness CoCs), the percentage of renters with children, the eviction filing rate, and the Gini index. None of these are particularly surprising, because they do not have a foundation in the literature for being significantly associated with homelessness, except for income inequality measured via the Gini index. Since the

Gini index is not noticeably different in the above-median homelessness CoCs when compared to those CoCs with below-median homelessness rates, this may be an early indication that my hypothesis that income inequality is positively and significantly associated with homelessness rates will not be supported.

4.2.2: Means comparison split by Housing First index scores

Another interesting means comparison is the means of variables for observations in which the Housing First index score was below median compared to observations in which the Housing First index score was above the median. The Housing First index is the independent variable of primary interest in this study, so it is important to understand the characteristics of CoCs that have adopted more of a Housing First model compared to CoCs that are relying more heavily on short-term shelter options when making conclusions about the outcomes of this study. Results of that means comparison can be found in Table 5 below.

Table 5: Means of variables stratified by observations with above- and below-median Housing First index scores

Variable	Full Sample	Below-Median HF Index Score	Above-Median HF Index Score
People per 1,000 homeless	1.97 (.036)	2.01 (.050)	1.94 (.051)
Total population (1000s)	729.81 (18.27)	703.76 (25.35)	767.35 (26.96)
% Bachelor's degree or higher	29.13 (.221)	26.96 (.241)	30.91 (.250)
Median household income	55,411 (360)	53,629 (363)	56,356 (372)
Median gross rent	894.72 (5.82)	852.00 (5.80)	922.27 (6.38)
Median home value (1000s)	214.50 (2.36)	203.70 (2.84)	222.64 (3.46)
% Renters	33.92 (.215)	32.36 (.204)	34.71 (.214)
% Renters with children	34.26 (.204)	34.94 (.172)	32.79 (.168)
% Renters, white non-Hispanic	63.79 (.405)	65.84 (.463)	60.80 (.489)
% Renters, no college	45.21 (.243)	46.60 (.227)	42.79 (.242)
Unemployment rate	8.41 (.055)	8.29 (.065)	8.44 (.062)
CoC funding per person	5.16 (.093)	3.37 (.077)	6.90 (.155)
Poverty rate	15.11 (.133)	14.70 (.135)	15.23 (.140)
Eviction filing rate	6.30 (.171)	5.41 (.156)	6.73 (.198)
% Rent-burdened	31.04 (.126)	30.32 (.065)	31.16 (.061)
Gini index	0.46 (.002)	0.45 (.001)	0.46 (.001)
Vacancy rate	12.65 (.126)	12.98 (.174)	11.94 (.156)
Mean temperature in Jan	35.45 (.302)	35.72 (.465)	34.11 (.351)
Total precipitation in Jan	2.96 (.049)	2.77 (.061)	3.07 (.068)
CoC category*	1.96 (.008)	2.05 (.012)	1.88 (.011)
Inclusionary zoning*	0.34 (.008)	0.32 (.012)	0.36 (.012)

Standard errors are in parentheses.
* Non-continuous variable. For CoC categories, 1 indicates a major city, 2 indicates a smaller town or county jurisdiction and 3 indicates a balance-of-state CoC. Inclusionary zoning is a dummy variable in which 1 indicates the adoption of an inclusionary zoning policy in at least one jurisdiction within the CoC and 0 indicates that no inclusionary zoning policies have been adopted within the CoC.

Areas with Housing First index scores above the median tend to have larger populations with higher incomes, home values, rent payments, rates of educational attainment, while also experiencing higher poverty rates, higher unemployment, more evictions, and a higher percentage of rent-burdened households. This tells me that areas that have adopted more of a Housing First approach tend to be a little wealthier, but more of the population may be vulnerable to homelessness. The renter populations are also noticeably different between the two groups. In CoCs with

Housing First index scores above the median, a larger percentage of the population rents, fewer of those renters have children, fewer are white non-Hispanic, and more have gone to college.

The largest difference in means that Table 6 shows me is that CoCs with Housing First index scores above the median receive over twice the number of grant dollars per person from HUD that CoCs with Housing First index scores below the median receive for assistance with programs and services designed to assist people experiencing homelessness. This makes HUD's preference for CoCs that have adopted a Housing First approach clear.

Despite these CoCs receiving over the twice the funding per person from HUD, CoCs with Housing First index scores above the median also experience slightly lower homelessness rates than CoCs with Housing First index scores below the median. This provides evidence that the increased funding is not linked to need, but rather, to a dedication to the strategies that HUD thinks are most likely to be effective in yielding positive result in reducing homelessness.

4.3: Distributions

Calculating the distributions of the values introduced in the means comparison provides a clearer understanding of the variables used in this study. To build off of the foundational means comparison, distributions were calculated for variable values with observations stratified again by the median homelessness rate. Descriptive statistics on the distribution of Housing First index scores and the homelessness rate are provided in Table 6 below. See Appendix 3 for a more complete accounting of distributions for all variables.

Table 6: Distribution descriptives for homelessness and the Housing First index

	Above and Below Median Homelessness Rates			Statistic	Std. Error
People per 1,000 Experiencing Homelessness	Below	Mean		.8550	.00777
		95% Confidence Interval for Mean	Lower Bound	.8397	
			Upper Bound	.8702	
		5% Trimmed Mean		.8600	
		Median		.8553	
		Variance		.095	
		Std. Deviation		.30769	
		Minimum		.02	
		Maximum		1.40	
		Range		1.38	
		Interquartile Range		.50	
		Skewness		-.137	.062
		Kurtosis		-.872	.123
	Above	Mean		3.0906	.05880
		95% Confidence Interval for Mean	Lower Bound	2.9753	
			Upper Bound	3.2059	
		5% Trimmed Mean		2.7505	
		Median		2.2144	
		Variance		5.431	
		Std. Deviation		2.33048	
		Minimum		1.40	
		Maximum		16.78	
		Range		15.38	
		Interquartile Range		1.73	
		Skewness		2.677	.062
		Kurtosis		8.507	.123
Housing First index	Below	Mean		.5371	.00436
		95% Confidence Interval for Mean	Lower Bound	.5285	
			Upper Bound	.5457	
		5% Trimmed Mean		.5424	
		Median		.5505	
		Variance		.030	

	Std. Deviation		.17352	
	Minimum		.00	
	Maximum		.97	
	Range		.97	
	Interquartile Range		.24	
	Skewness		-.419	.062
	Kurtosis		.013	.123
Above	Mean		.5377	.00359
	95% Confidence Interval for Mean	Lower Bound	.5306	
		Upper Bound	.5447	
	5% Trimmed Mean		.5411	
	Median		.5437	
	Variance		.020	
	Std. Deviation		.14224	
	Minimum		.10	
	Maximum		.87	
	Range		.78	
	Interquartile Range		.20	
	Skewness		-.317	.062
	Kurtosis		-.273	.124

There are a few results in Table 6 that really stand out. The five percent trimmed mean for people per 1,000 experiencing homelessness is 2.75 compared to a mean of 3.09, which is an indication that there may be outliers in that group of observations. The high variance, range, interquartile range (IQR), skewness, and kurtosis values further validate the presence of outliers and clustering on one side of a leptokurtic distribution, which in this case is clustering on the low end of the values according to the difference between the median and the mean. To confirm these interpretations of the table, the distributions are visualized as histograms in Figure 3 and Figure 4 below.

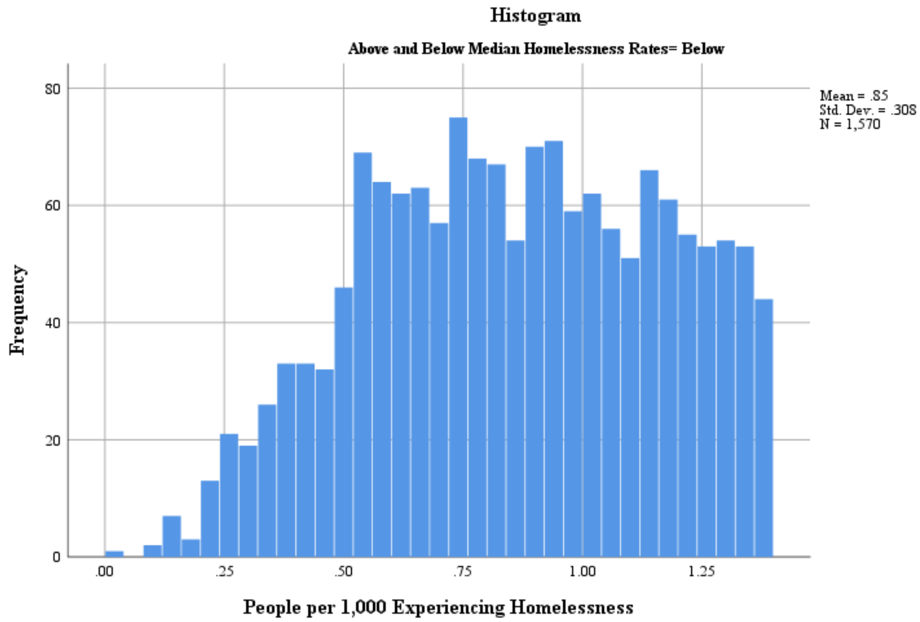

Figure 3: Distribution of homelessness rate observations below the median homelessness rate

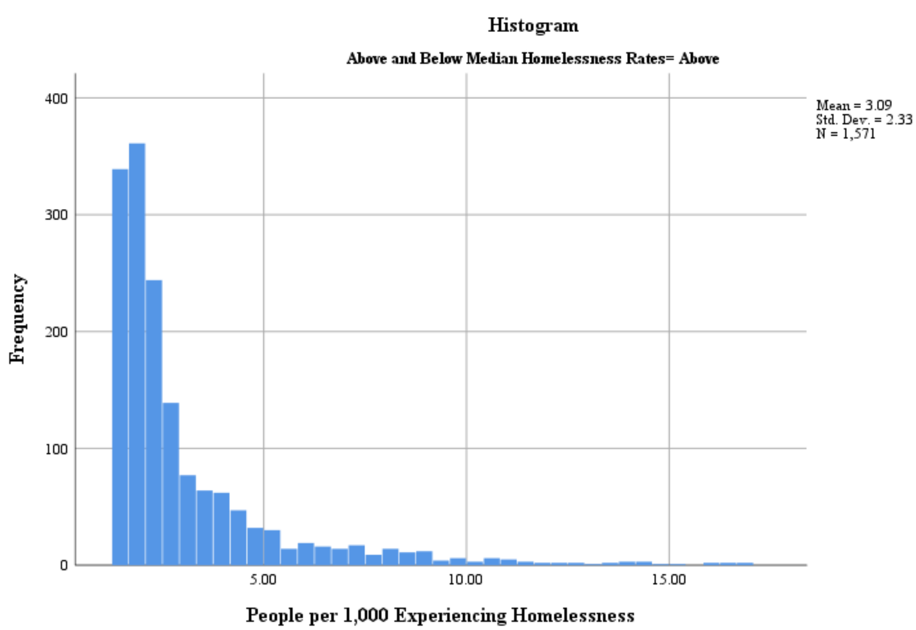

Figure 4: Distribution of homelessness rate observations above the median homelessness rate

As suspected, the distribution of homelessness rate observations below the median homelessness rate depicted in Figure 3 is relatively well-distributed while the distribution of homelessness rate observations above the median depicted in Figure 4 is heavily skewed and leptokurtic due to the presence of outliers on the high end of the spectrum. To address this, the outliers should be identified and coerced. Coercion replaces outliers with the nearest value inside an acceptable range, such as within the outer fence, which is three times the IQR. To identify the outliers, the categories were removed so that the entire dataset can be analyzed, and a box plot was created to visualize the distribution of specific cases as shown in Figure 5.

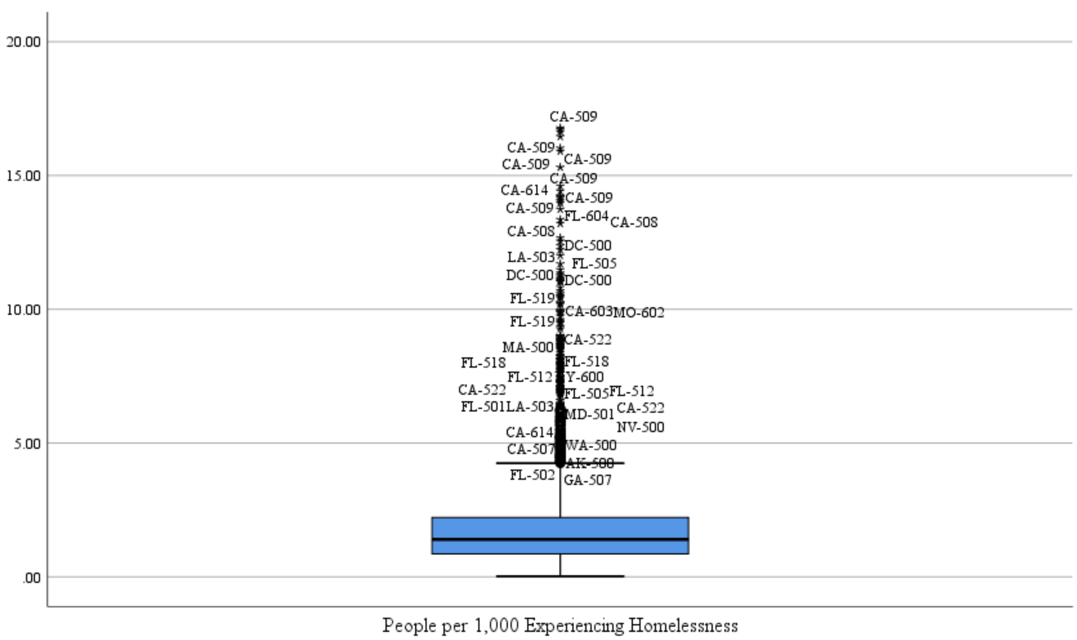

Figure 5: Box plot of homelessness rate cases

Due to the number of outliers, it is difficult to identify cases to coerce based on the box plot alone. Additionally, a box plot shows all cases outside of the inner fence as potential outliers, which in this case may be too restrictive. To calculate the outer fence, I need the IQR for the entire dataset. One way to determine the IQR is to calculate Tukey's Hinges from the percentiles, shown in Table 7 below.

Table 7: Homelessness rate percentiles

		Percentiles						
		5	10	25	50	75	90	95
Weighted Average (Definition 1)	People per 1,000 Experiencing Homelessness	.4381	.5696	.8553	1.3957	2.2147	4.0306	5.9313
Tukey's Hinges	People per 1,000 Experiencing Homelessness			.8557	1.3957	2.2144		

Box plots run in SPSS are based on a definition of quartiles that use Tukey's Hinges as the upper and lower limits of the box. To calculate the inner and outer fence, the following formulas were used.

Equation 3: Inner and outer fences

$$\iota = Q3 + IQR \times 1.5 \wedge Q1 - IQR \times 1.5$$

$$o = Q3 + IQR \times 3 \wedge Q1 - IQR \times 3$$

These values are simply the IQR multiplied by 1.5 in the case of the inner fence and the IQR multiplied by three in the case of the outer fence, which is then either added to the Tukey's Hinge value at the 75th percentile (Q3) or subtracted from the value at the 25th percentile (Q1). In the case of this study, the outer fence is the threshold used to determine whether a value is an outlier. Therefore, 6.2905 is the upper limit of the outer fence and the lower limit of the outer fence is a negative value, thereby negating the lower limit. A new variable was created by recoding homelessness rates into a dummy variable indicating that the case is an outlier when equal to or greater than 6.2905. This identified 139 observations across 31 CoCs[8] as outliers. The homelessness rates in these outlier values were then coerced to 6.2905 in a new variable called hlco so that the primary analyses may be conducted using both coerced and original values. In Appendix 3 of this study, the full list of outliers is included in Table 22, distribution descriptives for homelessness rates using coerced values are included in Table 23.

An updated box plot for homelessness rates using coerced values for the outliers beyond the outer fence is included in Figure 6 below, and an updated histogram showing homelessness rates above the median using coerced values for the outliers beyond the outer fence is included in Figure 7.

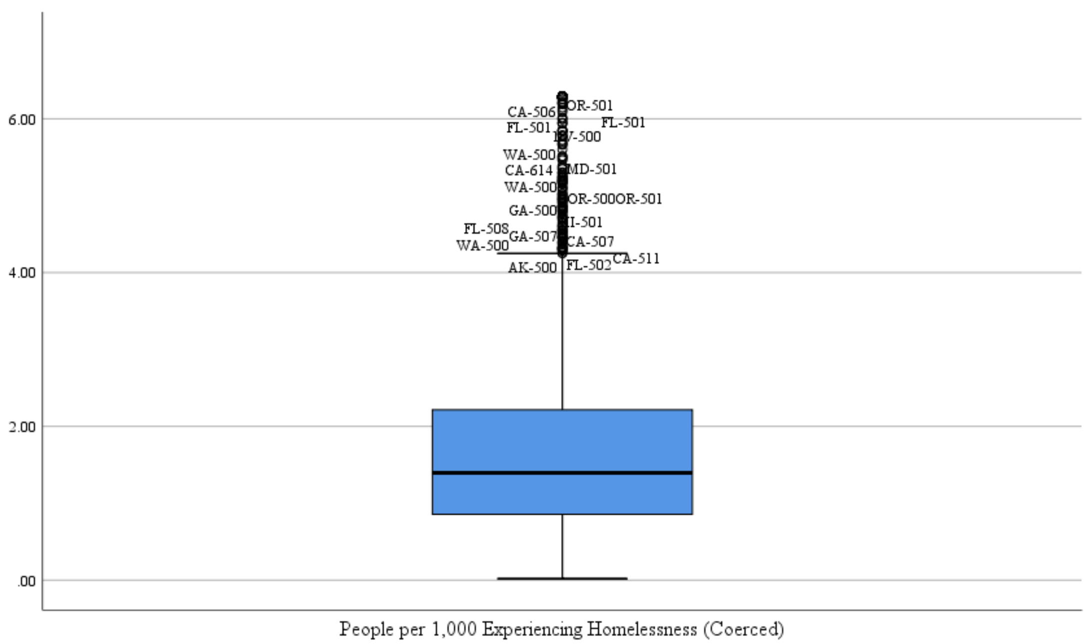

Figure 6: Box plot of homelessness rate cases using coerced values

[8] Outliers were found in CA-501, CA-504, CA-506, CA-508, CA-509, CA-522, CA-523, CA-524, CA-603, CA-613, CA-614, DC-500, FL-501, FL-505, FL-512, FL-517, FL-518, FL-519, FL-604, GA-500, HI-500, LA-503, MA-500, MA-504, MD-501, MD-508, MO-602, NC-516, NY-600, NY-607, and OR-500.

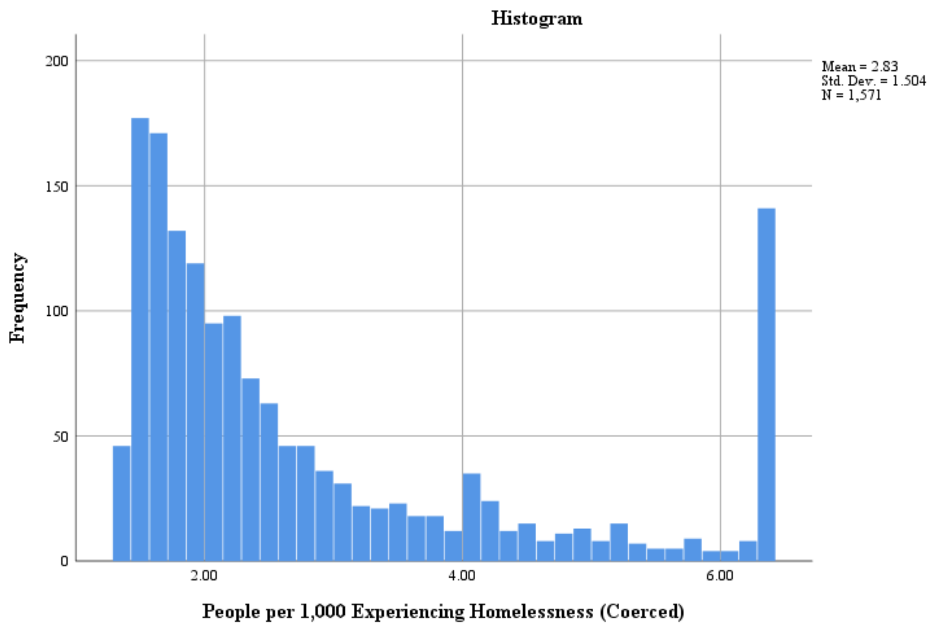

Figure 7: Distribution of homelessness rate observations above the median homelessness rate using coerced values

As shown in Figure 6, coercing values to the upper limit of the outer fence noticeably decreased the number of outliers. The primary analysis will still be performed using actual values but coercing the values of these outliers down to the upper limit of the outer fence will allow me to test if the results change as a result of questionably high homelessness rates in these outlier CoCs. Figure 7 shows that the number of CoCs with coerced values is significantly high.

4.4: Spatial Characteristics

The spatial distribution of homelessness rates and Housing First index scores in CoCs across the country is important information to consider when interpreting the results of the primary analysis. In this section, I have included maps showing average values of homelessness rates and Housing First index scores over the study period, as well as maps showing how homelessness rates and Housing First index scores have changed between 2009 and 2017 in CoCs across the country.

4.4.1: Homelessness rates across the United States

The map in Figure 8 shows how homelessness rates are distributed in CoCs across the United States. Dashed CoCs were among the 29 removed from the analysis due to CoC boundary mergers that occurred over the study period. See Table 14 in Appendix 1: Data Collection and Model Assembly Process for more information about CoCs removed from the analysis. Data from the remaining 355 CoCs are included in the maps in this section.

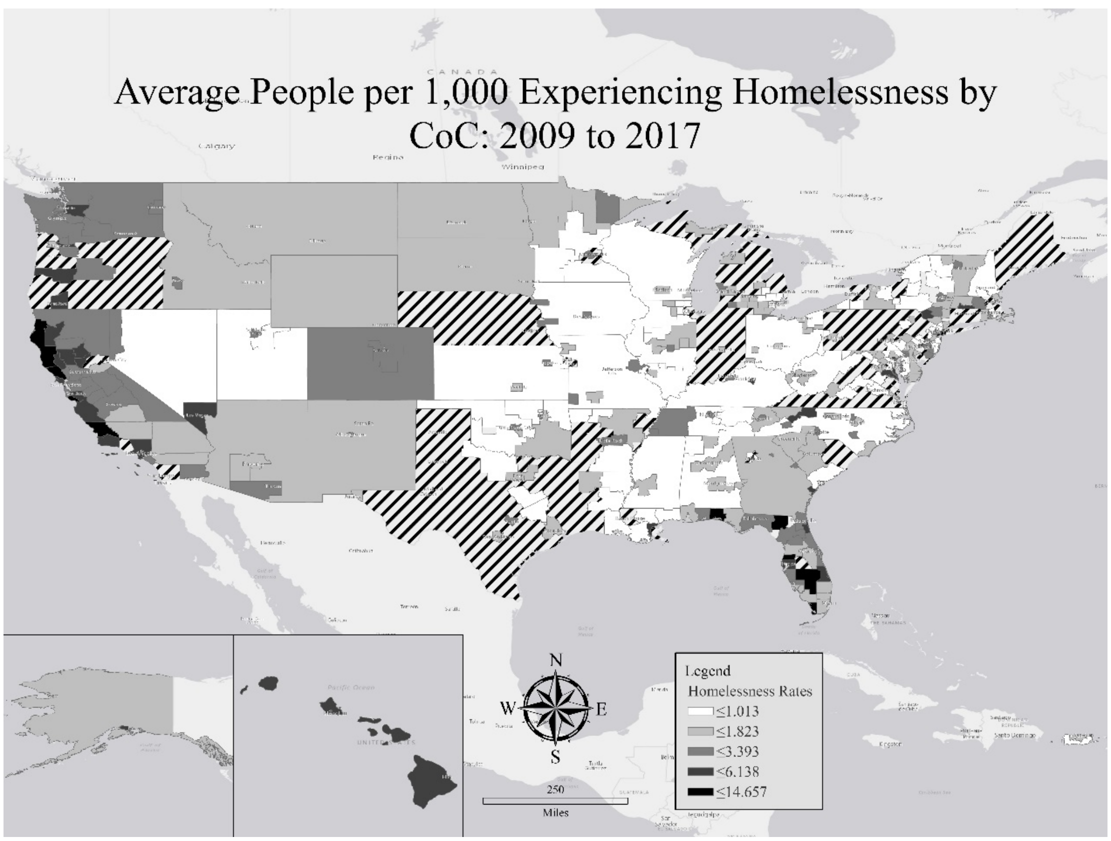

Figure 8: Map of average people per 1,000 experiencing homelessness by CoC: 2009 to 2017

As shown in Figure 8, homelessness rates are particularly high in California, Florida, and Hawaii. This intuitively lends support to the notion that homelessness rates are higher in these areas due to their favorable climate. However, other CoCs in the south experience very low homelessness rates, and higher homelessness rates extend farther north along the west coast where temperatures are considerably colder, so this tells us that other factors are likely influencing homelessness rates in a significant way.

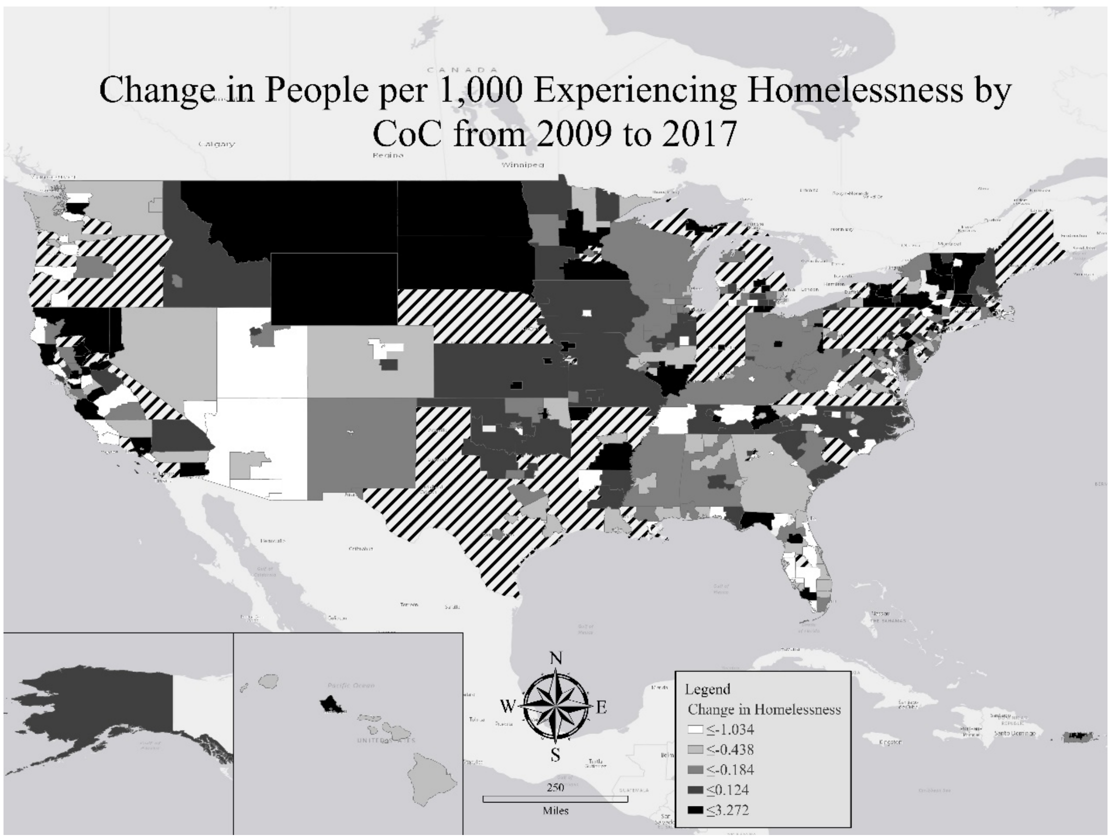

Figure 9: Map of change in people per 1,000 experiencing homelessness by CoC from 2009 to 2017

Figure 9 shows that homelessness rates have gone up the most over the course of the study period in Montana, Wyoming, the Dakotas, Puerto Rico, and parts of

New England. Large decreases have occurred in parts of Florida, California, Utah, Arizona, Washington, Colorado, and Georgia.

Those balance-of-state and other large multicounty CoCs stand out, but looking more closely at smaller CoCs, the distribution of CoCs with increasing or decreasing rates of homelessness do not appear to be spatially concentrated in any meaningful way. This tells me that factors that are specific to certain regions of the country, like precipitation and temperature, are not largely responsible for changes in homelessness rates.

4.4.2: Housing First index scores across the United States

The map in Figure 10 below shows the degree to which Housing First is implemented in CoCs across the United States. Again, dashed CoCs were among the 29 removed from the analysis due to CoC boundary mergers that occurred over the study period.

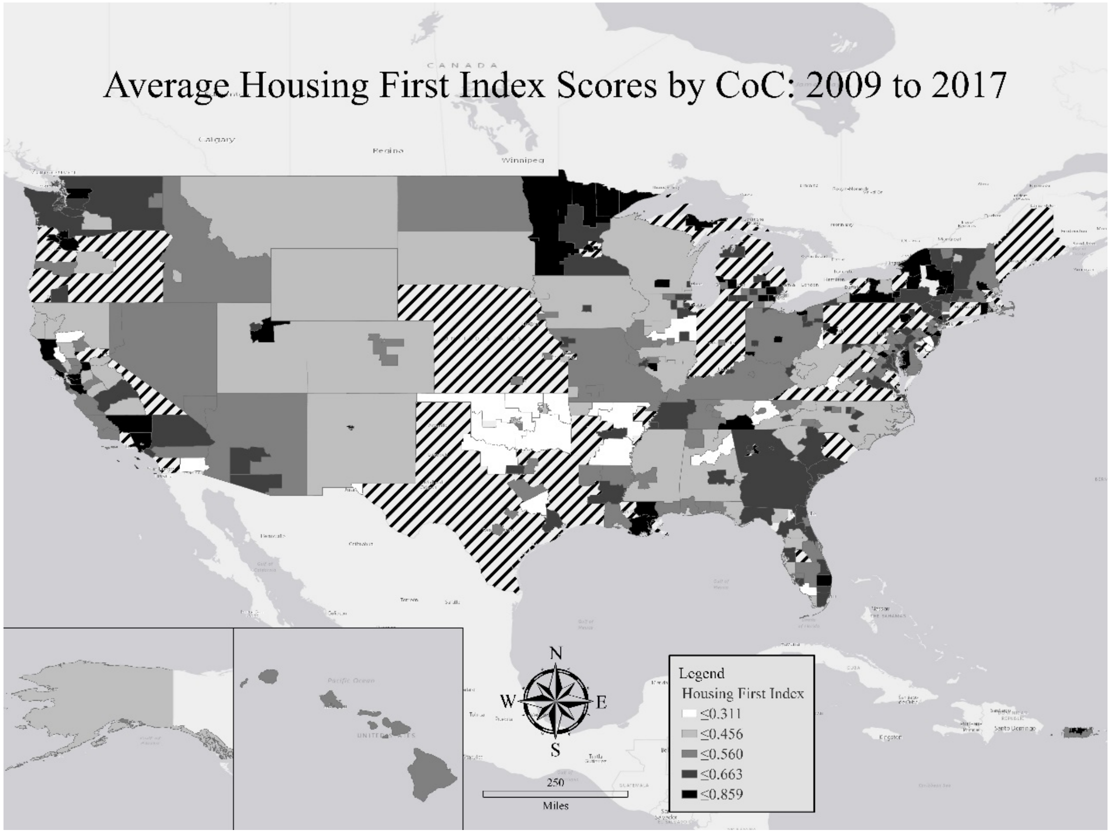

Figure 10: Map of average Housing First index scores by CoC: 2009 to 2017

As shown in Figure 10, a Housing First approach seems to be used by CoCs in Minnesota, Georgia, and parts of New York, California, Puerto Rico, and Florida, as well as other small CoCs scattered across the country.

Places that do not rely on a Housing First approach as strongly seem to be concentrated somewhat in the south and the mountainous regions of the west. However, some smaller, more densely populated CoCs are the exception to this rule.

This map reveals that there may be some geographic component to the distribution of the Housing First approach across the United States, because smaller CoCs seem to generally implement Housing First to a greater degree than larger balance-of-state CoCs.

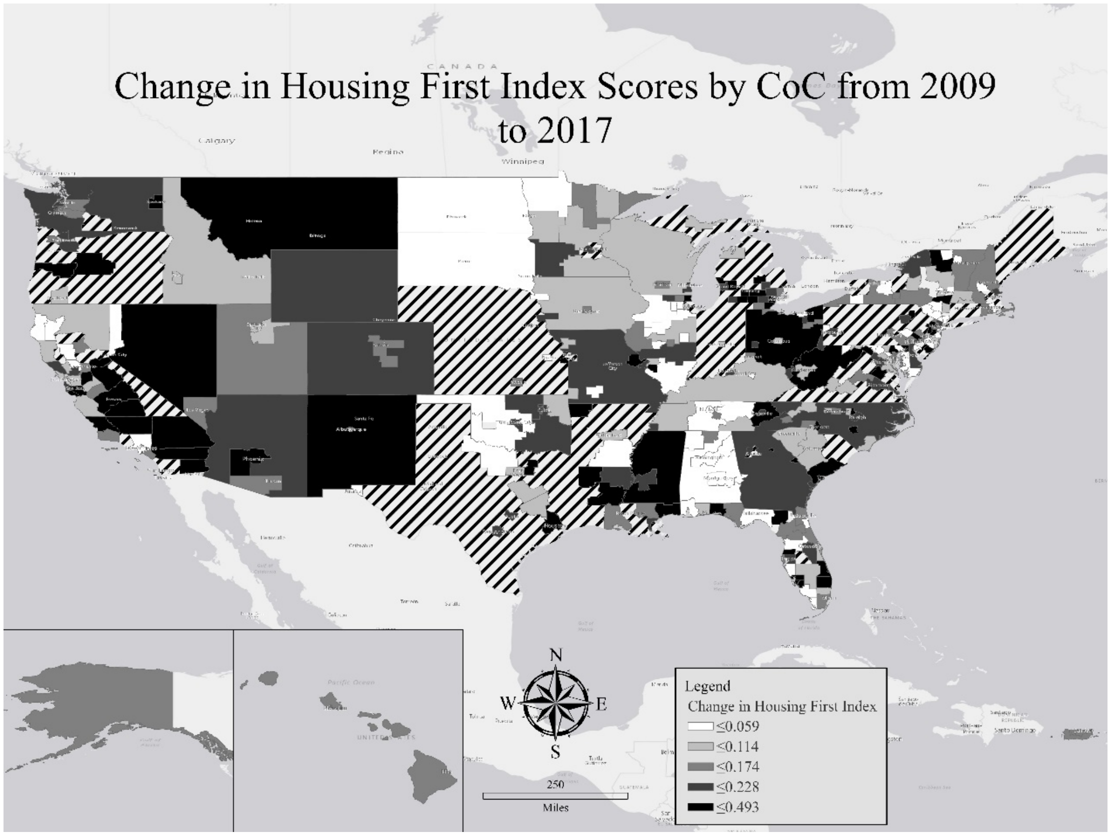

Figure 11: Map of change in Housing First index scores by CoC from 2009 to 2017

Figure 11 shows how Housing First index scores have changed in CoCs across the United States. It is difficult to discern a spatial pattern to the changes. Housing First index scores have increased significantly in some CoCs where the average score was low over the course of the study period, such as West Virginia, Mississippi, and Montana. In other places, like Alabama and South Dakota, the index score was low on average and does not appear to be increasing. There does not seem to be any identifiable pattern across smaller CoCs either.

This suggests that a CoC's decision to implement a Housing First approach is likely to be a decision made independently of their neighbors. The panel analysis used in this study helped to shed light on how that decision may have influenced homelessness rates in these CoCs, and on the relationship between homelessness rates and other variables identified by previous literature to be significant.

Chapter 5: Panel Analysis

This study uses a linear mixed model procedure to conduct a panel analysis, analyzing the relationship between homelessness rates and a Housing First index created for this study along with other variables thought to be associated with homelessness from the year 2009 to 2017 in CoCs across the United States. The benefits of the linear mixed model procedure and panel analyses more generally are described in Chapter 3, along with the methodology used in this study. This chapter will describe the results of the panel analysis.

5.1: Initial Model

All the factors and covariates were included in main effects testing in this initial model. In the specifications for the model's random effects, only the intercept and a single interaction term for the interaction between the recoded continuous variable for year and the CoC name variable were included. The CoC number and category variables were included as a subject grouping to test the random effects. The autoregressive covariance type was selected again for the random effect, because I expect a random effect on a residual to be most closely related to the random effect on a residual within the same CoC in the previous year. By including these random effects in the model, I can separate out the portion of the error in each observation that is due to the year and CoC in which an observation was made. However, the fixed effects results are the subject of this study.

Table 8: Type III tests of fixed effects in the first round of main effects testing

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	6859.020	.103	.748
coccat	2	311.003	4.061	.018
inczon	1	320.766	1.049	.307
pop	0	.	.	.
bach	1	810.553	3.016	.083
medinc	1	803.556	.468	.494
medren	1	922.549	18.395	.000
medval	1	828.139	10.432	.001
renfam	1	666.197	.540	.463
renocc	1	545.749	.164	.686
renwhi	1	585.687	3.854	.050
renedu	1	746.652	5.821	.016
unemp	1	1647.906	1.409	.235
pov	1	1320.456	.779	.378
evic	1	1422.967	.114	.736
burd	1	1729.809	6.754	.009
gini	1	1002.101	.046	.830
vac	1	452.685	2.584	.109
temp	1	1837.697	2.424	.120
precip	1	1696.294	1.837	.176
hf	1	1977.624	.299	.584
fund	1	753.774	24.652	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	633.257	.508	.476
evic2	1	1880.448	.146	.702
hf2	1	1966.959	1.150	.284
yearcoded	1	1339.173	23.222	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

As seen in Table 8, all of the variables discussed in the literature and in Chapter 2 of this study were tested in the panel analysis for a significant relationship with homelessness rates. Most of the independent variables have been used in past modeling studies, some more than others. The median rent is used frequently.

Unemployment, poverty, and the vacancy rate are also used fairly frequently. The rest, aside from the three new variables, have been used at least once in a past modeling study. For more detail on the model selection process, please see Appendix 2: Model Selection Process.

5.2: Final Model Results

The information criteria scores, type III tests of fixed effects results, and fixed effects estimates for Model 159 are included in Table 9, Table 10, and Table 11 below. Model 159 was also run on subsets of homelessness[9] as the dependent variable, and the results from those models are included in Appendix 6: Final Model Results for Subsets of Homelessness. The information criteria measure the quality of the model in measuring relationships between variables in an existing dataset, and lower scores indicate a better model. The scores are not meaningful by themselves; they are only meaningful in relation to other models analyzing the same dataset.

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[9] Subsets of homelessness included in Appendix 6 include sheltered, unsheltered, families with children, chronic, and veterans.

Table 9: Information criteria for final model

Information Criteria[a]	
-2 Restricted Log Likelihood	6496.511
Akaike's Information Criterion (AIC)	6500.511
Hurvich and Tsai's Criterion (AICC)	6500.516
Bozdogan's Criterion (CAIC)	6514.262
Schwarz's Bayesian Criterion (BIC)	6512.262

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 10: Type III tests of fixed effects for final model

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	731.017	10.247	.001
inczon	1	370.459	3.340	.068
coccat	2	358.777	6.309	.002
pop	0	.	.	.
bach	1	567.519	38.995	.000
medval	0	.	.	.
renwhi	1	452.256	5.032	.025
renedu	1	804.002	21.964	.000
pov	1	978.303	11.100	.001
vac	1	692.624	2.914	.088
temp	1	2576.312	4.665	.031
hf	1	1467.766	6.315	.012
fund	1	849.387	25.282	.000
pop2	0	.	.	.
hf2	1	1999.958	9.052	.003
yearcoded	1	1666.435	65.213	.000
renocc * hf	1	1016.894	13.133	.000
renocc * hf2	1	1654.524	16.773	.000
medren * vac	1	707.213	9.298	.002

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

The Type III tests of fixed effects table displays results similar to the full table of fixed effects estimates, except that it measures the overall significance of categorical variables, instead of separately measuring the significance of each individual category with homelessness rates. This is helpful in the case of the models compared in this study, because the CoC category variable and the inclusionary zoning variable are both categorical variables.

Table 11: Fixed effects estimates for final model

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.416004	1.175257	677.533	2.907	.004	1.108421	5.723587
[inczon=0]	-.315321	.172524	370.459	-1.828	.068	-.654570	.023928
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.903861	.340010	358.375	2.658	.008	.235194	1.572527
[coccat=2]	.056515	.302442	358.997	.187	.852	-.538265	.651296
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.285754E-7	1.872585E-7	360.187	-3.357	.001	-9.968326E-7	-2.603181E-7
bach	-.080024	.012815	567.519	-6.245	.000	-.105194	-.054853
medval	5.724649E-6	7.762778E-7	671.692	7.374	.000	4.200426E-6	7.248872E-6
renwhi	.010954	.004884	452.256	2.243	.025	.001357	.020552
renedu	-.051451	.010978	804.002	-4.687	.000	-.073000	-.029901
pov	.072196	.021670	978.303	3.332	.001	.029672	.114721
vac	-.052941	.031015	692.624	-1.707	.088	-.113835	.007953
temp	.005839	.002703	2576.312	2.160	.031	.000538	.011141
hf	-4.751981	1.890942	1467.766	-2.513	.012	-8.461218	-1.042743
fund	.066042	.013135	849.387	5.028	.000	.040262	.091822
pop2	7.07668E-14	2.28433E-14	359.300	3.098	.002	2.584347E-14	1.156903E-13
hf2	6.556069	2.179028	1999.958	3.009	.003	2.282666	10.829472
yearcoded	-.128228	.015879	1666.435	-8.075	.000	-.159372	-.097083
renocc * hf	.192248	.053048	1016.894	3.624	.000	.088151	.296345
renocc * hf2	-.256817	.062707	1654.524	-4.095	.000	-.379810	-.133823
medren * vac	9.134685E-5	2.995657E-5	707.213	3.049	.002	3.253240E-5	.000150

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

The fixed effects estimates table includes the estimate or coefficient associated with each variable, the standard error, degrees of freedom of the denominator, a t score, the statistical significance of each variable, and the confidence interval values. The most important results for answering my research question are the coefficients and the significance. The coefficient represents the value change in homelessness rates with an increase of one in the measured variable, just like a coefficient in a standard regression analysis. The significance value, or p score, is the result of a statistical test in which a value below 0.05 commonly justifies rejecting the null hypothesis. This was the threshold used in this study as well.

The results of the final model are discussed in terms of main effects, interaction effects, and how they answer the research question. Since the results related to the Housing First index are critical to understanding how the model answers the research question, I will start with those.

5.2.1: Results of the Housing First index

The relationship between the Housing First index (*hf*) and homelessness rates was measured in four different ways in the final model. This is because an interaction between the Housing First index and the percentage of renter-occupied households was included in the final model, and because the Housing First index was found to have a quadratic relationship with homelessness rates in which homelessness rates were lowest either when the Housing First index was very low or very high. Therefore, in Table 11, *hf* represents the relationship between the Housing First index and homelessness rates for base values of the Housing First index, and *hf2* represents the relationship between squared values of the Housing First index and homelessness rates. Refer to Figure 12 for a representation of the quadratic relationship between the Housing First index and homelessness rates.

Both the *hf* and the *hf2* variables have p scores below 0.05 in the final model, indicating that the Housing First index is associated with homelessness rates in a statistically significant way. Likewise, the interaction effect between the percentage of renter-occupied households (*renocc*) and the Housing First index is also associated with homelessness rates in a statistically significant way. The introduction of the interaction effect also flipped the coefficient of the Housing First index so that the *hf* coefficient is now negative and the *hf2* coefficient is now positive.

The hypothesis that homelessness rates would decrease as the Housing First index increases is somewhat supported by the results, but the relationship is more complex than hypothesized. Instead, the final model used in this study tells me that the relationship between the Housing First index and homelessness rates can be simplified by controlling for other effects in the model in Equation 4 below.

Equation 4: Estimating homelessness rates by the Housing First index and its interaction with the percentage of renter-occupied households

$$hl = 3.4160 - 4.7520(hf) + 6.5561(hf^2) + .1922(hf * renocc) - .2568(hf^2 * renocc)$$

In other words, ceteris paribus, a jurisdiction with 50 percent renter-occupied households and a Housing First index score of 0.50 would be expected to have a homelessness rate of 4.2740, or 4.2740 people experiencing homelessness per 1,000 people living in the CoC boundary. If the Housing First index score is reduced to 0.25, the estimated homelessness rate becomes 4.2378. If the Housing First index score is increased to 0.75, the estimated homelessness rate becomes 3.5248. The estimated homelessness rate decreases very slightly as the Housing First index score decreases from 0.50, and the homelessness rate decreases much more substantively as the Housing First index score increases from 0.50.

Since there is a statistically significant interaction effect between the Housing First index and the percentage of households that are renter-occupied in the final model as well, the relationship between Housing First and homelessness rates is altered by changes in the percentage of renter-occupied households. For example, with a Housing First index of 0.50, a drop in the percentage of renter-occupied households from 50 percent to 25 percent changes the estimated homelessness rate from 4.2740 to 3.4765. Likewise, with an increase in the percentage of renter-occupied households to 75 percent, the estimated homelessness rate changes to 5.0715. When the Housing First index is 0.25, a *renocc* value of 25 decreases the estimated homelessness rate from 4.2378 to 3.4378, and a *renocc* value of 75 increases the estimated homelessness rate to 5.0378. Finally, when the Housing First index is 0.75, a *renocc* value of 25 slightly increases the estimated homelessness rate from 3.5248 to 3.5323, and a *renocc* value of 75 slightly decreases the estimated homelessness rate to 3.5173.

Table 12: Estimated homelessness rates for values of the Housing First index and percentage of renter-occupied households

	renocc = 25	*renocc* = 50	*renocc* = 75
hf = 0.25	3.4378	4.2378	5.0378
hf = 0.50	3.4765	4.2740	5.0715
hf = 0.75	3.5323	3.5248	3.5173

My interpretation of these results is that the CoCs that have done very little to implement a Housing First approach tend to have slightly lower homelessness rates than jurisdictions that have done some implementation, because the slightly lower homelessness rates do not encourage the political will to adopt a Housing First approach. In other words, in CoCs where the Housing First index is low, the homelessness rates are driving the Housing First index, as opposed to the Housing First index driving the homelessness rate. In CoCs that are leading the country in adoption of a Housing First approach, as indicated by higher Housing First index scores, homelessness rates are substantially lower than both jurisdictions that have done very little implementation and jurisdictions with average index scores, and in those CoCs it seems that the implementation of a Housing First approach is driving the lower homelessness rates.

Interestingly, a higher percentage of renter-occupied households seems to result in substantively higher estimated homelessness rates, except when the Housing First index is high. The implementation of a Housing First approach seems to nullify the association between renter-occupied households and homelessness rates. This could be an indication that while a larger renting population generally means that a higher proportion of the population is unstable in their housing and more vulnerable to episodes of homelessness, that population can be stabilized and protected from episodes of homelessness by adopting a Housing First approach. This approach makes it possible to help renters in a financial or other type of crisis that may have otherwise resulted in homelessness by immediately moving them in to new permanent supportive housing or a housing unit without associated supportive services through a rapid rehousing program.

5.2.2: Other main effects results and interpretation

The inclusionary zoning variable (*inczon*) was pushed beyond the 0.05 p value significance threshold but was still fairly significant with a p value of 0.068. Counter to my hypothesis, the adoption of an inclusionary zoning policy was positively associated with homelessness rates. This could be due to higher homelessness rates driving the adoption of inclusionary zoning policies. However, the adoption of an inclusionary zoning policy only increases the estimated homelessness rate by approximately 0.3 people experiencing homelessness per 1,000 residents and the variable is insignificant at the 0.05 p value level. Therefore, the results show that this variable does not have a very substantively meaningful relationship with homelessness rates. This could be due to incomplete data in the Grounded Solutions database at the time that data were exported and a lack of nuance by treating the adoption of an inclusionary zoning policy as a dummy variable when there is a fair amount of complexity in the differences between inclusionary zoning policies as they are adopted across the country that is not considered in the available data.

The eviction filing rate (evic) was removed from the final model because the variable's relationship with homelessness rates was statistically insignificant. It also did not have a statistically significant relationship with homelessness rates in an interaction term with another variable. It is possible that this absence of a relationship was due to the incompleteness of these data, so I propose future research expanding this database so that the relationship can be studied more effectively in the future. I include more discussion about this in Chapter 6.

The CoC category (*coccat*) is significant, but not each category is statistically significant. The difference between Category 1, which indicates a major city CoC, and Category 3, which indicates a balance-of-state CoC, is statistically significant. However, there is no statistically significant difference between homelessness rates in Category 2, which indicates a smaller town or county CoC, compared to homelessness rates in other CoC categories. Homelessness rates are about 0.9 people per thousand higher in major city CoCs than in balance-of-state CoCs. Since housing affordability, rent, race, poverty, and other variables that tend to highlight socioeconomic differences between rural and urban areas were included in the model, and furthermore, no significant interaction effects including CoC categories emerged from the model refinement process, I consider it more likely that this difference is attributable to the way that the dependent variable is measured. Homelessness is measured through the point-in-time (PIT) count, which involves a collection of volunteers that the CoC is responsible for recruiting counting people experiencing homelessness in the CoC. Both balance-of-state CoCs and major city CoCs are likely to weigh their count data based on a sample, but the increased area to cover in a balance-of-state CoC would make an undercount much more likely due to the increased difficulty in coordinating the PIT count.

Total population (*pop*) is statistically significant and negatively associated with homelessness, but not substantively relevant. A CoC with 1 million residents has experiences a 0.08 reduction in their homelessness rate compared to a CoC with 10 thousand residents. The effect of total population on homelessness rate estimates is likely always spurious in nature and is nullified in the model by controlling for many of the factors typically associated with changes in total population.

The percentage of the population with a bachelor's degree or higher (*bach*) was statistically significant and negatively associated with homelessness. Ceteris paribus, a 10 percent increase in the percentage of the population with a bachelor's degree or higher is estimated to decrease the homelessness rate by approximately 0.8 people per thousand. This could mean that populations more highly educated residents are more likely to politically support effective solutions to homelessness.

Median value of an owner-occupied home (*medval*) is statistically significant and positively associated with homelessness rates. A $10,000 increase in the median value of an owner-occupied home results in an increase of 0.057 person experiencing homelessness per thousand residents in a CoC. This is not a very substantive increase, largely because renter-occupied households are more vulnerable to homelessness and the vulnerability of renter-occupied households is more directly measured by other variables in the model.

The percentage of renters identifying as white, non-Hispanic (*renwhi*) is statistically significant and positively associated with homelessness rates, but it is not very substantively meaningful. A 10 percent increase in the percentage of renters identifying as white, non-Hispanic only increases the estimates homelessness rate by 0.110 people experiencing homelessness per thousand residents. The positive association is interesting nonetheless, since black and Hispanic populations are disproportionately experiencing homelessness (HUD, 2018a). CoCs with a larger proportion of non-white residents tend to do a better job of safeguarding their residents from homelessness, ceteris paribus, and yet non-white residents are much more likely to experience homelessness. This seems to mean that CoCs with a higher proportion of non-Hispanic white residents, even when they are renters who are more vulnerable to homelessness than owner-occupied households, are less likely to prioritize strategies that prevent or end peoples' homelessness, and non-white residents in those jurisdictions are the people to disproportionately experience homelessness.

The percentage of renters without any college education (*renedu*) is statistically significant and negatively associated with homelessness rates. This seems to run counter to the variable measuring the percentage of residents with a bachelor's degree or higher (*bach*) that is also negatively associated with homelessness, but the variables are measuring education in different populations. The *bach* variable is measuring educational attainment across all residents while the *renedu* variable is only measuring educational attainment among renters. This model seems to tell me that high levels of educational attainment in the overall population, particularly among owner-occupied units helps alleviate homelessness, while high levels of educational attainment among renters seems to exacerbate the problem of homelessness. My interpretation of these results is that the *renedu* variable is picking up a spurious relationship with homelessness rates due to the absence of a variable measuring rental affordability like the *medren* or *burd* variables did before they were removed due to statistical insignificance, and that a higher level of educational attainment among the renter population is more indicative of an unaffordable housing stock than higher levels of educational attainment across the population as a whole.

The poverty rate (*pov*) is statistically significant and positively associated with homelessness rates. With a 10 percent increase in the poverty rate, the estimated homelessness rate would increase by 0.722 people experiencing homelessness per thousand residents in the CoC. As people become more financially vulnerable, they are more susceptible to homelessness. This result did not line up with my hypothesis that poverty and income would not be statistically significant, but that income inequality, as measured through the Gini index (*gini*), would be statistically significant and positively associated with homelessness rates. Instead, the Gini index was removed from the model for statistical insignificance and the poverty rate was statistically significant and positively associated with homelessness rates.

The vacancy rate (*vac*) is not statistically significant at the 0.05 p score level, but it is still significant below the 0.10 p score level, and the vacancy rate is negatively associated with homelessness rates. The results did not support my hypothesis that the vacancy rate would be statistically insignificant. The negative association with homelessness rates is likely due to the fact that vacancy rates are low in tight housing markets, where the most vulnerable households are less likely to find housing that they can afford.

The mean temperature in January (*temp*) is statistically significant and positively associated with homelessness rates. The results did support my hypothesis, except that I also hypothesized that precipitation would be another statistically significant variable and that it would be negatively associated with homelessness.

Precipitation was removed from the model during the model refinement process due to statistical insignificance. While temperature is statistically significant, it is not very substantively relevant. With a 10 degree (Fahrenheit) increase in mean January temperature, the estimated homelessness rate only increases by about 0.058 people experiencing homelessness per thousand residents in the CoC. Therefore, though people experiencing homelessness who are able to travel may seek out a place with milder winters, the proportion of people experiencing homelessness in CoCs with warmer temperatures who traveled there for the temperature is miniscule.

HUD CoC funding in the previous year per person (*fund*) is statistically significant and positively associated with homelessness rates. For every dollar increase in CoC funding per resident, the estimated homelessness rate increases by 0.066 people experiencing homelessness per thousand residents. This is likely because HUD awards more funding to CoCs with larger homelessness problems, so homelessness is driving funding as opposed to funding driving homelessness.

Lastly, the year for which data were collected (*yearcoded*) was statistically significant and negatively associated with homelessness. In the linear mixed model, the year was included as the repeated measures variable with an autoregressive covariance structure to ensure that the model accounted for the fact that observations in the same CoC were not considered to be independent from one another and that each subsequent observation was most likely to be correlated with the previous observation in the same CoC. By including the year as its own independent variable in the model as well, I can attribute a decrease of 0.128 people experiencing homelessness per thousand each year over the study period. This is a substantial decrease, and it is due to forces otherwise outside the scope of the variables studied in this model. This tells me that strategies being implemented across the country are working. I know that the Housing First approach is gaining traction and the model used in this study tells me that increases in the Housing First index does have a statistically significant and substantive association with a decrease in homelessness rates. The year variable could be picking up on characteristics of the Housing First approach that this study leaves out, such as reducing barriers to housing and improving access to supportive services. The index used in this study does not know if a person experiencing homelessness had to graduate from a religious program before the permanent supportive housing unit became available to them. The index only knows the proportion of units in a CoC that are permanent supportive housing units and uses that information to assume that barriers are breaking down, because programs with a lot of barriers in place would typically need a higher proportion of emergency shelter and transitional housing units. Therefore, the change in homelessness rates attributable to the year may be picking up on progress that the index does not.

5.2.3: Other interaction effects results and interpretation

The only other significant interaction effect in the final model besides the interaction effect involving the Housing First index (*hf*) and the percentage of renter-occupied households (*renocc*) discussed above was an interaction effect between the median gross rent of renter-occupied households (*medren*) and the vacancy rate (*vac*). The main effect of the vacancy rate remained in the final model, but the median gross rent of renter-occupied households was removed due to statistical insignificance, and it remained in the final model only through its statistically significant interaction with vacancy rates.

The equation for this interaction effect is less complex than the interaction between *hf* and *renocc*, because neither of the variables in this interaction have a relationship with homelessness rates best expressed by a polynomial, such as the quadratic relationship between the Housing First index and homelessness rates. Instead, the interaction between *medren* and *vac* is simplified by controlling for other effects in the model in Equation 5 below.

Equation 5: Estimating homelessness rates by the vacancy rate and its interaction with the median gross rent of renter-occupied households

$$hl = 3.4160 - .05294(vac) + .00009(vac * medren)$$

This shows that changes in median gross rent affects the relationship between vacancy rates and homelessness rates. In other words, ceteris paribus, increases in the vacancy rate will be associated with homelessness rates differently depending on the median gross rent. See Table 13 below for examples of how changes in each value of this interaction term result in changes in estimated homelessness rates.

Table 13: Estimated homelessness rates for values of the vacancy rate and median gross rent

	$medren = 500$	$medren = 800$	$medren = 900$	$medren = 1000$
$vac = 10$	3.3366	3.6066	3.6966	3.7866
$vac = 12$	3.3207	3.6447	3.7527	3.8607
$vac = 14$	3.3048	3.6828	3.8088	3.9348

The interaction between vacancy rates and median gross rent illuminates a very interesting caveat to the negative association between homelessness rates and the vacancy rate. Inclusion of this interaction term shows me that homelessness rates only decrease as the vacancy rate increases when the median gross rent in a CoC is very low. Otherwise, the homelessness rate estimated by my final model actually increases as the vacancy rate increases.

This provides evidence that the vacancy rate is actually more of a metric for the gap between supply and demand of affordable housing than it is an indication of a tight housing market. In other words, as median gross rent increases and the positive relationship between the vacancy rate and the homelessness rate becomes more substantive, the model shows that the available housing stock is built or renovated for a shrinking proportion of potential renters in the market. Therefore, vacancy is increasing not because peoples' housing demands are being met, but because peoples' housing demands are being ignored by the development community.

5.2.4: Implications of the final model

The results of the final model show that it was an important choice to include interaction effects in the analysis, because two of these interaction effects turned out to be significant in answering the research question. They add nuance to an understanding of the relationship between homelessness and Housing First as well as the relationship between homelessness and other variables deemed by prior literature to be a significant determinant of homelessness rates.

Without needing to force the inclusion of the Housing First index in the model, the index turned out to have a statistically significant, substantively relevant, and nuanced relationship with homelessness rates. I will now cover the implications of that relationship in the conclusion.

Chapter 6: Conclusion

This chapter summarizes the key takeaways from this study, including the answer to the research question, policy recommendations as a result of the findings, limitations of this study, and some suggested avenues for future research.

6.1: Housing First and Homelessness

HUD is giving preference to CoCs that implement a Housing First approach to ending homelessness in their communities, and it is important to know if that preference is justified. Some of the most vulnerable members of our society depend on professionals responsible for homelessness services using the limited resources available to them to most effectively reduce and end homelessness.

Across the country's CoCs, this study found that those that implemented a Housing First approach to ending homelessness saw a statistically significant and relatively substantive decrease in estimated homelessness rates in most, but not all, cases. As a reminder, the research question of this study was the following:

Are Continuums of Care (CoC) that have adopted a Housing First approach by dedicating a higher proportion of their resources towards permanent housing and support services associated with a lower proportion of people experiencing homelessness between the years 2009 and 2017 than CoCs that dedicate a higher proportion of their resources towards emergency shelter and other short-term solutions? Additionally, how does that relationship between the implementation of a Housing First approach and homelessness rates change as the values of median rent, unemployment, and other covariates typically associated with homelessness rates change?

I found in this study that the relationship between the Housing First index, used to measure the degree to which a CoC had implemented a Housing First approach, and homelessness rates was more complex than originally hypothesized. In areas with low proportions of renter-occupied households, the Housing First approach seems to be ineffective in reducing estimated homelessness rates as predicted by this study's final model. Implementation of the Housing First approach typically manifests as an intervention in the rental market, so it stands to reason that the approach would be less impactful in places with a large majority of owner-occupied households.

Across the observations used in this study, the median percentage of renter-occupied housing units was about 32 percent, and the percentages ranged from 12.56 at the lowest to 69.22 at the highest. In a CoC with the median percentage of renter-occupied households, the Housing First index begins to decrease estimated homelessness rates after the index score increases above 0.42. To provide more clarity as to what this means, the median Housing First index score was 0.55 and ranged from 0 to 0.97. So in a CoC with a median percentage of renters and a median Housing First index score, increasing the degree to which that CoC adheres to a Housing First approach will decrease the estimated homelessness rate produced by the final model of this study. However, in a CoC with the lowest observed percentage of renters, at 12.56 percent, increasing the Housing First index never decreased estimated homelessness rates. The formula produced by the final model of this study estimates that the percentage of renters living in a CoC needs to be at least 27 percent before the homelessness rate is estimated to decrease as a result of an increase in the Housing First index score from the median of 0.55 to 0.65.

Also, as the Housing First index increases in a CoC, the estimated homelessness rate rises slightly before decreasing more substantially. This quadratic relationship with homelessness is likely because homelessness needs to rise to a certain level of severity before CoCs begin to engage in more sophisticated approaches to ending homelessness in their communities than emergency shelters. So, homelessness rates drive the Housing First index until the index gets to about 0.42, and then the Housing First index begins to drive homelessness rates down more substantially in CoCs that have dedicated themselves to taking intentional steps in following a Housing First model.

The relationship between Housing First and homelessness was more complex than I hypothesized. The results show that implementation of a Housing First approach will be associated with decreases in homelessness in most cases. In about 21.2 percent of the observations used in this study, the percentage of renter-occupied households was under 27 percent and increases in the Housing First index do not relate to decreases in the estimated homelessness rates in those cases. In the remaining 78.8 percent of observations, increases in the Housing First index does relate to estimated decreases in homelessness with the decrease becoming larger as the percentage of renters living in the CoC increases. For example, in a CoC with a million residents and 50 percent renters, an increase in the Housing First index score from 0.5 to 0.8 decreases the estimated number of people experiencing homelessness by 993 people.

The relationship explained by this research helps to shed some light on the question posed by O’Flaherty (2019) by providing a foundation from which researchers can begin to understand how Housing First is related to homelessness. The nuance of this relationship should be studied further by researchers interested in understanding homelessness and taken into account when developing policy recommendations that are flexible enough to account for differences in local conditions.

6.2: Policy Recommendations

Despite the complexity of the relationship between Housing First and homelessness rates, the results of this study support continued investment in the Housing First approach. Due to the finding that increases in the Housing First index are not associated with decreases in estimated homelessness rates in the 21.2 percent of observations where the percentage of renters was under 27 percent, HUD should send representatives specializing in homelessness alleviation to CoCs where the percentage of renters is under 27 percent to better understand the challenges service agencies face and to provide technical assistance. HUD should also sponsor additional research to better understand the relationship between the Housing First approach and homelessness rates in areas with a large percentage of owner-occupied units in the housing market. I will discuss this more in the recommendations for future research.

In the 78.8 percent of observations where the percentage of renters was at least 27 percent, this study found that increases in the Housing First index score were associated with estimated decreases in the homelessness rate. In CoCs where the percentage of renters is over 27 percent, HUD should also send representatives specializing in homelessness alleviation who will provide additional technical assistance, particularly to those with low Housing First index scores, to ensure that they have agencies that are proficient in providing permanent supportive housing, rapid re-entry programs, case management, coordinated entry services, and other functions necessary for successful implementation of the Housing First model. Over the span of the next several funding cycles, HUD should require CoCs to transition from a model that utilizes a high proportion of emergency shelter and transitional housing to a Housing First model that utilizes a large proportion of permanent housing units, especially in CoCs with low Housing First index scores or high percentages of renter-occupied households. Plans laid out in CoC applications for funding should be reviewed critically to ensure that all necessary partner agencies are committed, and to ensure that the plan is feasible. Each plan should include a monitoring and evaluation component to ensure that important transition benchmarks are met and to evaluate whether implemented strategies are working as designed.

This study conducted an analysis with the best data available, but the quality of future homelessness research and an understanding of homelessness in the United States would be improved if researchers could rely on the availability of high-quality homelessness data. HUD should require that CoCs conduct a PIT count every year instead of every two years in order to apply for CoC grant funding. Many CoCs already conduct a new count every year, and this would improve the ability to conduct research related to homelessness and evaluate the efficacy of programs and funded projects in each CoC. HUD should also provide more oversight to ensure that CoCs are using consistent methodologies to conduct their PIT counts and that the counts are being conducted as their methodologies state they will be. HUD should send a representative to monitor counts every three years and to require corrective actions based on any deficiencies in the way the PIT count is conducted.

This study found that in most cases, following a Housing First approach is associated with lower homelessness rates. Implementing the Housing First approach requires the availability of affordable housing units that can be used in a rapid rehousing program or as permanent supportive housing for people who need wrap-around services. Across the country and in most CoCs, housing markets suffer from an affordable housing shortage. The Housing First approach cannot be effectively implemented without increasing the supply of affordable units. The next two policy recommendations address this need.

State housing agencies that administer housing credits from the low-income housing tax credit (LIHTC) program to give additional preference to applications that include a percentage of units available to people experiencing homelessness, either as permanent supportive housing units or units available as part of rapid re-housing program. This provision should be included in the qualified allocation plan (QAP) by the housing credit agency that most often operates at the state level as part of the selection criteria for projects applying for housing credits. State housing agencies should work with the National Council of State Housing Agencies (NCSHA), the Internal Revenue Service (IRS), HUD, and their Congressional representatives to ensure that a coordinated approach to addressing homelessness through the LIHTC program is developed. Furthermore, additional housing credits should be made available to areas with the greatest shortages of affordable housing.

To further expand the inventory of affordable housing while leveraging the existing housing stock, the federal legislature should eliminate the sequestration spending caps and increase funding for Housing Choice Vouchers. Additionally, in places where a high percentage of vouchers are being returned due to an inability of the recipient to find a unit, the process for determining Fair Market Rents, approving units, and investigating Fair Housing complaints should be critically evaluated to ensure that every voucher recipient is given a fair opportunity to acquire housing.

Implementing these policy recommendations would put the country in a much better position to address the problem of people experiencing homelessness in many communities.

6.3: Limitations of this Study

When considering the results of this study, the following limitations should be taken into consideration.

The most significant limitation of this study is one that has affected all studies of homelessness to date, which is the quality of homelessness data available for research. Implementation of my policy recommendations related to the PIT count would help to alleviate this issue in the future.

Another limitation of this study is that I was forced to leave important elements of the Housing First approach out of the Housing First index used in this study due to the scope. Longitudinal studies of the efficacy of the Housing First approach conducted in the past have evaluated specific programs to ensure that the program has eliminated barriers to housing and is providing appropriate levels of voluntary wrap-around services before the program can even qualify as following a Housing First model. Since this study was conducted by a single researcher evaluating data from every CoC in the country, that level of detail was not possible. The Housing First index used in this study instead looked at the proportion of units available to people experiencing homelessness in each CoC, and assumed that CoCs with a higher proportion of permanent housing units was following more of a Housing First approach, because a CoC with many programs that enforced strict barriers to housing would be forced to utilize a higher proportion of emergency shelter and transitional housing units, because people would not make it through the programs to the point when they are placed in a permanent housing unit. There are likely some CoCs in which this assumption is violated, and in those cases the Housing First index is too simple of a tool for measuring the degree to which that jurisdiction is truly following a Housing First approach. Case study research could help to uncover when the Housing First index is helpful as a tool and when it is not.

The final model used in this study may unfortunately suffer from endogeneity bias to some degree. After interpreting the results of this study, it is possible that in CoCs where the Housing First index is low, the homelessness rates are driving the Housing First index, as opposed to the Housing First index driving the homelessness rate. I did not control for the possibility that the dependent variable may be influencing independent variables. In prior research in the field, this possibility was dismissed due to the size of the population of people experiencing homelessness being too small to influence socio-economic variables in the community in which they live. However, because the Housing First approach is a direct response to homelessness, that concern should not be dismissed.

These limitations should all be taken into account when considering the results of this study, and future research should attempt to mitigate for as many of these limitations as possible.

6.4: Scholarly Implications

The results of this study provided several interesting scholarly implications and possible avenues for future research. It is important that funding be made available to pursue a greater understanding of homelessness so that we can, as a society and a community, do a better job of providing everyone a safe and decent home.

Due to the continued need for improved homelessness data, additional research should be conducted on data collected as part of the point-in-time (PIT) count and the housing inventory count (HIC). An example would be to research the methodologies of counts used in CoCs across the country and to evaluate the quality of those methodologies through field research on the days of counts and through analysis of their numbers to look for outliers or inexplicable increases or decreases in the results. Another example would be to evaluate HIC data to determine the feasibility of sorting housing units into more descriptive categories to indicate the presence of barriers or restrictions, such as transitional housing units that are only available to single men, or permanent housing units that are only available after graduation from a program that requires Bible study and a long period of abstinence from addictive substances.

The formula provided by the final model used in this study yielded results showing that increases in the Housing First index scores was only associated with decreases in estimated homelessness rates after the Housing First index score increased above 0.42 and only in CoCs where at least 27 percent of housing units were renter-occupied. This effectively meant that increases in the Housing First index was only associated with decreases in estimated homelessness rates for about 78.8 percent of cases. This result merits research into why that is the case. Case study research could be conducted in one or several CoCs with housing units that are over 73 percent owner-occupied to gain a more comprehensive understanding of the challenges associated with implementing a Housing First model in a place where a large majority of residents own their homes.

Another important avenue of future research is to evaluate how the Housing First index could be expanded upon or improved to better determine the degree to which a CoC is implementing a Housing First approach. The index used in this study provides a starting point for a variable that has not been used in this way in the past. If PIT or HIC data were improved to include more specificity regarding whether beds or units provided were done so within the context of a Housing First program, that would help improve the quality of a future index. The index may also be reconfigured to measure how effectively a CoC is serving the needs of a subset of people experiencing homelessness. For example, if the researcher's primary focus was on people experiencing chronic homelessness, then it may be appropriate to reconfigure the index to put a greater focus on permanent supportive housing units than on permanent units provided through a rapid re-housing program. The index is also far too simple of a tool to use in case study research, because it is designed with the limitations of the national database in mind. In case study research, the index should be expanded to include considerations for how people are placed into units, what types of services are available, how the ownership structure is designed, how long people have to wait for a unit, and other potentially relevant factors that may vary across different CoCs. This case study research could help future researchers to understand when it is appropriate to use a standardized measure like the Housing First index and when another method may be more appropriate.

The inclusionary zoning variable used in this study was statistically significant, but the presence of an inclusionary zoning policy was positively associated with homelessness rates instead of negatively associated with homelessness rates, as hypothesized. The best explanation for this phenomenon that I can construct is that homelessness rates drives the adoption of inclusionary zoning policies, as opposed to inclusionary zoning policies affecting homelessness rates. Future research should investigate this question more thoroughly. Grounded Solutions is currently in the process of updating their database. Perhaps an updated, more comprehensive database will result in different results. Or perhaps to properly research the relationship between inclusionary zoning policies and homelessness, the inclusionary zoning variable should be constructed in a way that allows the model to consider differences in the policies, instead of treating the presence of an inclusionary zoning policy as a dummy variable.

The Eviction Lab database that provided the eviction filing rate used in this study is another great step forward in the availability of data for research purposes. However, there was still a fair amount of missing data and it is likely that many of the evictions against the most vulnerable households that are most likely to experience homelessness are not evicted legally. Future research should focus on building upon the existing eviction database and augmenting these data on legal evictions with estimates of evictions that are done outside of the court system as well. This could be done via confidential interviews with landlords or perhaps by comparing a database for utility bills or tenant registries with court records, if the database differentiated between tenants that left voluntary versus those that did not.

In prior research, Quigley et al. (2001) tested a theory that homelessness increases with the degree of income inequality in a community. This study did not research the relationship between income inequality and homelessness rates in as detailed of a way as Quigley et al. (2001) did, but it should be noted that this study did not find that income inequality as measured by the Gini index was related to homelessness rates in a statistically significant way. Future research should investigate why these findings were inconsistent.

This study also merits follow-up research on homelessness rates in balance-of-state CoCs and other CoCs that rely largely on emergency shelters, because this study found that balance-of-state CoCs tended to have lower homelessness rates and lower Housing First index scores. It would be interesting to know if balance-of-state CoCs experience lower homelessness rates simply because they encompass a larger area and PIT counts are more difficult to coordinate, thereby resulting in an undercount, or if there is some other explanation. Also, the quadratic relationship between the Housing First index and homelessness rates revealed that homelessness rates increase slightly before decreasing substantially as the Housing First index increases. The implication of this result is that there are potentially CoCs where most of the beds available are in short-term emergency shelters and increasing the Housing First index would have an adverse impact on homelessness. Conversely, it could also mean that lower homelessness rates are driving the lack of sophisticated responses to homelessness, because there is not as great a need or perceived need. It could also imply that there is something more intentional happening in these CoCs that drives the lower homelessness rate outside the realm of the Housing First model.

The panel analysis method used by Corinth (2017) and Hanratty (2017) provides benefits over simple multivariate regression analyses, because a panel analysis can better control for the passing of time over a multiyear period. The results of this study show the importance of studying interaction terms in panel analyses. Two interaction terms that were included in the final model of this study provided a deeper and more complex understanding of the relationship between the independent variables included in this analysis and homelessness rates.

Future research should continue to build upon this study and the work of other scholars to provide a more complete understanding of the problem of homelessness so that communities may be better equipped with the knowledge necessary to end this critical problem once and for all.

Appendix 1: Data Collection and Model Assembly Process

Data Collection

Data were gathered from the U.S. Census Bureau 5-year estimates, Princeton University's Eviction Lab database, and the National Oceanic and Atmospheric Administration's Climate Divisional Database at the county level, from the Grounded Solutions Network at the point level, and from HUD at the CoC level. Data were then aggregated to CoC boundaries, which are the geographies used for the dependent variables in this study and are primarily counties or groups of counties.

Estimates of homelessness rates and CoC data

Homelessness data were gathered from the United States Department of Housing and Urban Development (HUD), downloaded from the HUD Exchange. The number of people experiencing homelessness, sheltered homelessness, unsheltered homelessness, families experiencing homelessness, chronic homelessness, and who were veterans experiencing homelessness were gathered from point-in-time (PIT) count data (HUD, 2018b). Data related to the services available in each CoC, which were used to gauge the extent that a CoC's response to homelessness follows a Housing First model, were gathered from housing inventory count (HIC) data (HUD, 2018b).

Unfortunately for the purposes of this study, 61 CoC mergers occurred during the study period sometime between 2009 and 2017, thus changing the geography of the area in which homelessness point-in-time counts and housing inventory counts were conducted. These 61 CoC mergers affected 29 of the 384 CoCs included in this study, listed in Table 14 below. For the primary analysis, those 29 CoCs were removed from the dataset. Data from the remaining 355 CoCs were analyzed for this study.

Table 14: CoC Mergers, 2009-2017

CoC Number Pre-Merger	CoC Number Post Merger	Merger Year	CoC Number Pre-Merger	CoC Number Post Merger	Merger Year
AR-502	AR-503	2010	**VA-518**	VA-513	2012
AR-506	AR-503	2010	**CA-605**	CA-611	2013
AR-509	AR-503	2010	**CT-501**	CT-505	2013
AR-510	AR-503	2010	**MA-512**	MA-516	2013
AR-511	AR-503	2010	**NJ-505**	NJ-503	2013
CT-504	CT-505	2010	**NJ-520**	NJ-503	2013
CT-507	CT-505	2010	**NY-524**	NY-508	2013
MI-522	MI-500	2010	**TX-501**	TX-607	2013
SC-504	SC-503	2010	**TX-504**	TX-607	2013
TX-613	TX-607	2010	**VA-509**	VA-521	2013
CA-610	CA-601	2011	**VA-510**	VA-521	2013
CT-500	CT-505	2011	**VA-517**	VA-521	2013
CT-509	CT-505	2011	**CT-506**	CT-503	2015
CT-510	CT-505	2011	**CT-508**	CT-503	2015
IL-505	IL-511	2011	**CT-512**	CT-505	2015
MN-510	MN-503	2011	**FL-516**	FL-503	2015
NE-503	NE-500	2011	**MA-513**	MA-516	2015
NE-504	NE-500	2011	**MA-520**	MA-511	2015
NE-505	NE-500	2011	**NJ-518**	NJ-503	2015
NE-506	NE-500	2011	**NY-509**	NY-505	2015
NJ-519	NJ-516	2011	**NY-517**	NY-508	2015
OR-504	OR-505	2011	**PA-507**	PA-509	2015
TX-704	TX-607	2011	**PA-602**	PA-601	2015
VA-512	VA-501	2011	**TX-703**	TX-607	2015
VA-519	VA-501	2011	**CT-502**	CT-505	2016
AR-507	AR-503	2012	**NY-502**	NY-505	2016
ME-501	ME-500	2012	**IN-500**	IN-502	2017
NY-605	NY-603	2012	**LA-504**	LA-509	2017
TX-610	TX-607	2012	**MA-518**	MA-516	2017
TX-702	TX-607	2012	**ME-502**	ME-500	2017

CoCs were only included in the database for this study if they existed in 2017, at the end of the study period. Many of the CoC mergers that occurred in the study period resulted in several smaller CoCs joining a larger CoC, so the smaller CoCs that no longer existed in 2017 were not collected in the initial data collection phase. For this reason, the overall impact of CoC mergers on the study dataset were limited.

Census estimates of county or county equivalent data

The majority of county or county equivalent data were collected from the United States Census Bureau's American FactFinder service (Census, 2013-2017). Data were downloaded using the Advanced Search functionality, using "All Counties within the United States and Puerto Rico" as the geographic filter and American Community Survey (ACS) 5-year estimates as the dataset. County or county equivalent estimates were gathered for total population, educational attainment, income, rent, home value, occupied housing units, race, unemployment, poverty, tenure, family composition, rent burden, and economic inequality.

Table 15: Census data source tables

Data	Source Table
Total population	B01003
Educational attainment	S1501
Median household income	B19013
Median gross rent	B25064
Median owner-occupied home value	B25077
Demographic characteristics for occupied housing units	S2502
Occupancy characteristics	S2501
Employment status	S2301
Poverty status in the past 12 months	S1701
Median gross rent as a percentage of household income	B25071

The ACS was chosen for this study because there are updates available every year, which is essential for a longitudinal panel analysis like the one used in this study. The 5-year estimates were chosen for this study because they use the largest sample size, are therefore the most reliable estimates, and data are available for counties of all populations. The ACS 3-year estimates are only available for areas with populations of 20,000 or more and the ACS 1-year estimates are only available for areas with populations of 65,000 or more (U.S. Census Bureau, 2019). These datasets would filter out many of the more rural counties. Since the ACS 5-year estimates are based on 60 months of collected data, they are the least current. This is less important than reliability in the case of the panel analysis used in this study, because the goal of the study is to accurately determine the importance of implementation of the Housing First approach in association with homelessness rates, not to project present-day trends. The ACS was started in 2005, so ACS 5-year estimates are available as early as 2009, which makes 2009 the beginning of the study period.

Climate data

Average January temperature and precipitation data were collected from the National Oceanic and Atmospheric Administration's (NOAA) Gridded Climate Divisional Database (2014b). Temperature is measured in degrees Fahrenheit and precipitation is measured in inches to 100ths. Data are available from 1895 through the latest month available and are updated monthly. Climate data have been used in previous studies of variables associated with homelessness, but the Gridded Climate Divisional Database (nClimDiv) was established relatively recently in 2014 and improves the quality of climate data by including additional station networks, quality assurance reviews, and temperature bias adjustments along with improvements to computational method (Vose et al., 2014a).[10]

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[10] Methodology statement from NOAA: County values in nClimDiv were derived from area-weighted averages of grid-point estimates interpolated from station data. A nominal grid resolution of 5 km was used to ensure that all divisions had sufficient spatial sampling (only four small divisions had less than 100 points) and because the impact of elevation on precipitation is minimal below 5 km. Station data were gridded via climatologically aided interpolation to minimize biases from topographic and network variability. The Global Historical Climatology Network (GHCN) Daily dataset is the source of station data for nClimDiv. GHCN-Daily contains several major observing networks in North America, five of which are used here. The primary network is the National Weather Service (NWS) Cooperative Observing (COOP) program, which consists of stations operated by volunteers as well as by agencies such as the Federal Aviation Administration. To improve coverage in western states and along international borders, nClimDiv also includes the National Interagency Fire Center (NIFC) Remote Automatic Weather Station (RAWS) network, the USDA Snow Telemetry (SNOTEL) network, the Environment Canada (EC) network (south of 52°N), and part of Mexico's Servicio Meteorologico Nacional (SMN) network (north of 24°N). Note that nClimDiv does not incorporate precipitation data from RAWS because that networks tipping-bucket gauges are unheated, leading to

Climate data from the nClimDiv are stored as text files without file extensions and were opened in Excel by specifying custom delimiters used in the file. State codes used in the climate data differed from state codes used in data gathered from the Census Bureau, so it was necessary to convert state codes in the climate database prior to transferring climate data to a common database with Census data via FIPS codes. The two variables used from the nClimDiv database were average temperature and total precipitation in January of each year within the study period. January values were used to align with when the point-in-time (PIT) counts are conducted, which are the source of this study's dependent variables.

Eviction filing data

This study will analyze the relationship between eviction filing rates and homelessness rates by utilizing a relatively new dataset (Desmond et al., 2018b) from The Eviction Lab at Princeton University.[11] The threat of eviction looms over the same vulnerable low-income households that are the most susceptible to experiencing

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suspect cold-weather data. All GHCN-Daily stations are routinely processed through a suite of logical, serial, and spatial quality assurance reviews to identify erroneous observations. For nClimDiv, all such data were set to missing before computing monthly values, which in turn were subjected to additional serial and spatial checks to eliminate residual outliers. Stations having at least 10 years of valid monthly data since 1950 were used in nClimDiv. For temperature, bias adjustments were computed to account for historical changes in observation time, station location, temperature instrumentation, and siting conditions. Changes in observation time are only problematic for the COOP network whereas changes in station location and instrumentation occur in almost all surface networks. As in the U.S. Historical Climatology Network version 2.5, the method of Karl et al. (1986) was applied to remove the observation time bias from the COOP network, and the pairwise method of Menne and Williams (2009) was used to address changes in station location and instrumentation in all networks. Because the pairwise method also largely accounts for local, unrepresentative trends that arise from changes in siting conditions, nClimDiv contains no separate adjustment in that regard.

[11] This research uses data from The Eviction Lab at Princeton University, a project directed by Matthew Desmond and designed by Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. The Eviction Lab is funded by the JPB, Gates, and Ford Foundations as well as the Chan Zuckerberg Initiative. More information is found at evictionlab.org.

homelessness, so this is an important relationship to study now that researchers have the means to do so.

The Eviction Lab database was created by assembling court records for eviction cases gathered from court clerks via Freedom of Information Act (FOIA) requests or automated record collection, when possible. Eviction Lab researchers supplemented these data by purchasing additional eviction data from two companies, LexisNexis Risk Solutions and American Information Research Services (Desmond et al., 2018a). The Eviction Lab database includes both an eviction rate, representing the number of legal evictions[12] per 100 renter homes, and an eviction filing rate, representing the number of eviction filings per 100 renter homes. This study uses the eviction filing rate due to a greater availability of data.

Eviction filing data were also gathered at the county or county equivalent level, so it was simple to combine eviction data from Princeton University's Eviction Lab with data from the U.S. Census Bureau.

Inclusionary zoning data

Inclusionary zoning, also known as inclusionary housing, policy data were collected from the Grounded Solutions Network Inclusionary Housing Database (2018). The purpose of inclusionary zoning policies is to incentivize or mandate the construction of affordable housing as a part of residential development projects. An effective inclusionary zoning policy should increase the supply of affordable housing

[12] It is important to note that the eviction filing rate used in this study is very likely an underestimate of the number of evictions that actually take place. Desmond estimates that informal evictions that happen without an eviction case being filed account for 48 percent of all forced moves and that formal evictions only account for 24 percent. Another 23 percent of forced moves are due to landlord foreclosure and the remaining five percent are a result of building condemnations (Desmond, 2016).

in the jurisdiction compared to the amount of affordable housing that would exist in the absence of such a policy.

Data from the Grounded Solutions Network includes x-y coordinates for the center of jurisdictions that have adopted inclusionary zoning policies. These x-y coordinates were imported into ArcGIS Pro and a Spatial Join was executed to identify CoC boundaries that included at least one jurisdiction that has adopted an inclusionary zoning policy. Of the 355 CoCs analyzed as a part of this study, 121 of them included a jurisdiction that has adopted an inclusionary zoning policy. These data are not available in a longitudinal form, so the dummy values 1 (indicating the presence of a policy) and 0 (indicating the absence of a policy) based on 2018 data were used for every year of the study period. It is possible that some of these policies did not exist during the study period, or only existed for part of the study period, so the results regarding this variable are to be interpreted with caution.

Additionally, this dummy variable does not allow for differentiation between a CoC with 10 adopted inclusionary zoning policies across its jurisdictions versus a CoC with only one adopted policy. Though this differentiation is possible and readily available via a simple GIS analysis, the quality of the data available from the Grounded Solutions Network did not allow for an accurate measurement of the degree to which these policies were being implemented or the scale of their impact.

There were 1,169 points in the inclusionary zoning database at the time of collection. At that time, 238 of the points included a survey completed by the jurisdiction with information about the program (e.g. income restrictions, number of units created, affordability period, mandatory vs voluntary, incentives, minimum numbers of units for the policy requirements to kick in, etc.) and 931 of the points were for a policy with no survey. For those 931 points, no information is available regarding the policy. Therefore, attempting to measure the degree to which inclusionary zoning requirements were implemented within a CoC based on the number of policies that exist within its boundaries may be very misleading. A CoC with 10 municipalities or counties that have all passed voluntary programs with very little result is not necessarily indicative of a stronger commitment to providing affordable housing via an inclusionary zoning policy than a single jurisdiction that adopted a mandatory policy with incentives that resulted in thousands of affordable units being developed.

The data simply do not include enough information to make a reliable determination of scale. A dummy variable can still show me which CoCs include jurisdictions that have adopted policies, so it may still provide value in the panel analysis.

Data Assembly and Constructing the Model

The model was constructed and analyzed using three different programs. ESRI's ArcGIS Pro was used for geographic aggregation of county-level data to CoC boundaries. Microsoft's Excel was used for cleaning data and constructing pivot tables, which summarize spreadsheet data by identifying characteristics, such as CoC numbers. IBM's SPSS was used for statistical analysis of the database in its final format. Data used in this study from any of these programs are available upon request.

Assembling county-level data

A spreadsheet containing every county or county equivalent in rows was created using county-level population estimates from the U.S. Census Bureau's American Community Survey (ACS) five-year estimates to ensure that every county or county equivalent intended for study was included in the spreadsheet. This included 3,209 counties or county equivalents from the 50 states, the District of Columbia, and Puerto Rico. County-level data downloaded from the U.S. Census Bureau and Princeton University's Eviction Lab were first cleaned in Excel by removing all fields that were not to be used in the study and assigning variable names to the first row of each column. The sheet used to house aggregated data is in "wide" format with estimates from multiple years for a single variable stored in multiple columns and a single row for each county or county equivalent. Each row in the sheet includes a five-digit county Federal Information Processing Standard (FIPS) code in the first column, the name of each county or county equivalent in the second column, and all subsequent columns are used to store variable values.

Since not all county-level data are observed in every county every year, separate sheets stored data for individual variables on each year. Data were moved to the assembly sheet using IF statements that included the VLOOKUP function to use county FIPS codes to match data to the appropriate rows and the IFERROR function to leave cells blank in the case of missing data. After data were moved into the assembly sheet, each column was copied and pasted in place as values to avoid overburdening the program and the computer's memory, and also to sever connections to the original data source that could otherwise be a potential source of errors if original data sources were moved or deleted.

Converting county-level data to CoC-level data

Boundaries for counties or county equivalents were downloaded from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) database (2017). CoC boundaries were downloaded from the HUD Exchange website (2017a). Both the county or county equivalent boundaries and CoC boundaries were imported into ArcGIS Pro.

Using the Spatial Join tool in ArcGIS Pro, county or county equivalent boundaries were identified as the target feature, CoC boundaries were identified as the join feature, and "have their center in" was the selected match option.[13] This operation assigned a CoC to each county or county equivalent with a center that falls within the boundaries of a CoC to ensure an accurate assignment. The Table to Excel tool was then used to convert the attribute table of the output feature of the Spatial Join into an Excel spreadsheet. In the assembly sheet, the VLOOKUP tool was used to populate fields with CoC numbers and names.

Before summarizing county or county equivalent-level data at the CoC level, it was important to weigh counties by the number of occupied housing units so that data from lesser-populated counties did not disproportionately impact CoC values. To create weights for county-level weights, a pivot table was created on a new sheet

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[13] It was not necessary to specify a join operation or a merge rule because no join features share the same spatial relationship with a single target feature in this operation. This is because the "have their center in" match option was chosen. There are a few cases where more than one CoC overlaps with a county boundary, but no cases in which multiple CoC boundaries overlap the center of a county. This is because CoC boundaries do not overlap with one another.

using the assembly sheet as its data source. CoC numbers were loaded as the rows, columns were set to values, and the number of occupied housing units were loaded as values. Value fields were summarized by their sum, thus giving the total number of occupied housing units in each CoC. The results of this pivot table were then copied and pasted into a new sheet as values only. In the assembly sheet, a new column was created for weights in each of the study period years. These weights were calculated by dividing the number of occupied housing units in each county or county equivalent by the total number of occupied housing units in the associated CoC. A second column was then created adjacent to variables in the assembly sheet to store weighted values for those variables. The values in these new columns were calculated by multiplying variable values by the weight of each county or county equivalent. An IFERROR function was used to avoid errors in cases of missing values.

A second pivot table was then created on a new sheet using the assembly sheet as its data source. CoC numbers were loaded as the rows, columns were set to values, and each of the weighted value columns from the assembly sheet were loaded into the pivot table as values. Value fields were summarized by their sum, thus giving a weighted average of each county or county equivalent-level variable at the CoC level.

Adding additional CoC-level and point data

After county and county-equivalent data were assembled at the CoC level, additional data available as points, such as inclusionary zoning policy data from the Grounded Solutions Network, and homelessness or service data from HUD available at the CoC level were added.

Inclusionary zoning policy data from the Grounded Solutions Network was available as a table with x-y coordinates. This table was added to a map file in ArcGIS Pro that also included a layer for CoC boundaries downloaded from HUD. Using ArcGIS Pro's Make XY Event Layer geoprocessing tool, the x-y coordinates in the table were converted to spatial data and displayed on the map. This layer file was then exported as a saved feature class to allow for further manipulation and the original table and visualization layer were removed from the project. A Spatial Join was then conducted to identify all CoCs that contained at least one point for an adopted inclusionary zoning policy within their boundaries.

The results of the Spatial Join were exported from ArcGIS Pro via the Table to Excel tool. The table values were then brought into the primary worksheet via Excel's VLOOKUP tool using CoC numbers as the common identifier.

CoC data gathered from HUD Exchange included the number of people experiencing homelessness, the number of people experiencing sheltered homelessness, the number of people experiencing unsheltered homelessness, the number of people in families experiencing homelessness, the number of people experiencing chronic homelessness, the number of veterans experiencing homelessness, the amount of HUD CoC funding distributed to each CoC, and housing inventory count data.[14] Each of the variables measuring the number of people experiencing homelessness were divided by the total population within the CoC and

[14] Housing inventory count data show the total number of beds available for people experiencing homelessness in a CoC each year. Beds are separated by categories, including emergency shelter, safe haven, transitional housing, rapid re-housing, permanent supportive housing, and other permanent housing.

then multiplied by 1,000 to convert the estimates into homelessness rates measuring the number of people experiencing homelessness per 1,000 people living in the CoC. HUD CoC funding in the previous year was also divided by the total population in each CoC to calculate a rate measuring the amount of HUD CoC funding in the previous year per person. Since these data were gathered at the CoC level, they were all added to the primary worksheet in Excel via the VLOOKUP tool without any necessary conversions.

Importing study data into SPSS

To conduct descriptive statistics and the primary panel analyses used in this study, data were migrated from Excel to SPSS after data collection and conversion to CoC geographies was complete. To do this, data were imported into SPSS and restructured from a wide format database to a long format database using the Restructure tool in the SPSS Data menu. The "long" format is necessary for descriptive statistics and panel analyses to be run in SPSS.

Using the Restructure tool, each of the variables that previously used a separate column for each year of the study period were manually placed into groups and listed in chronological order for each variable. The CoC numbers were used for case group identification and an index variable was created for years and applied to variables in the order in which they were listed in the groups. To properly index variables based on the years of the study period, some placeholders were included in variable groups and then subsequently removed after the data were restructured. For example, the poverty rate, Gini index, and the percentage of renters in families with children are variables that were not included in the 2009 ACS five-year estimates. To properly index these variables, 2010 data for those variables were included in the group list twice to fill the space for 2009 data.

After the data were restructured, the index variable was renumbered from 1 to 9 to 2009 to 2017 to reflect the years of the study and duplicate data were removed from variables that were missing either 2009 or 2017 data. Cases that previously included only one row for each of the CoCs now included nine rows for each CoC with a separate row for each year of the study period. Variable data that were previously spread across nine columns (or fewer, in cases where data were not available for each year of the study period) for each variable were now consolidated into a single column for each variable. Descriptive labels were then applied to each of the variables to facilitate effective visualization in graphs and tables.

Appendix 2: Model Selection Process

The model selection process began by regressing homelessness rates by individual variables to determine whether each variable that could potentially be included in the panel analysis as a covariate had a statistically significant relationship with homelessness rates in a linear or polynomial regression. Next, main effects of each variable were tested using the linear mixed models procedure and variables with main effects that were not related to homelessness rates in a statistically significant way were removed from the model and tested for interaction effects one at a time in order of the weakness of the relationship as measured by the p value. Finally, main effect variables that remained in the model after all independent variables were significant were tested for interaction effects to determine if any additional interaction effects were significant and could further decrease the AIC or change the significance of main effect variables. The model with the lowest AIC and statistically significant independent variables was the final preferred model of this study. Because the Housing First index is the independent variable of primary interest in this study, it was not removed from the model.

Individual variable regressions

A full description of the results of each regression can be found in Appendix 4: Individual Variable Regressions. A summary of each variable and their associated individual regression results, including significance, the R^2 value, and the regression type that provided the best fit can be found in Table 16 below. Factor values of each variable were created to test linear, quadratic, cubic, and quartic regressions.

Table 16: Summary of individual variable regression results

Variable	Sig	Direction	R^2	Best fit
Total population (1000s)	.000	U-shaped	.021	Quadratic
% Bachelor's degree or higher	.000	Positive	.005	Linear*
Median household income	.001	Inverse U-shaped	.004	Quadratic
Median gross rent	.000	Positive	.053	Linear
Median home value (1000s)	.000	Positive	.118	Linear
% Renters	.000	Positive	.145	Linear
% Renters with children	.000	U-shaped	.019	Quadratic
% Renters, white non-Hispanic	.000	Negative	.018	Linear
% Renters, no college	.000	Negative	.024	Linear*
Unemployment rate	.000	Positive	.032	Linear
CoC funding per person	.000	Positive	.152	Linear
Poverty rate	.000	Positive	.016	Linear
Eviction filing rate	.000	U-shaped	.008	Quadratic
% Rent-burdened	.000	Positive	.081	Linear
Gini index	.000	Positive	.072	Linear
Vacancy rate	.000	Positive	.017	Linear
Mean temperature in Jan	.000	Positive	.090	Linear
Total precipitation in Jan	.000	Positive	.026	Linear
Housing First index	.000	Inverse U-shaped	.009	Quadratic

* See Figure 42 and Figure 49 in Appendix 4: Individual Variable Regressions for both a cubic and linear regression plot for the % bachelor's degree or higher variable and the % renters, no college variable, respectively. Both of these variables shared a very similar pattern in which the linear regression showed a significant relationship between homelessness rates and the variable in question, the significance was lost in the quadratic regression, and returned in the cubic regression, and the R^2 value came close to doubling from the linear to cubic regression. However, based on the scatterplot, this seemed to be a coincidence and this author could think of no substantive explanation for a cubic relationship between education and homelessness, so the linear regressions were used for both.

The individual variable regressions revealed that five of the relationships were best expressed quadratically. These included the relationships between homelessness rates and total population, median household income, the percentage of renters with children, the eviction filing rate, and the Housing First index. To account for these quadratic relationships in a linear mixed model, factor values of these five covariates were included in the model (IBM, 2019). The quadratic relationship between homelessness rates and the Housing First index appears as an inverse u-shape on the scatterplot, and values on the scatterplot appear to be close to randomly distributed. If not for the dense clustering of homelessness rate values, the relationship may not have appeared statistically significant at all, and the explanatory power of the quadratic regression is quite low at an R^2 value of 0.009. Unless accounting for random within-subject effects reveals hidden significance of the Housing First index, this may be an early indication that the variable is not very significant.

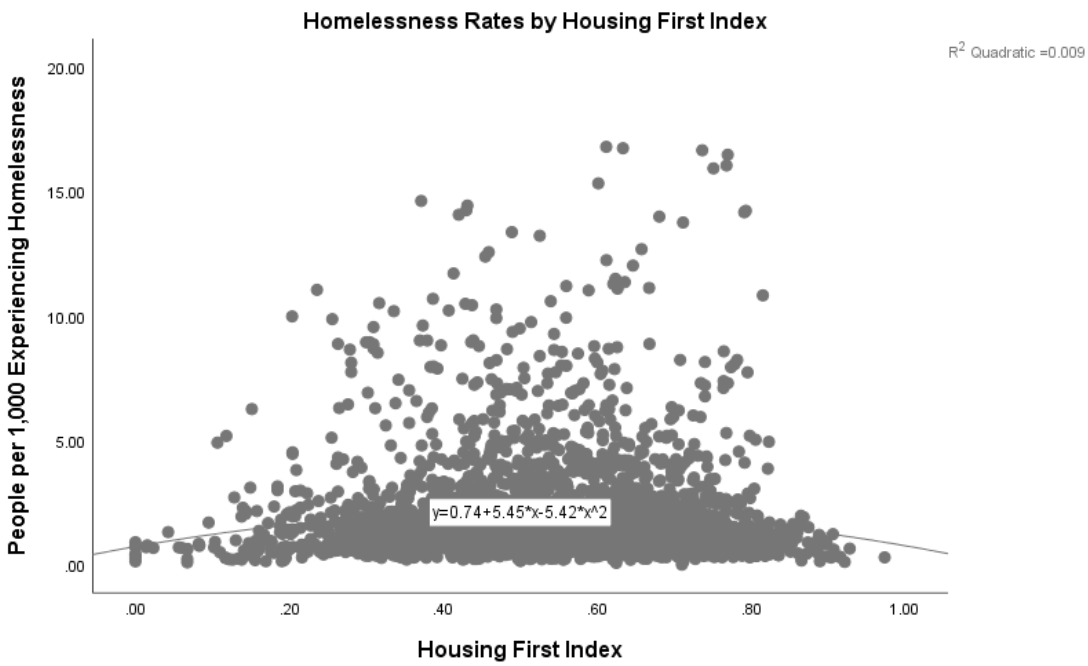

Figure 12: Quadratic relationship between homelessness rates and the Housing First index

The variable regressions found every variable to be significantly associated with homelessness rates, at least individually. This means that every variable will be included in a preliminary version of the linear mixed model panel analysis for main effects testing.

All but one of the variables' best fit regressions were highly significant with a p score of .000 except for median household income, which came very close with a p score of .001 and was also highly significant. This is to be expected with many of the variables that are strongly supported by the literature, but for new or less-tested variables like the Housing First index, the eviction filing rate, the Gini index, CoC funding, and rent-burden/affordability, it is more surprising that all of the variables had a statistically significant relationship with homelessness rates. However, two of the variables, total population and the Housing First index, with best fit regressions that were quadratic in nature were not significant in a linear relationship with homelessness rates.

Model testing

A preliminary version of the linear mixed model panel analysis was created to test the significance of main effects of each variable on homelessness rates. The CoC name and category variables were included as the subjects and a variable for years that had been recoded to continuous values 0 through 8 was entered as the repeated variable with an autoregressive repeated covariance type. This means that the model will expect within-CoC values across observations repeated over the study period years to be more correlated with one another than between-CoC values, and any observed value is likely to be most correlated with the value within the same CoC from the previous observed year.

Homelessness rates were included as the dependent variable, the inclusionary zoning variable and the CoC names were included as factors because they are nominal variables that are categorical in nature, and the rest of the variables tested for their individual relationship with homelessness rates were included as covariates in this initial model. Factor values for the five covariates that have quadratic relationships with homelessness rates were also included as separate covariates to account for their polynomial relationship with the dependent variable. Additionally, the recoded continuous variable for year was included as a covariate.

In the specifications for the model's fixed effects, only main effects were included for now. All the factors and covariates were included in main effects testing in this initial model. In the specifications for the model's random effects, only the intercept and a single interaction term for the interaction between the recoded continuous variable for year and the CoC name variable were included. The CoC number and category variables were included as a subject grouping to test the random effects. The autoregressive covariance type was selected again for the random effect, because I expect a random effect on a residual to be most closely related to the random effect on a residual within the same CoC in the previous year. By including these random effects in the model, I can separate out the portion of the error in each observation that is due to the year and CoC in which an observation was made. However, the fixed effects results are the subject of this study.

The first round of main effects testing resulted in an AIC score of 5123.713. The goal of refining linear mixed models is to bring this number down while maintaining statistically significant variables, which indicates that the model has increased its explanatory power or eliminated redundant variables.

Table 17: Information criteria for first round of main effects testing

Information Criteria[a]	
-2 Restricted Log Likelihood	5117.713
Akaike's Information Criterion (AIC)	5123.713
Hurvich and Tsai's Criterion (AICC)	5123.725
Bozdogan's Criterion (CAIC)	5143.484
Schwarz's Bayesian Criterion (BIC)	5140.484

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

The relationship between homelessness rates and thirteen of the variables became insignificant in the first round of main effects testing. This is likely because the regression analyses did not control for correlations of repeated measures in the same CoC or over time, so those correlations are inappropriately associated with the independent variable being tested. The main effects testing also simply includes more variables, so collinearity issues and controlling for changes in other variables reduces the significance of individual variables. The Housing First index was one of the variables that became insignificant during the first round of main effects testing.

Out of the thirteen variables with insignificant relationships with homelessness rates, the Gini index had the highest p value at .830 (see Table 18 below) and therefore had the weakest direct association with homelessness rates and was removed from main effects testing to be tested for interaction effects.

Table 18: Type III tests of fixed effects in the first round of main effects testing

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	6859.020	.103	.748
coccat	2	311.003	4.061	.018
inczon	1	320.766	1.049	.307
pop	0	.	.	.
bach	1	810.553	3.016	.083
medinc	1	803.556	.468	.494
medren	1	922.549	18.395	.000
medval	1	828.139	10.432	.001
renfam	1	666.197	.540	.463
renocc	1	545.749	.164	.686
renwhi	1	585.687	3.854	.050
renedu	1	746.652	5.821	.016
unemp	1	1647.906	1.409	.235
pov	1	1320.456	.779	.378
evic	1	1422.967	.114	.736
burd	1	1729.809	6.754	.009
gini	1	1002.101	.046	.830
vac	1	452.685	2.584	.109
temp	1	1837.697	2.424	.120
precip	1	1696.294	1.837	.176
hf	1	1977.624	.299	.584
fund	1	753.774	24.652	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	633.257	.508	.476
evic2	1	1880.448	.146	.702
hf2	1	1966.959	1.150	.284
yearcoded	1	1339.173	23.222	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

The model was rerun every time a main effect variable was removed, or interaction variables were added to test for changes in variable significance and the AIC score. While there are too many iterations of the model to include in this study, the full set of model testing results are available in SPSS upon request. A summary of noteworthy models from the first phase of testing are included in Table 19 below, and the results from those models are included in Appendix 5: Model Testing Results.

Table 19 covers the first phase of the model refinement process, in which variable significance was prioritized over decreases in the AIC. The first phase ended once all remaining variables in the model were significant.

For some of the models, Table 19 indicates that a part of an interaction effect is significant. What this means is that one or both variables used in the interaction term are polynomials, and the interaction between some, but not all, of the directions of a quadratic relationship with homelessness rates is significant. A practical example of this can be found in Model 62, in which an interaction between the percentage of renter-occupied households (*renocc*) and the Housing First index (*hf*) was included in the model, and the interaction between *renocc* and *hf* was insignificant, but the interaction between *renocc* and *hf2* was significant. This means that for squared values of the Housing First index, changes in the percentage of renter-occupied households changes the Housing First index's relationship with homelessness rates in a statistically significant way, and changes in squared values of the Housing First index affect the relationship between the percentage of renter-occupied households and homelessness rates in a statistically significant way as well. Interestingly, when accounting for the interaction between *hf* and *renocc*, the main effect of the *hf* coefficients switched their signs so that the coefficient for *hf* became negative and the coefficient for *hf2* became positive.

Table 19: Summary of results from the first phase of model testing

	Model Change	AIC
Model 1	First model testing only main effects of all variables	5123.713
Model 2	Removed gini (increased AIC)	5126.298
Model 3	Added inczon * gini interaction (insignificant, lowered AIC)	5116.382
Model 4	Added coccat * gini interaction (insignificant, lowered AIC)	5107.325
Model 21	Added gini * hf interaction (insignificant, lowered p score of hf, lowered AIC)	5108.665
Model 24	Removed evic (lowered AIC)	5106.639
Model 45	Removed renocc (substantially increased AIC)	6549.698
Model 50	Added renocc * medinc interaction (significant, increased AIC)	6619.417
Model 62	Added renocc * hf interaction (part significant, lowered AIC, flipped hf quadratic coefficients)	6544.710
Model 65	Removed renfam (lowered AIC)	6526.660
Model 84	Removed precip (lowered AIC)	6518.533
Model 102	Removed unemp (increased AIC)	6546.904
Model 119	Removed medinc (lowered AIC, lowered p score of hf)	6508.198
Model 122	Added pop * medinc interaction (part significant, increased AIC)	6795.405
Model 124	Added medinc * medren interaction (significant, increased AIC)	6556.442
Model 125	Added medinc * medval interaction (significant, increased AIC)	6553.851
Model 126	Added medinc * renwhi interaction (significant, increased AIC)	6575.396
Model 127	Added medinc * renedu interaction (part significant, increased AIC)	6575.481
Model 128	Added medinc * pov interaction (significant, increased AIC)	6560.349
Model 129	Added medinc * burd interaction (part significant, increased AIC)	6559.636
Model 130	Added medinc * vac interaction (significant, increased AIC)	6563.869
Model 132	Added medinc * hf interaction (part significant, increased AIC)	6607.937
Model 133	Added medinc * fund interaction (significant, increased AIC)	6566.545
Model 134	Added medinc * yearcoded interaction (significant, increased AIC)	6570.855
Model 135	Removed burd (lowered AIC)	6502.810
Model 141	Added medval * burd interaction (significant, increased AIC)	6528.730
Model 150	Removed medren (lowered AIC)	6490.568
Model 155	Added medren * medval interaction (significant, increased AIC)	6521.769
Model 156	Added medren * renwhi interaction (significant, increased AIC)	6505.315
Model 158	Added medren * pov interaction (significant, increased AIC)	6499.428
Model 159	Added medren * vac interaction (significant, increased AIC)	6500.511
Model 164	Removed renwhi (lowered AIC)	6484.055
Model 167	Added pop * renwhi interaction (part significant, increased AIC)	6579.869
Model 168	Added bach * renwhi interaction (significant, increased AIC)	6495.177
Model 169	Added medval * renwhi interaction (significant, increased AIC)	6501.534
Model 173	Added renwhi * temp interaction (significant, increased AIC)	6495.668
Model 174	Added renwhi * hf interaction (significant, increased AIC)	6491.493

With the removal of the percentage of renter-occupied households (*renocc*) variable in Model 45, the AIC jumped considerably from 5106.639 to 6549.698, indicating a substantial weakening of the model with the removal of an insignificant variable. This likely means that the significance of the percentage of renter-occupied households was masked by collinearity with other variables or that it was serving a valuable function as a control variable, and *renocc*, along with any other variables removed that resulted in an increase to the AIC, was reintroduced to the model in the second phase of model testing. Aside from the major leap upwards in Model 45 and small increases in the AIC with the removal of the Gini index and the unemployment rate in Models 2 and 102, the AIC generally trended downwards with the elimination of statistically insignificant variables, indicating improvement of the model. While all models with interaction effects that either lowered the AIC or were significant were noted in Table 19, interaction effects were not kept in the model unless they both lowered the AIC and were at least partially significant.

In the second phase of the model refinement process, decreases in the AIC were prioritized over the significance of individual variables. In this phase, all main effect variables that increased the AIC when they were removed during the first phase were reintroduced to the model in the order that they were removed and were kept if their reintroduction lowered the AIC. Then, any insignificant interactions that lowered the AIC in the first phase will be reintroduced in the order they were tested in the first phase. Finally, all main effect variables remaining in the model were tested for interaction effects. A summary of the results of the second phase of model testing can be found in Table 20 below.

Table 20: Summary of results from the second phase of model testing

	Model Change	AIC
Model 177	Reintroduced gini (lowered AIC, included)	6478.585
Model 178	Reintroduced renocc (increased AIC, not included)	6480.641
Model 179	Reintroduced unemp (increased AIC, not included)	6484.303
Model 180	Reintroduced inczon * gini interaction (lowered AIC, included)	6471.642
Model 181	Reintroduced coccat * gini interaction (lowered AIC, included)	6456.868
Model 182	Reintroduced gini * hf interaction (lowered AIC, included)	6441.414
Model 201	Added medval * pov interaction (lowered AIC, included)	6438.321
Model 215	Added pov * hf interaction (lowered AIC, included)	6431.524
Model 221	Added vac * yearcoded interaction (lowered AIC, included)	6429.769
Model 224	Added temp * yearcoded interaction (lowered AIC, included)	6425.655
Model 225	Added fund * hf interaction (lowered AIC, included)	6424.719

A total of 227 models were run across both phases of testing. The second phase of testing prioritized lowering the AIC score over variable significance, and the AIC was only lowered from 6478.585 to 6424.719, which is still higher than the baseline model AIC of 5123.713 that included only main effects for all variables. In both the baseline model and Model 225, which provided the lowest AIC score at the conclusion of second phase testing, most variables used in the model were statistically insignificant. Since the primary purpose of this study is to understand relationships between homelessness and other variables as opposed to making predictions about homelessness, the reduction in the AIC is not substantial enough to justify sacrificing statistical significance of the variables.

Therefore, the results of the second phase of model testing are discarded in favor of Model 159. I chose Model 159 instead of Model 164, because the difference in the AIC is only 21.926, and by adding an interaction term for the median rent and vacancy rate, the percentage of renters who are white is shown to have a statistically significant relationship with homelessness rates, which is supported by the literature and I hypothesize that this relationship is meaningful. Inclusionary zoning and the vacancy rate are no longer significant at the 0.05 p-score level in Model 159, but they are still significant at the 0.10 p-score level, so I do not have to sacrifice much to continue to consider the relationship between race and homelessness in the model.

Appendix 3: Additional Descriptive Statistics

Table 21: Descriptive summary of variables

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Percentage of Population with a Bachelor's Degree or Higher	3141	11.37	74.10	28.9309	9.91841	1.011	1.223
Median Household Income	3141	17208.45	129588.00	54989.4340	14631.66806	1.382	2.617
Median Gross Rent of Renter-Occupied Housing Units	3141	390.50	1973.00	887.0583	243.95126	1.118	1.309
Median Home Value of Owner-Occupied Housing Units	3141	67165	927400	213148.08	125688.878	2.029	5.112
Number of Occupied Housing Units	2792	11644	3281845	272360.46	369437.518	4.627	27.287
Percentage of Renters in a Family with Children	2795	13.90	58.04	33.8157	6.45946	.297	1.021
Percentage of Renter-Occupied Housing Units	3141	12.56	69.22	33.5296	8.37018	.913	1.738
Percentage of Renters Identifying as White, Non-Hispanic	3141	.73	98.40	63.3276	19.02170	-.461	-.227
Percentage of Renters Without any College Education	3141	13.20	68.64	44.7024	9.49701	-.251	-.168
Unemployment Rate	3141	2.68	19.68	8.3145	2.50746	.937	1.426
Poverty Rate	2795	3.20	48.38	14.8705	5.16948	1.256	6.101
Eviction Filing Rate	2347	.00	39.52	6.0189	6.06029	1.694	3.035
Percentage of Rent-Burdened Households	3141	22.69	39.50	30.7397	2.53258	.491	.212
Gini Index	2795	.36	.55	.4516	.03019	.285	.560
Vacancy Rate	3141	3.67	46.47	12.4655	6.57217	1.778	4.426

Mean Temperature in January in Fahrenheit	3039	-12.80	72.50	34.9229	13.06098	.236	-.208
Total Precipitation in January in Inches	3031	.01	24.56	2.9166	2.50880	2.604	10.806
CoC Category	3141	1	3	1.96	.456	-.148	1.761
Adoption of an Inclusionary Zoning Policy	3141	0	1	.34	.474	.668	-1.554
Housing First Index	3136	.00	.97	.5375	.15871	-.388	.035
HUD CoC Funding in the Previous Year per Person	3091	.01	46.90	5.1527	5.15511	2.902	11.663
People per 1,000 Experiencing Homelessness	3141	.02	16.78	1.9731	2.00319	3.219	13.614
People per 1,000 Experiencing Sheltered Homelessness	3141	.01	12.19	1.2273	1.08133	3.979	24.899
People per 1,000 Experiencing Unsheltered Homelessness	3141	.00	16.37	.7458	1.54983	4.746	29.416
People per 1,000 in Families Experiencing Homelessness	3141	.00	13.55	.6886	.86739	5.720	51.790
People per 1,000 Experiencing Chronic Homelessness	3141	.00	6.30	.3691	.56605	4.358	25.824
Veterans Experiencing Homelessness per 1,000 People	2448	.00	1.85	.1743	.21014	2.837	10.953
People per 1,000 Experiencing Homelessness (Coerced)	3141	.02	6.29	1.8405	1.46589	1.693	2.362

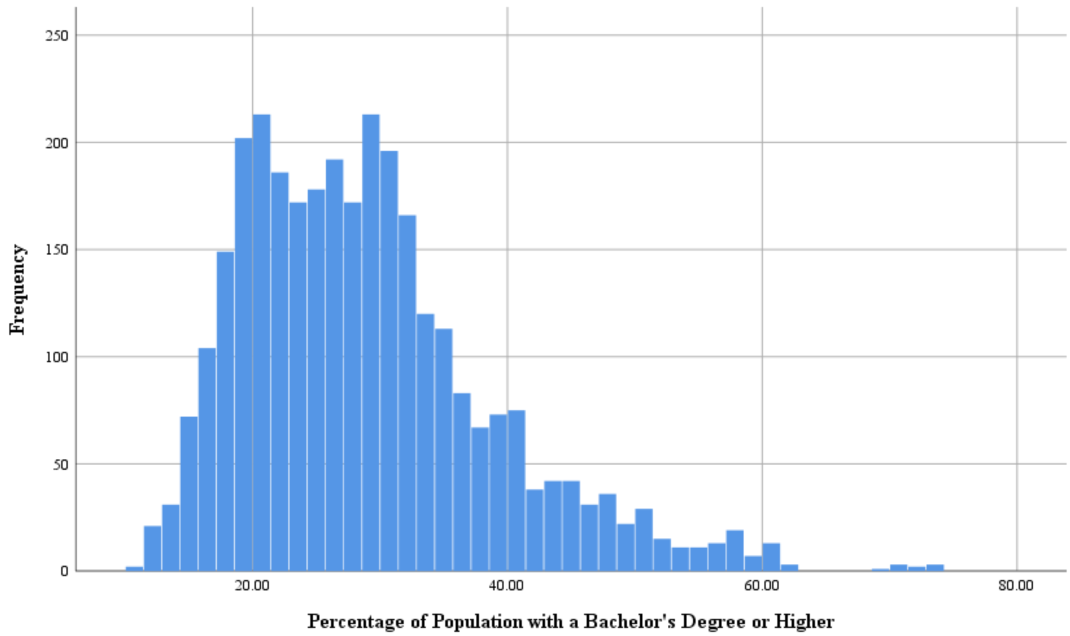

Figure 13: Distribution histogram for variable: bach

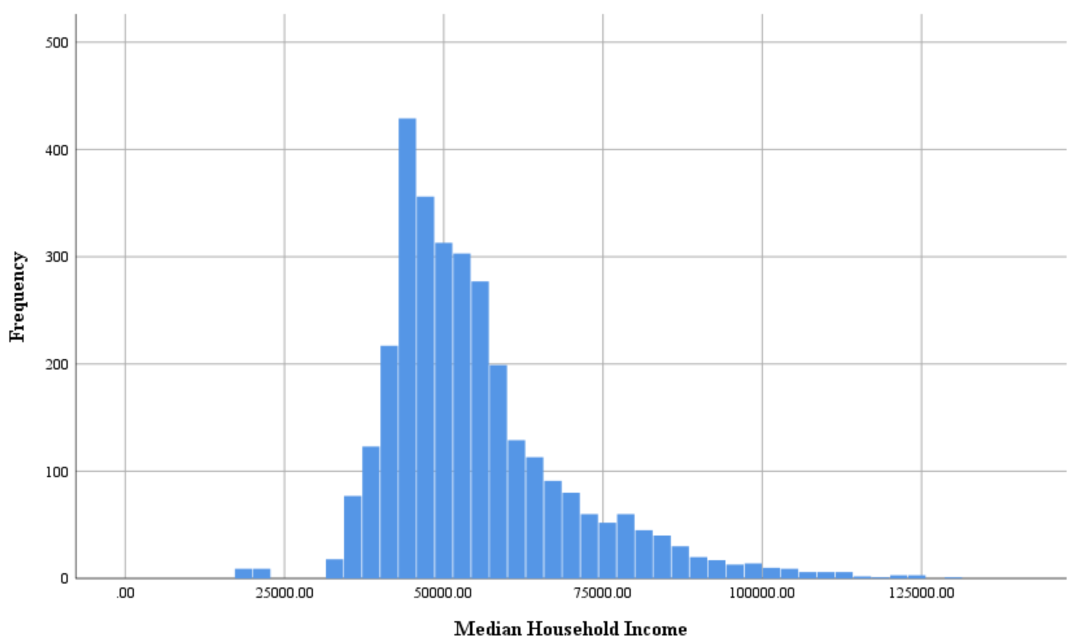

Figure 14: Distribution histogram for variable: medinc

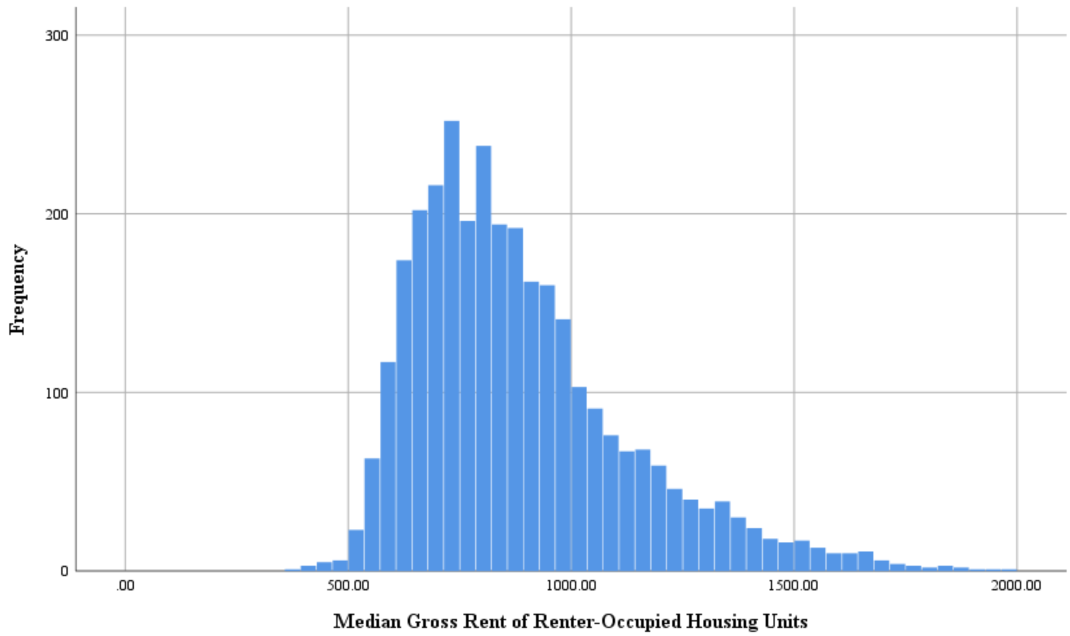

Figure 15: Distribution histogram for variable: medren

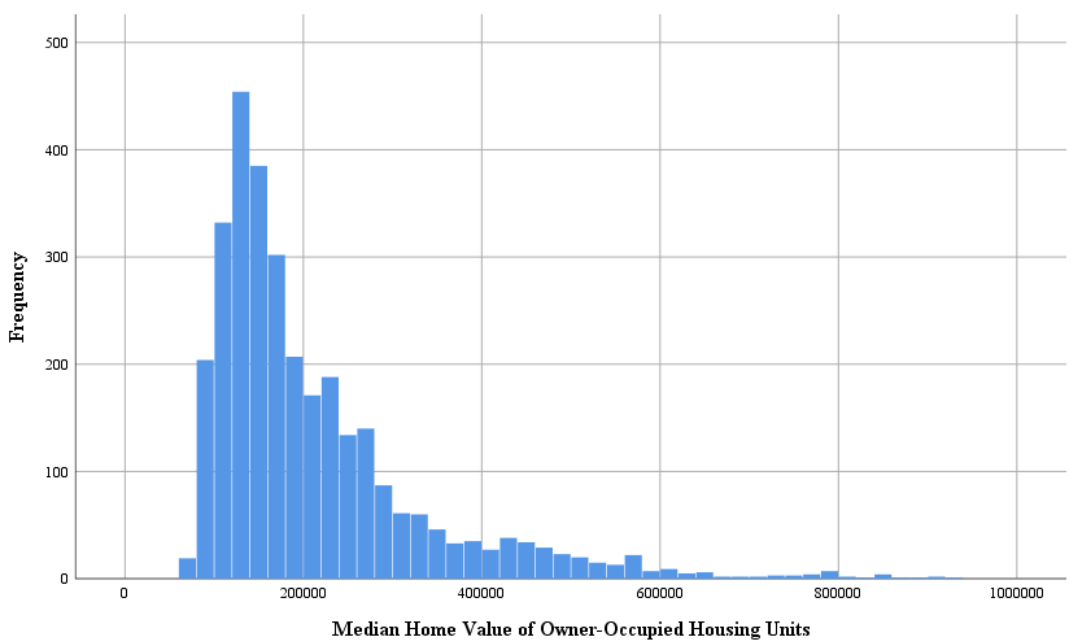

Figure 16: Distribution histogram for variable: medval

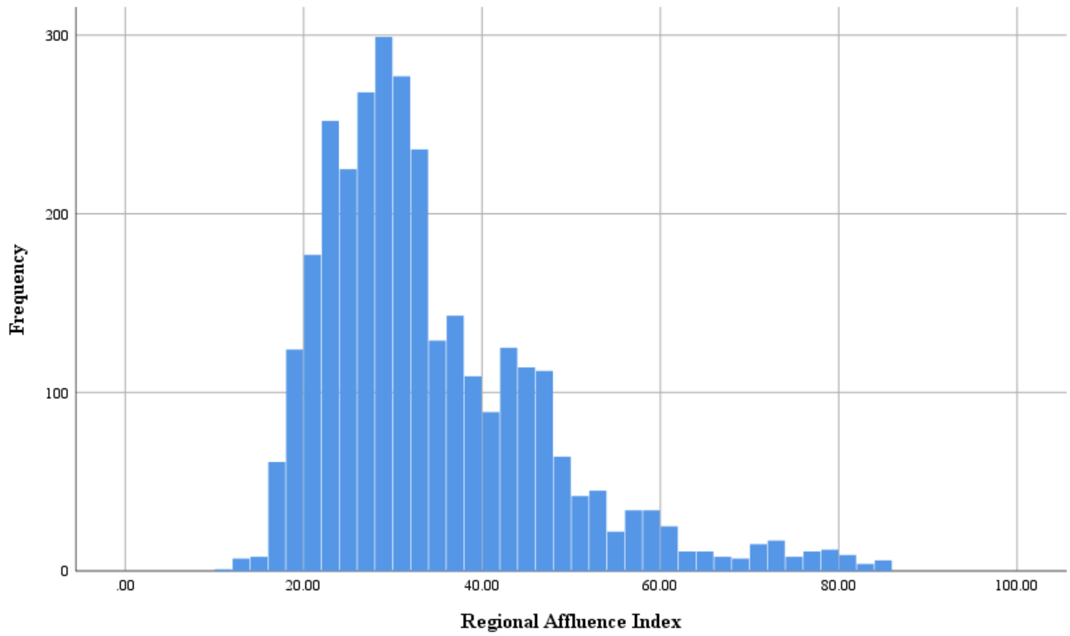

Figure 17: Distribution histogram for variable: aff

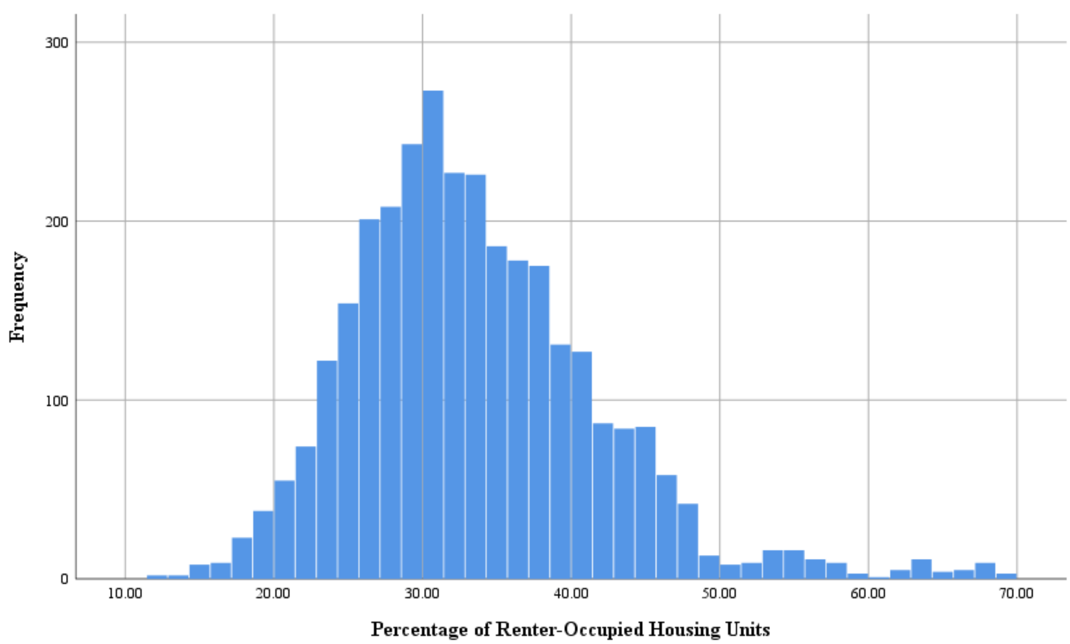

Figure 18: Distribution histogram for variable: renocc

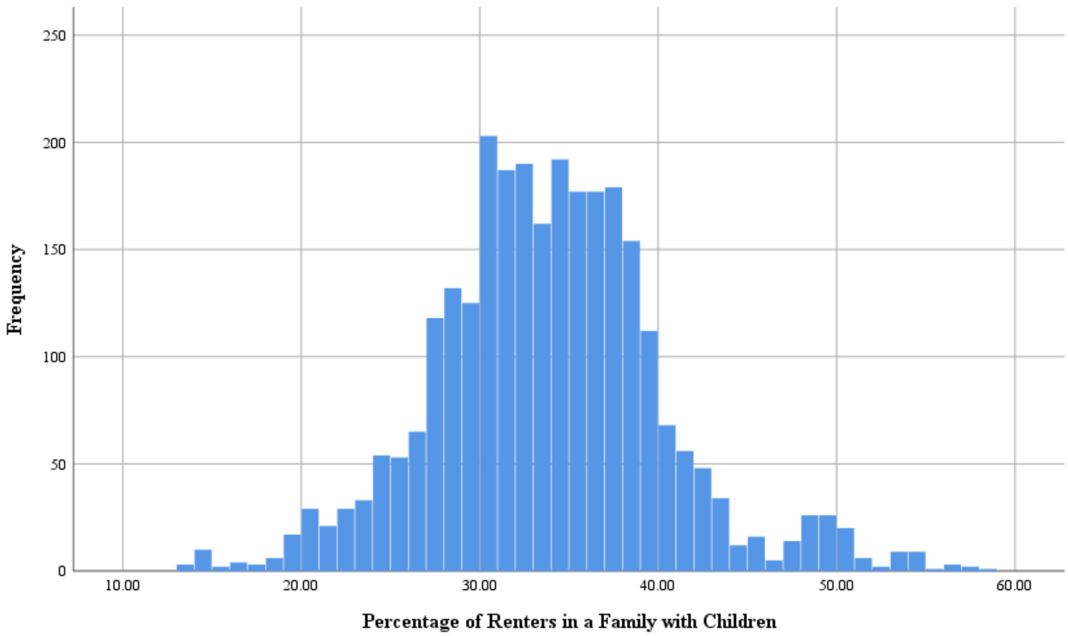

Figure 19: Distribution histogram for variable: renfam

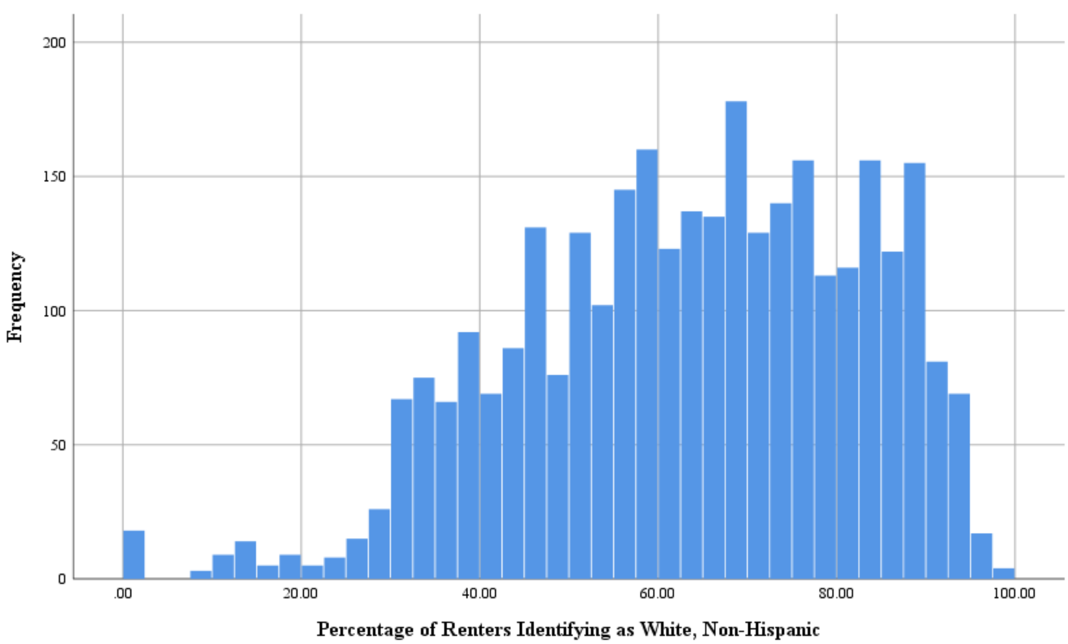

Figure 20: Distribution histogram for variable: renwhi

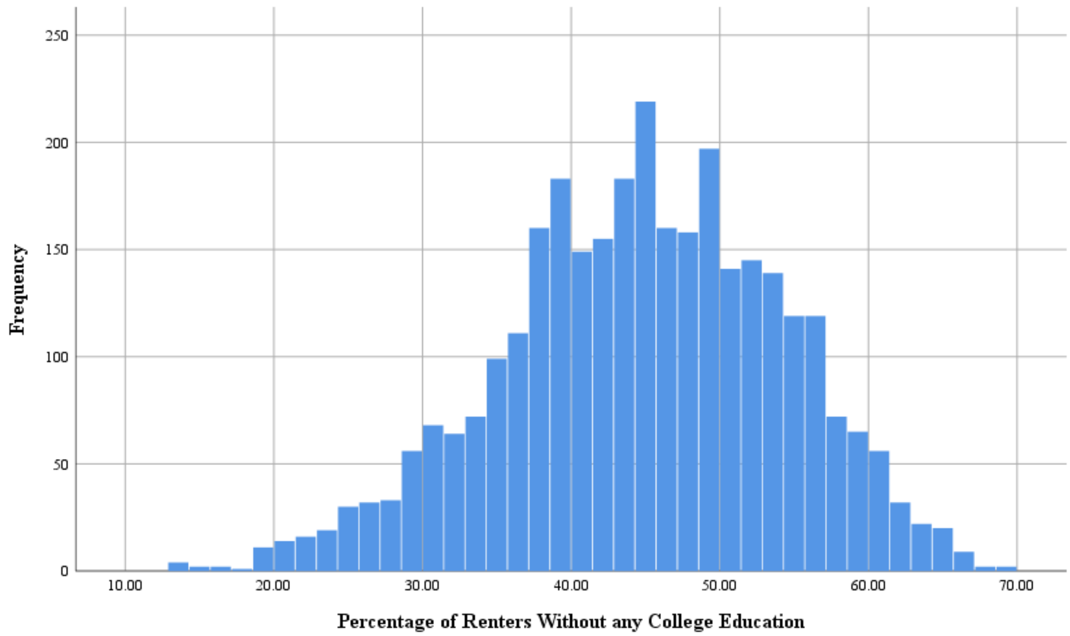

Figure 21: Distribution histogram for variable: renedu

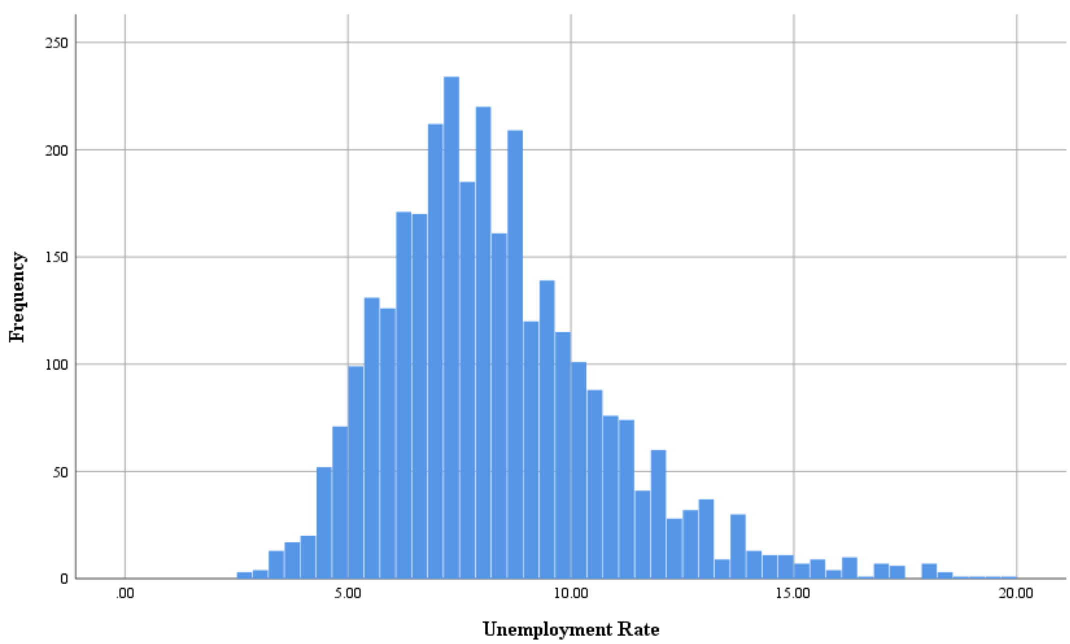

Figure 22: Distribution histogram for variable: unemp

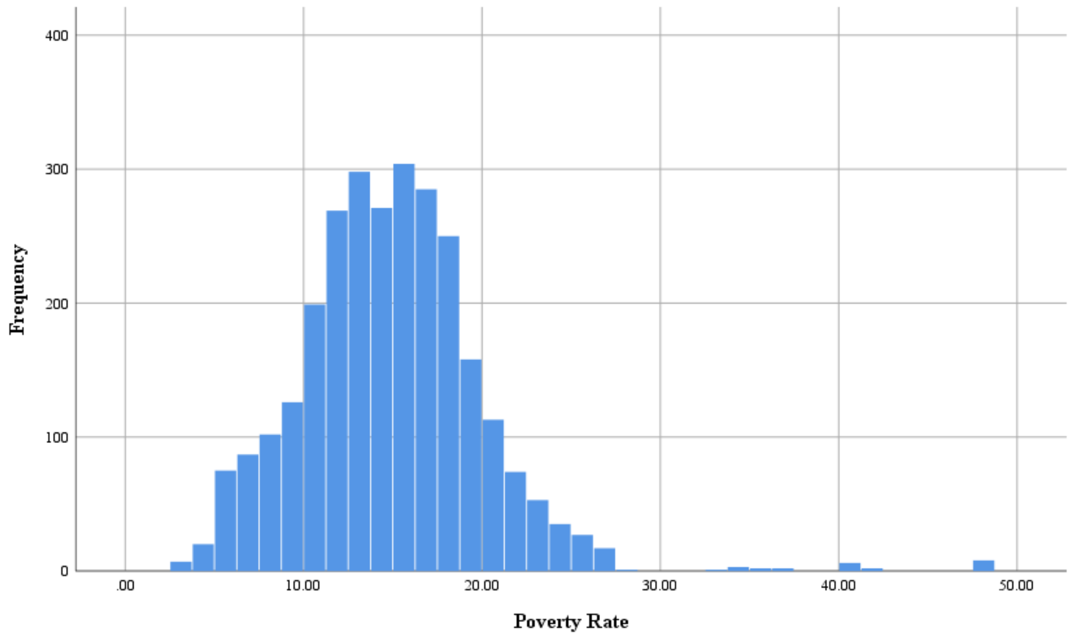

Figure 23: Distribution histogram for variable: pov

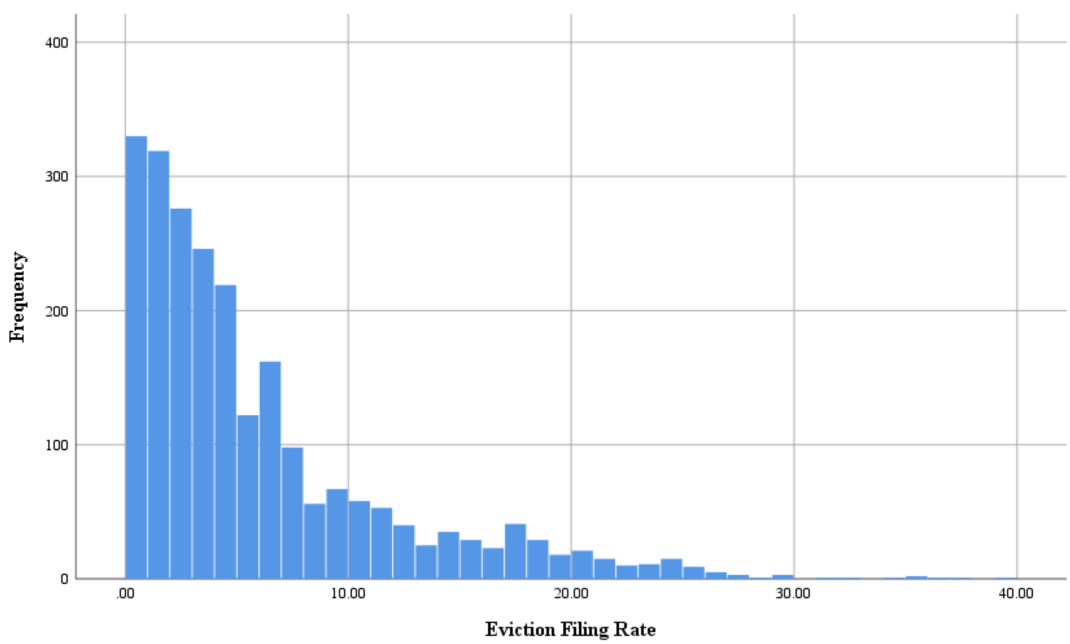

Figure 24: Distribution histogram for variable: evic

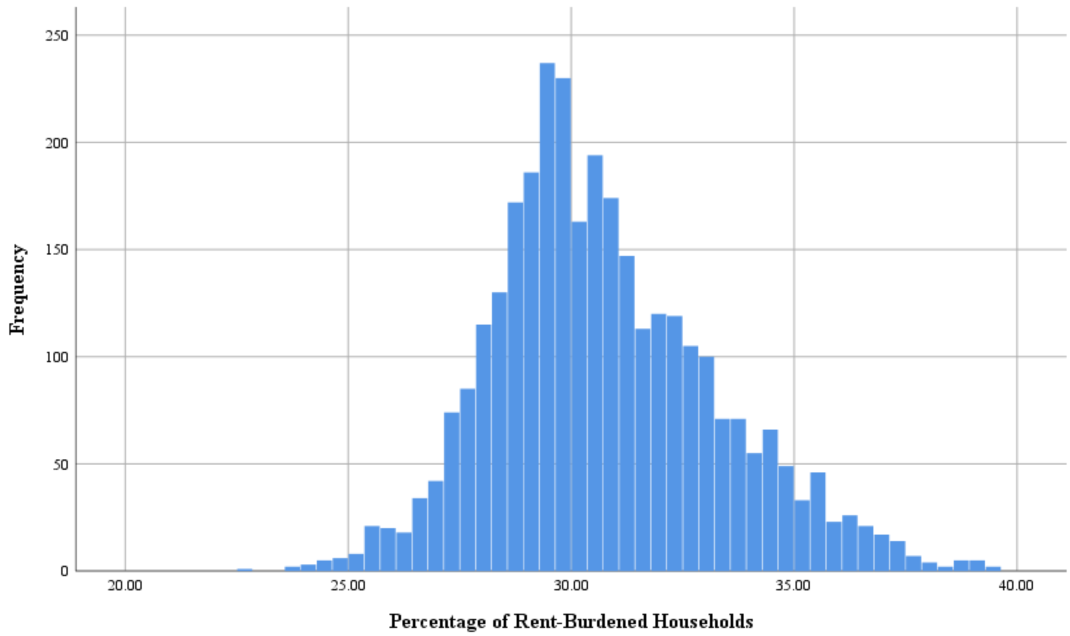

Figure 25: Distribution histogram for variable: burd

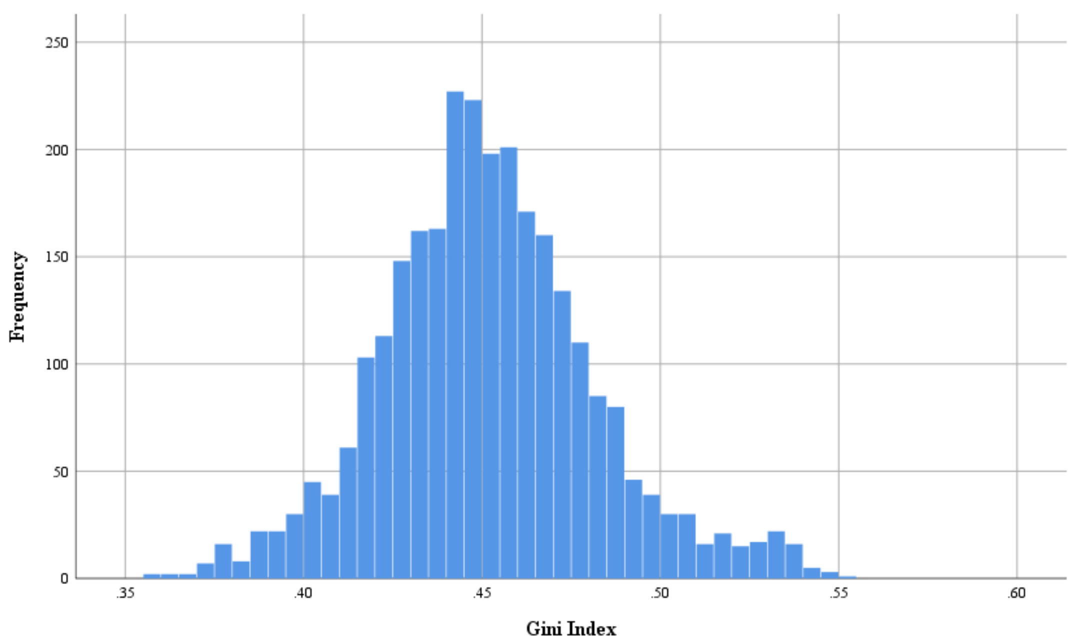

Figure 26: Distribution histogram for variable: gini

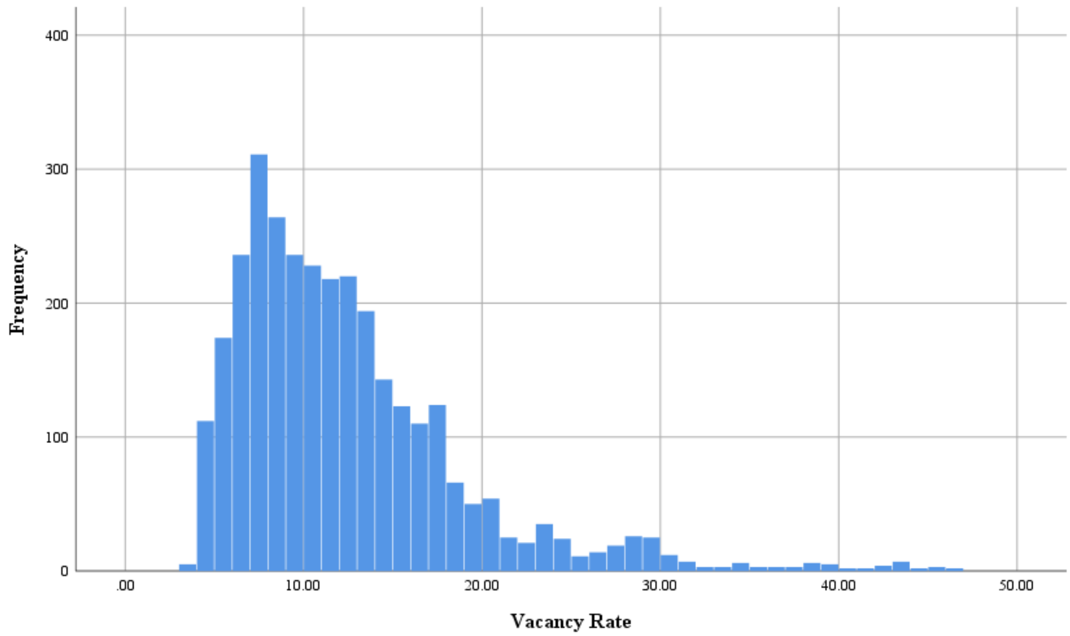

Figure 27: Distribution histogram for variable: vac

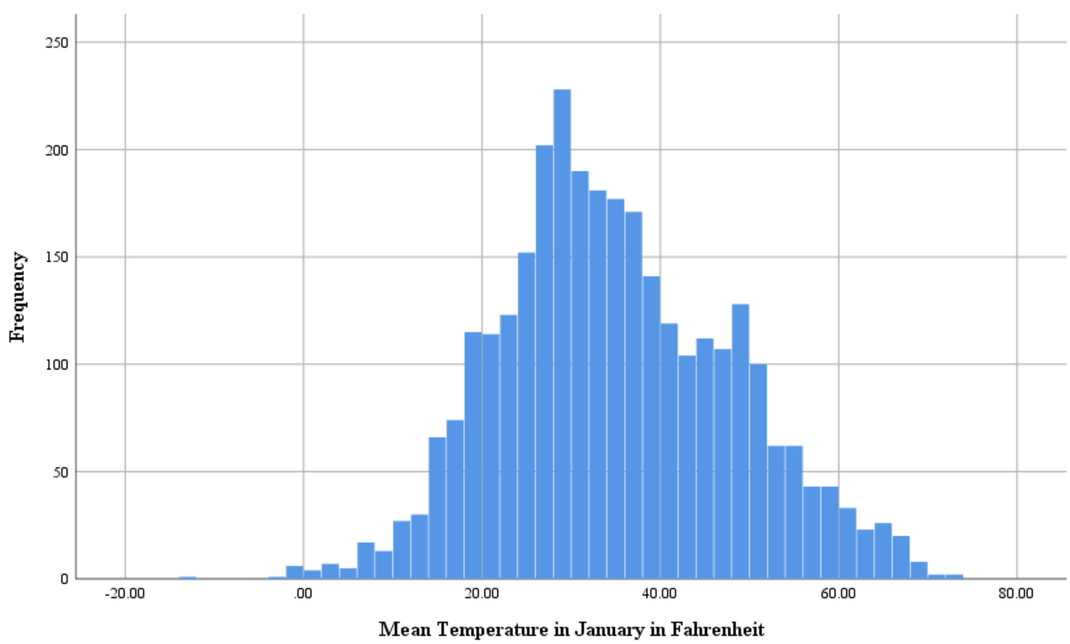

Figure 28: Distribution histogram for variable: temp

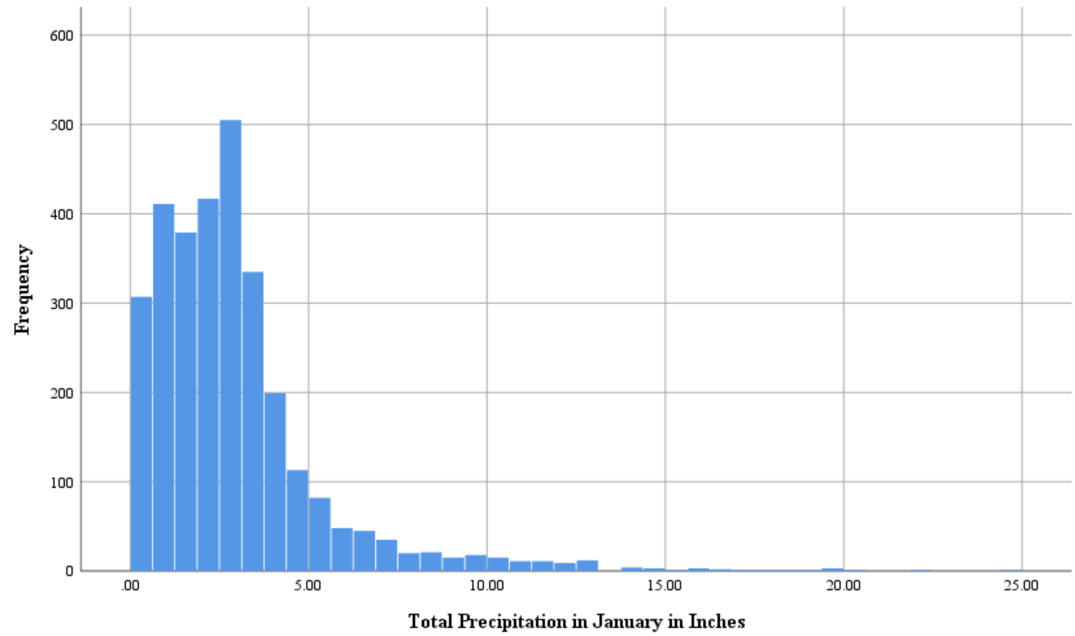

Figure 29: Distribution histogram for variable: precip

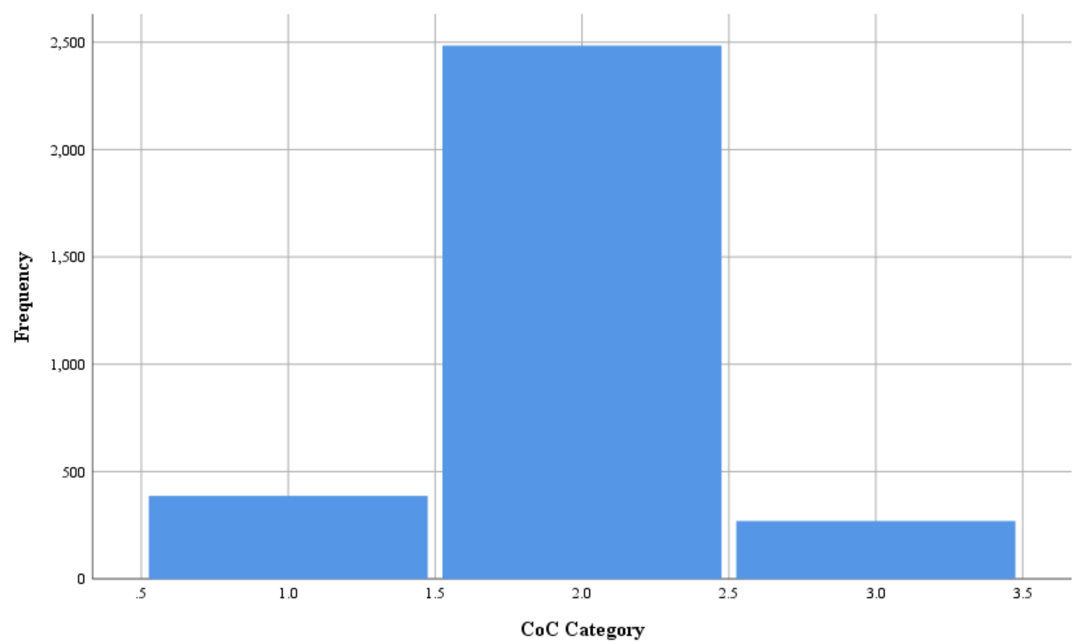

Figure 30: Distribution histogram for variable: coccat

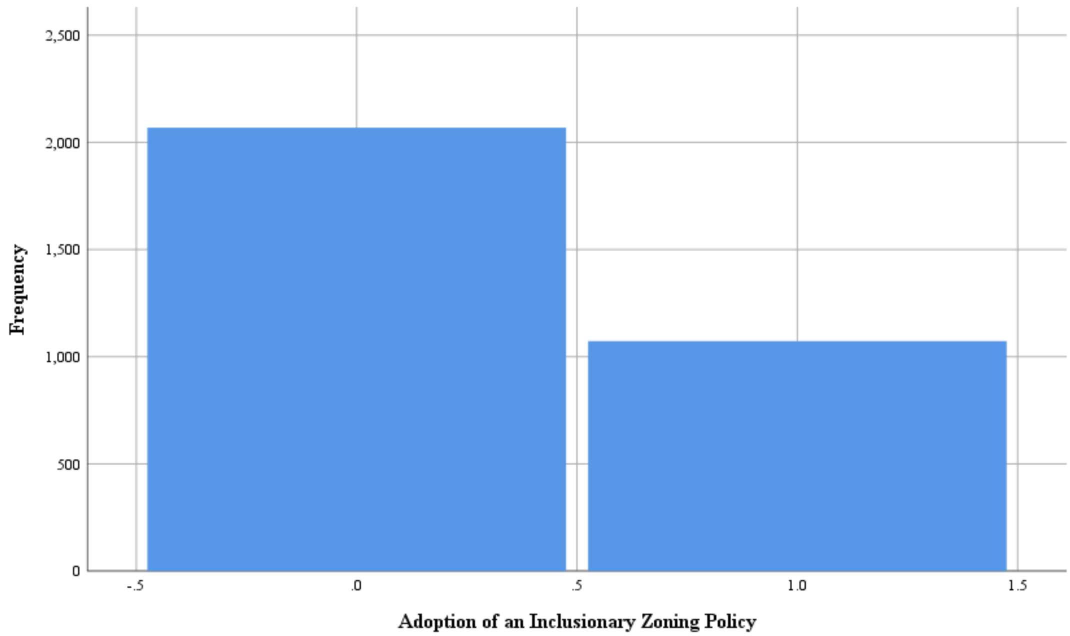

Figure 31: Distribution histogram for variable: inczon

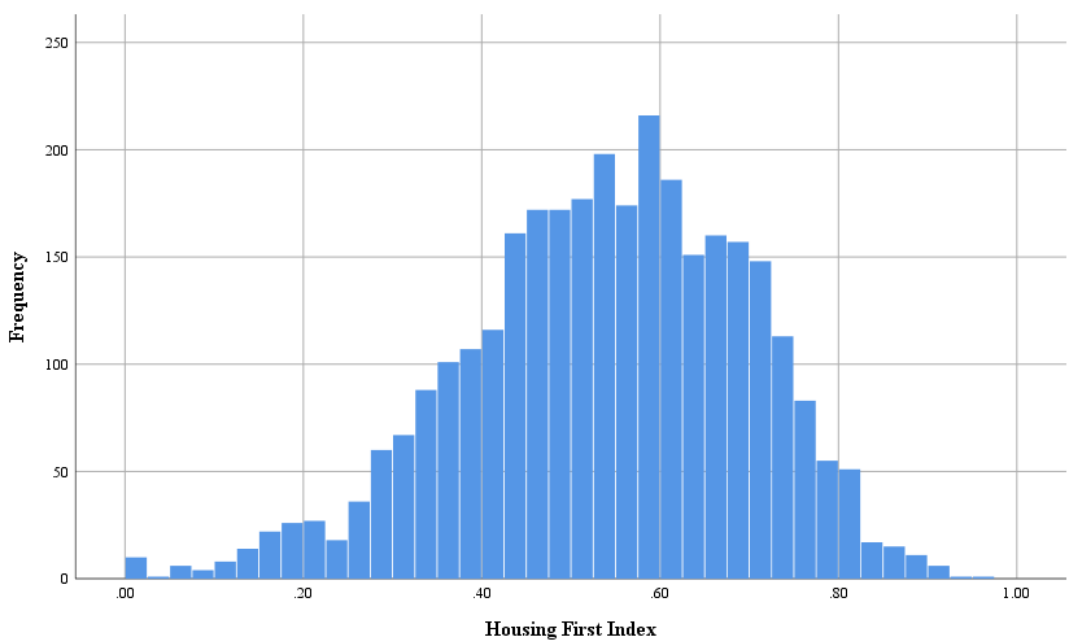

Figure 32: Distribution histogram for variable: hf

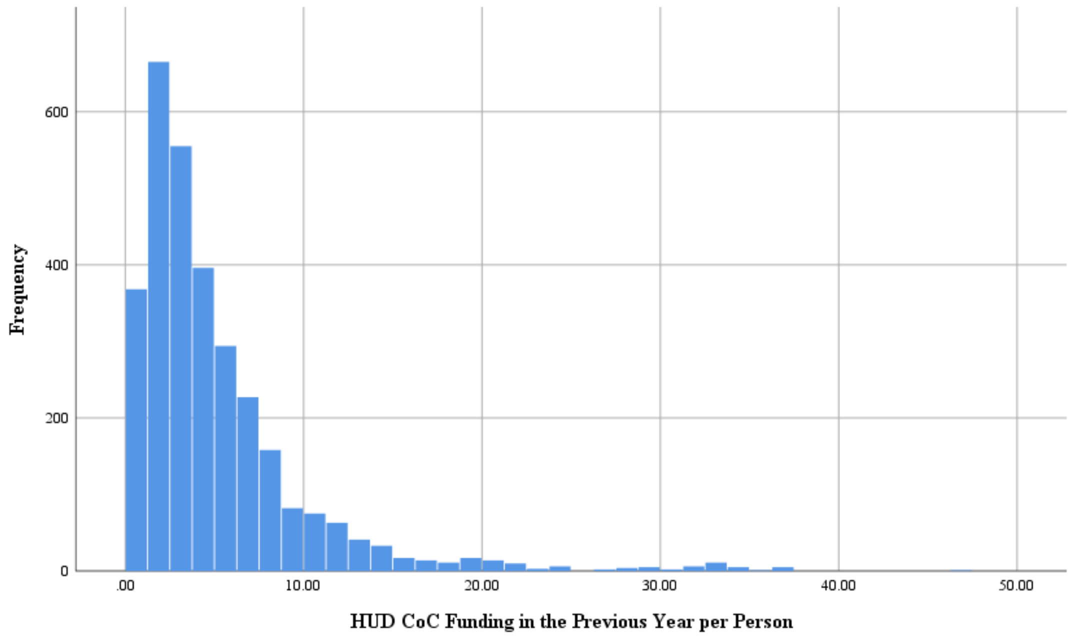

Figure 33: Distribution histogram for variable: fund

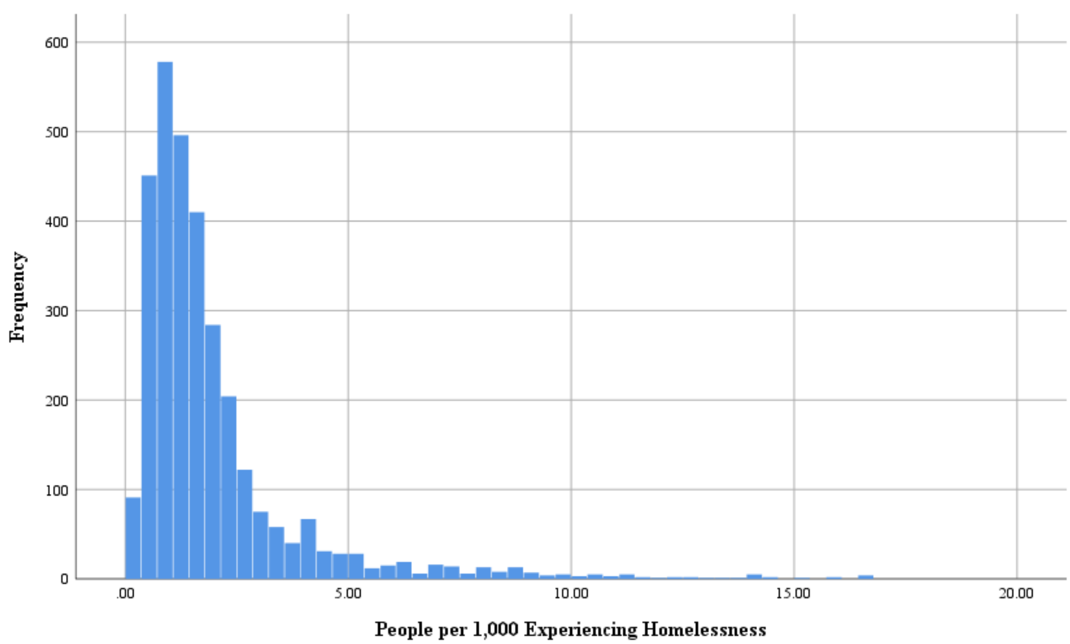

Figure 34: Distribution histogram for variable: hl

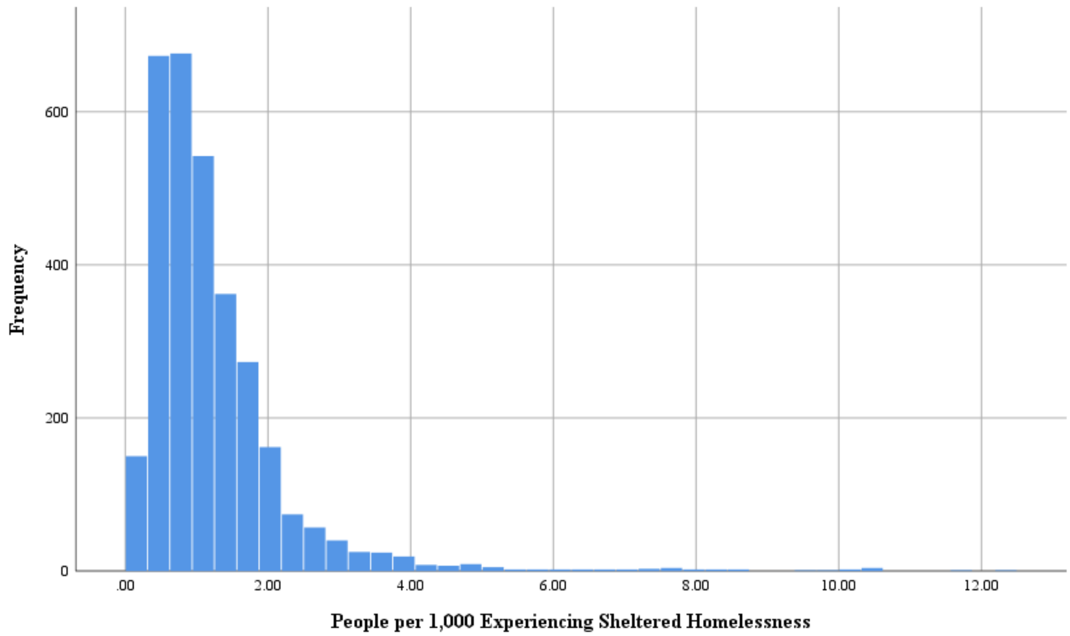

Figure 35: Distribution histogram for variable: hls

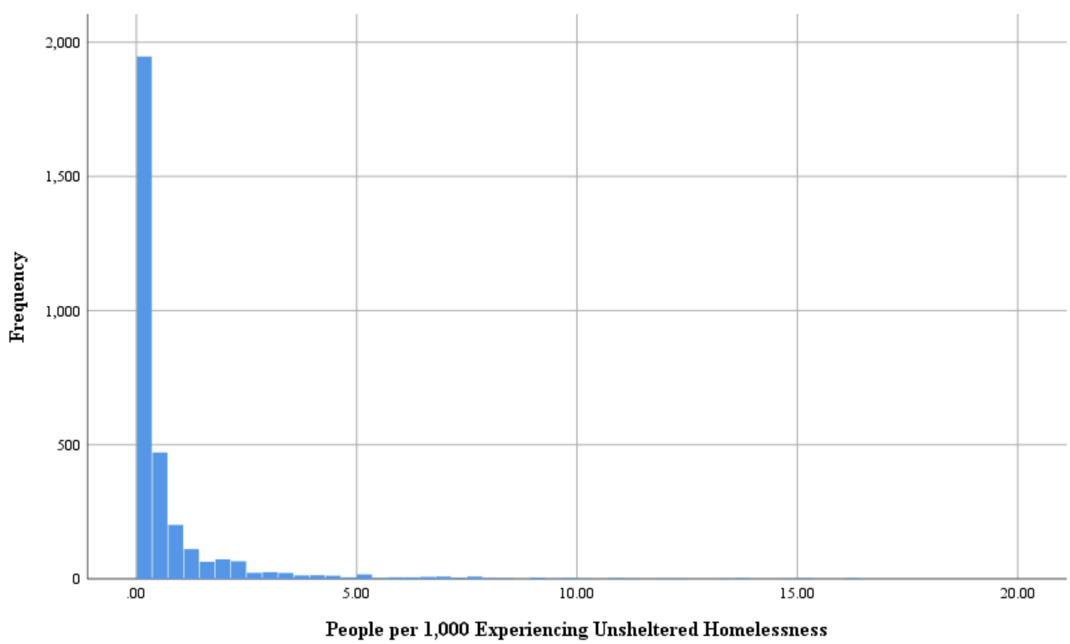

Figure 36: Distribution histogram for variable: hlu

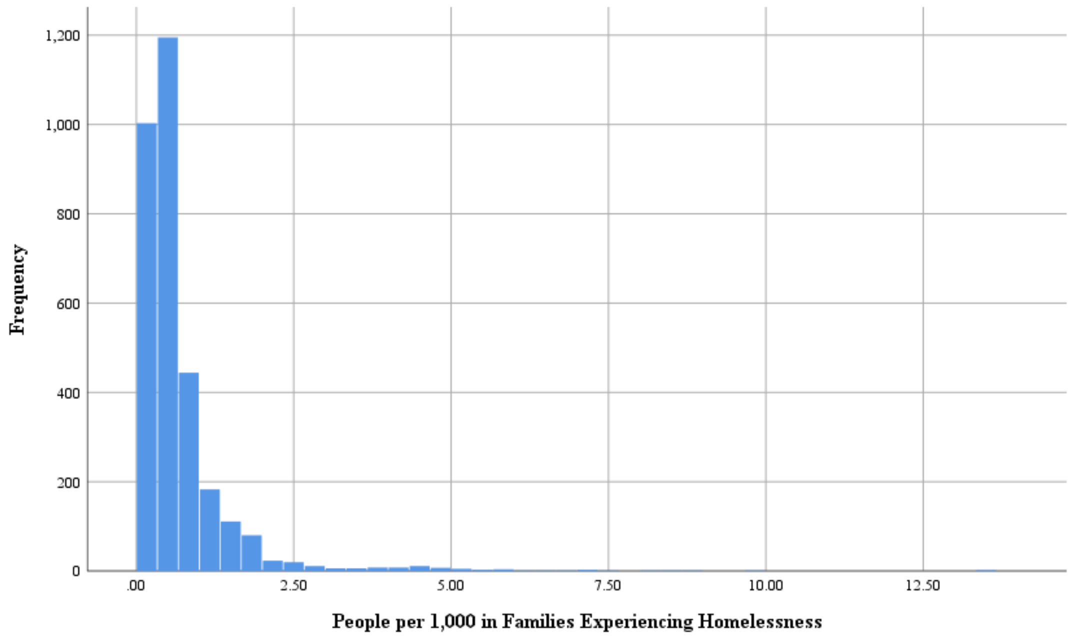

Figure 37: Distribution histogram for variable: hlf

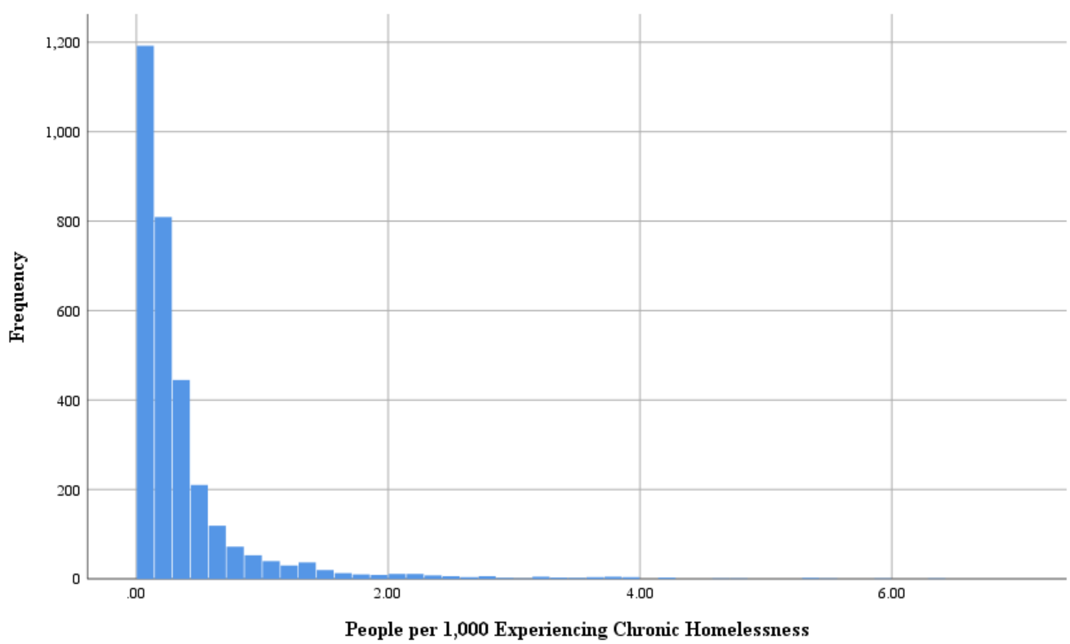

Figure 38: Distribution histogram for variable: hlc

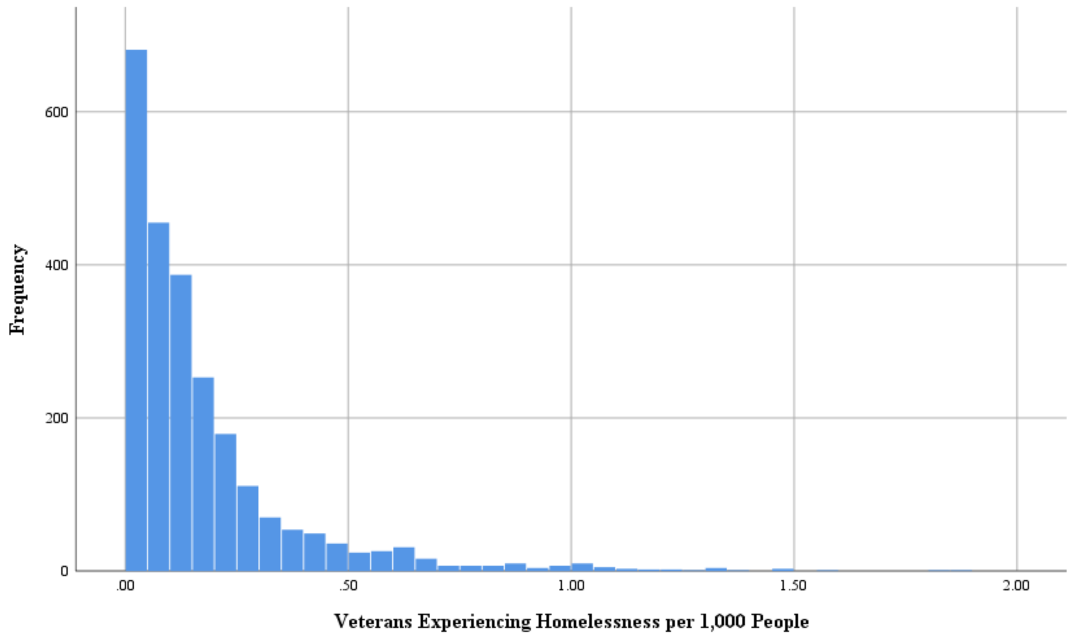

Figure 39: Distribution histogram for variable: hlv

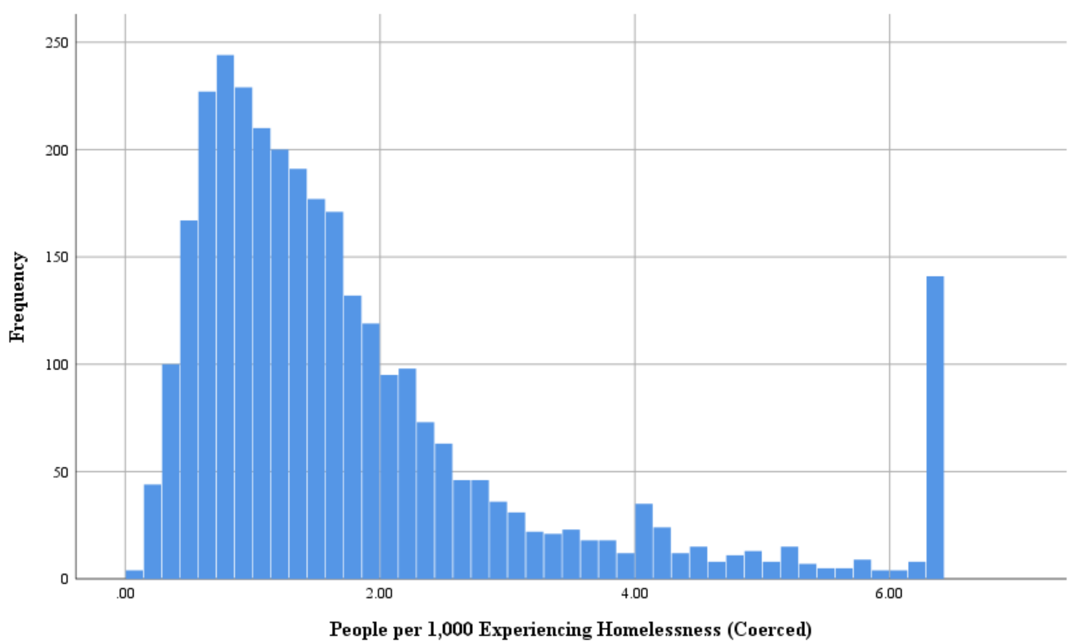

Figure 40: Distribution histogram for variable: hlco

Table 22: Outliers

	CoC Number	Year	People per 1,000 Experiencing Homelessness
1	FL-517	2009	16.78
2	FL-517	2010	16.72
3	CA-509	2011	16.64
4	CA-509	2012	16.45
5	CA-509	2014	16.03
6	CA-509	2013	15.91
7	FL-517	2013	15.31
8	CA-614	2009	14.61
9	CA-614	2010	14.42
10	FL-604	2010	14.23
11	CA-509	2016	14.21
12	CA-509	2017	14.15
13	FL-604	2009	14.05
14	CA-509	2009	13.97
15	CA-509	2010	13.74
16	CA-508	2013	13.35
17	CA-508	2014	13.21
18	DC-500	2016	12.67
19	FL-604	2012	12.55
20	FL-604	2011	12.37
21	DC-500	2014	12.23
22	LA-503	2010	12.01
23	FL-505	2011	11.70
24	DC-500	2012	11.48
25	LA-503	2009	11.35
26	DC-500	2015	11.27
27	DC-500	2010	11.19
28	DC-500	2017	11.11
29	DC-500	2013	11.08
30	CA-523	2013	11.04
31	DC-500	2011	11.02
32	CA-509	2015	10.82
33	CA-508	2011	10.68
34	DC-500	2009	10.58
35	CA-522	2009	10.50
36	FL-505	2009	10.48
37	CA-508	2012	10.43

38	CA-603	2009	10.25
39	FL-505	2012	10.21
40	CA-522	2010	10.18
41	FL-519	2009	9.97
42	FL-519	2010	9.92
43	CA-603	2010	9.91
44	MO-602	2012	9.86
45	FL-519	2011	9.75
46	FL-505	2010	9.61
47	FL-518	2013	9.55
48	CA-504	2011	9.49
49	FL-519	2012	9.35
50	CA-504	2012	9.27
51	FL-604	2014	9.01
52	CA-508	2009	9.01
53	CA-523	2014	9.01
54	FL-518	2011	8.94
55	NY-600	2015	8.94
56	NY-600	2017	8.94
57	CA-524	2013	8.87
58	LA-503	2011	8.87
59	FL-518	2012	8.86
60	CA-508	2010	8.82
61	FL-604	2013	8.79
62	CA-504	2013	8.78
63	CA-522	2015	8.74
64	NY-600	2016	8.69
65	CA-504	2014	8.67
66	CA-614	2013	8.66
67	FL-518	2009	8.64
68	CA-614	2014	8.63
69	CA-501	2013	8.57
70	MA-500	2015	8.55
71	FL-518	2010	8.51
72	FL-518	2016	8.48
73	CA-522	2016	8.39
74	FL-518	2015	8.28
75	CA-508	2017	8.23
76	CA-501	2016	8.23
77	FL-604	2017	8.22

78	NY-607	2012	8.15
79	MA-500	2016	8.13
80	NY-600	2014	8.12
81	FL-604	2015	8.10
82	CA-501	2015	8.06
83	MA-500	2014	8.00
84	MA-500	2013	7.99
85	FL-518	2014	7.96
86	CA-614	2011	7.95
87	CA-501	2017	7.94
88	GA-500	2010	7.91
89	CA-614	2012	7.88
90	MA-500	2017	7.86
91	MD-508	2009	7.80
92	NY-600	2013	7.75
93	MA-500	2012	7.74
94	CA-501	2014	7.73
95	MA-500	2011	7.68
96	MD-508	2010	7.67
97	GA-500	2011	7.50
98	FL-512	2011	7.48
99	FL-604	2016	7.45
100	OR-500	2010	7.43
101	CA-501	2010	7.38
102	GA-500	2012	7.33
103	CA-501	2009	7.30
104	CA-501	2012	7.30
105	MA-500	2010	7.29
106	CA-508	2015	7.29
107	FL-512	2013	7.29
108	FL-512	2012	7.23
109	CA-508	2016	7.23
110	NY-607	2013	7.21
111	GA-500	2009	7.11
112	CA-501	2011	7.10
113	FL-519	2014	7.10
114	FL-512	2009	7.07
115	FL-519	2013	7.06
116	CA-504	2010	7.06
117	NC-516	2009	7.01

118	CA-504	2009	6.99
119	HI-500	2016	6.99
120	MA-500	2009	6.98
121	FL-512	2010	6.93
122	NY-600	2012	6.91
123	CA-522	2014	6.91
124	FL-512	2014	6.89
125	CA-506	2017	6.84
126	FL-505	2013	6.84
127	NY-607	2011	6.77
128	MD-501	2011	6.60
129	NY-600	2010	6.58
130	OR-500	2009	6.49
131	CA-522	2011	6.45
132	HI-500	2015	6.44
133	CA-522	2013	6.42
134	MA-504	2015	6.41
135	CA-613	2017	6.41
136	FL-501	2009	6.40
137	FL-505	2014	6.39
138	LA-503	2012	6.33
139	CA-522	2012	6.30

Table 23: Distribution descriptives for homelessness using coerced values

	Above and Below Median Homelessness Rates			Statistic	Std. Error
People per 1,000 Experiencing Homelessness (Coerced)	Above	Mean		2.8255	.03794
		95% Confidence Interval for Mean	Lower Bound	2.7510	
			Upper Bound	2.8999	
		5% Trimmed Mean		2.7109	
		Median		2.2144	
		Variance		2.261	
		Std. Deviation		1.50366	
		Minimum		1.40	
		Maximum		6.29	
		Range		4.89	
		Interquartile Range		1.73	
		Skewness		1.256	.062
		Kurtosis		.335	.123
	Below	Mean		.8550	.00777
		95% Confidence Interval for Mean	Lower Bound	.8397	
			Upper Bound	.8702	
		5% Trimmed Mean		.8600	
		Median		.8553	
		Variance		.095	
		Std. Deviation		.30769	
		Minimum		.02	
		Maximum		1.40	
		Range		1.38	
		Interquartile Range		.50	
		Skewness		-.137	.062
		Kurtosis		-.872	.123

Appendix 4: Individual Variable Regressions

Table 24: Model fit results regressing homelessness rates by total population

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.003[a]	.000	.000	2.00350	.000	.026	1	3139	.873
2	.144[b]	.021	.020	1.98286	.021	66.704	1	3138	.000
3	.144[c]	.021	.020	1.98317	.000	.016	1	3137	.899
4	.146[d]	.021	.020	1.98295	.001	1.703	1	3136	.192

a. Predictors: (Constant), Total Population

b. Predictors: (Constant), Total Population, pop2

c. Predictors: (Constant), Total Population, pop2, pop3

d. Predictors: (Constant), Total Population, pop2, pop3, pop4

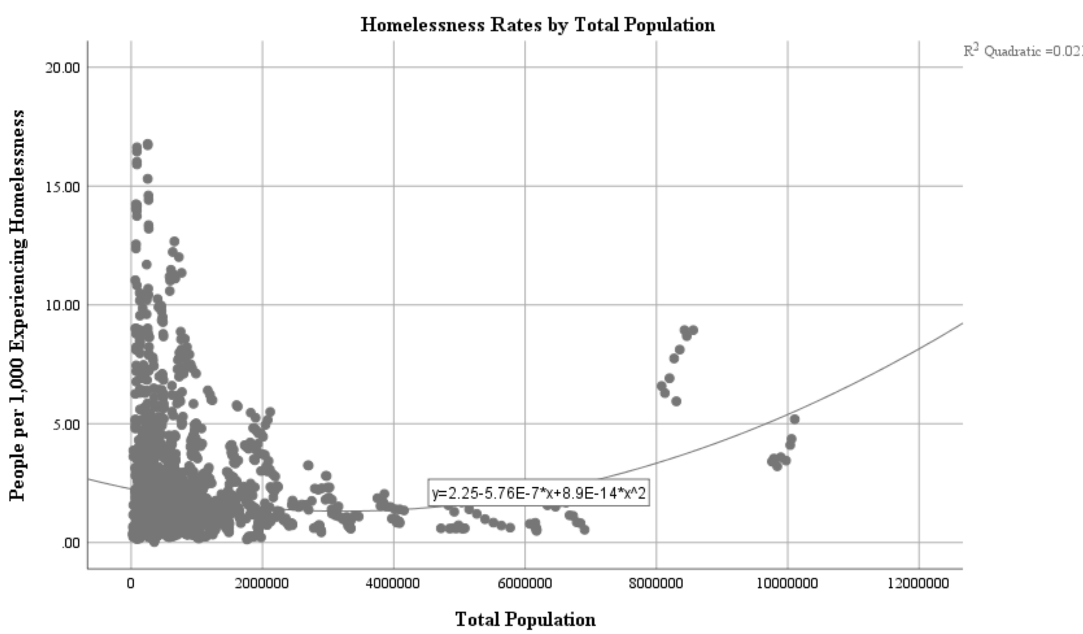

Figure 41: Homelessness rates by total population quadratic regression

Table 25: ANOVA table regressing homelessness rates by total population

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.103	1	.103	.026	.873[b]
	Residual	12600.021	3139	4.014		
	Total	12600.124	3140			
2	Regression	262.366	2	131.183	33.365	.000[c]
	Residual	12337.758	3138	3.932		
	Total	12600.124	3140			
3	Regression	262.429	3	87.476	22.242	.000[d]
	Residual	12337.695	3137	3.933		
	Total	12600.124	3140			
4	Regression	269.125	4	67.281	17.111	.000[e]
	Residual	12330.999	3136	3.932		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Total Population

c. Predictors: (Constant), Total Population, pop2

d. Predictors: (Constant), Total Population, pop2, pop3

e. Predictors: (Constant), Total Population, pop2, pop3, pop4

Table 26: Coefficient table regressing homelessness rates by total population

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.969	.044		44.927	.000
	Total Population	5.516E-9	.000	.003	.160	.873
2	(Constant)	2.253	.056		40.534	.000
	Total Population	-5.758E-7	.000	-.298	-7.295	.000
	pop2	8.896E-14	.000	.334	8.167	.000
3	(Constant)	2.258	.068		32.977	.000
	Total Population	-5.904E-7	.000	-.306	-4.216	.000
	pop2	9.514E-14	.000	.357	1.898	.058
	pop3	-5.228E-22	.000	-.017	-.126	.899
4	(Constant)	2.194	.084		26.069	.000
	Total Population	-3.420E-7	.000	-.177	-1.447	.148
	pop2	-9.104E-14	.000	-.342	-.602	.547
	pop3	3.778E-20	.000	1.218	1.275	.203
	pop4	-2.246E-27	.000	-.665	-1.305	.192

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 27: Model fit results regressing homelessness rates by percentage of population with a bachelor's degree or higher

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.070[a]	.005	.005	1.99858	.005	15.508	1	3139	.000
2	.073[b]	.005	.005	1.99854	.000	1.112	1	3138	.292
3	.099[c]	.010	.009	1.99431	.005	14.330	1	3137	.000

a. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher

b. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher, bach2

c. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher, bach2, bach3

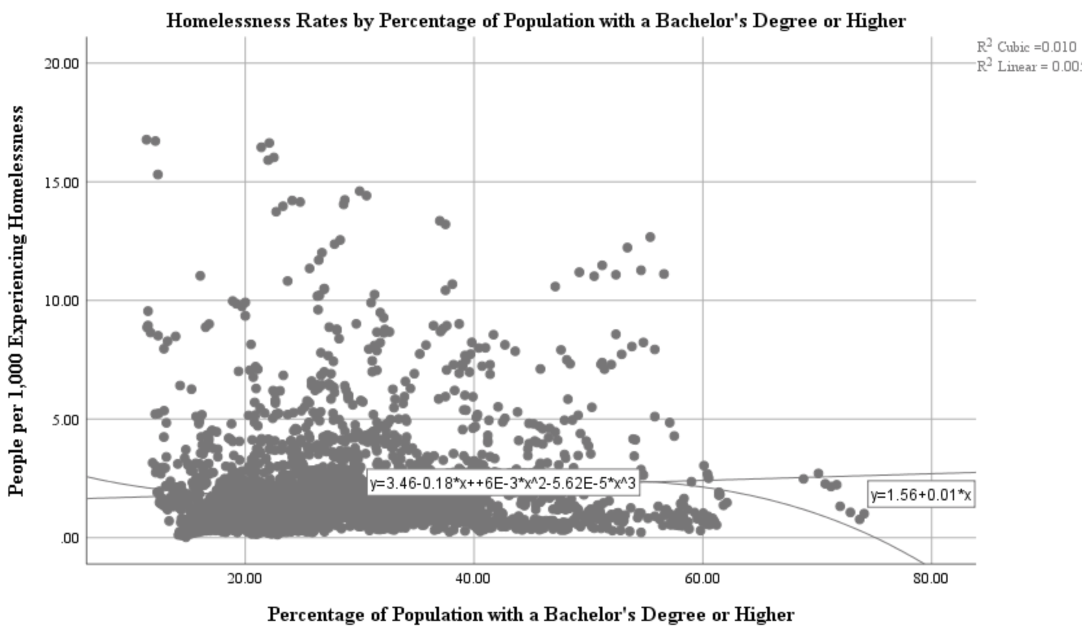

Figure 42: Homelessness rates by percentage of population with a bachelor's degree or higher cubic and linear regressions

Table 28: ANOVA table regressing homelessness rates by percentage of population with a bachelor's degree or higher

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.944	1	61.944	15.508	.000[b]
	Residual	12538.180	3139	3.994		
	Total	12600.124	3140			
2	Regression	66.387	2	33.194	8.311	.000[c]
	Residual	12533.737	3138	3.994		
	Total	12600.124	3140			
3	Regression	123.380	3	41.127	10.340	.000[d]
	Residual	12476.744	3137	3.977		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher

c. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher, bach2

d. Predictors: (Constant), Percentage of Population with a Bachelor's Degree or Higher, bach2, bach3

Table 29: Coefficient table regressing homelessness rates by percentage of population with a bachelor's degree or higher

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.563	.110		14.216	.000
	Percentage of Population with a Bachelor's Degree or Higher	.014	.004	.070	3.938	.000
2	(Constant)	1.298	.275		4.729	.000
	Percentage of Population with a Bachelor's Degree or Higher	.032	.017	.157	1.864	.062
	bach2	.000	.000	-.089	-1.055	.292
3	(Constant)	3.463	.634		5.461	.000
	Percentage of Population with a Bachelor's Degree or Higher	-.180	.058	-.892	-3.081	.002
	bach2	.006	.002	2.065	3.591	.000
	bach3	-5.621E-5	.000	-1.153	-3.785	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 30: Model fit results regressing homelessness rates by median household income

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.043[a]	.002	.002	2.00167	.002	5.764	1	3139	.016
2	.065[b]	.004	.004	1.99965	.002	7.348	1	3138	.007
3	.066[c]	.004	.003	1.99976	.000	.663	1	3137	.416

a. Predictors: (Constant), Median Household Income

b. Predictors: (Constant), Median Household Income, medinc2

c. Predictors: (Constant), Median Household Income, medinc2, medinc3

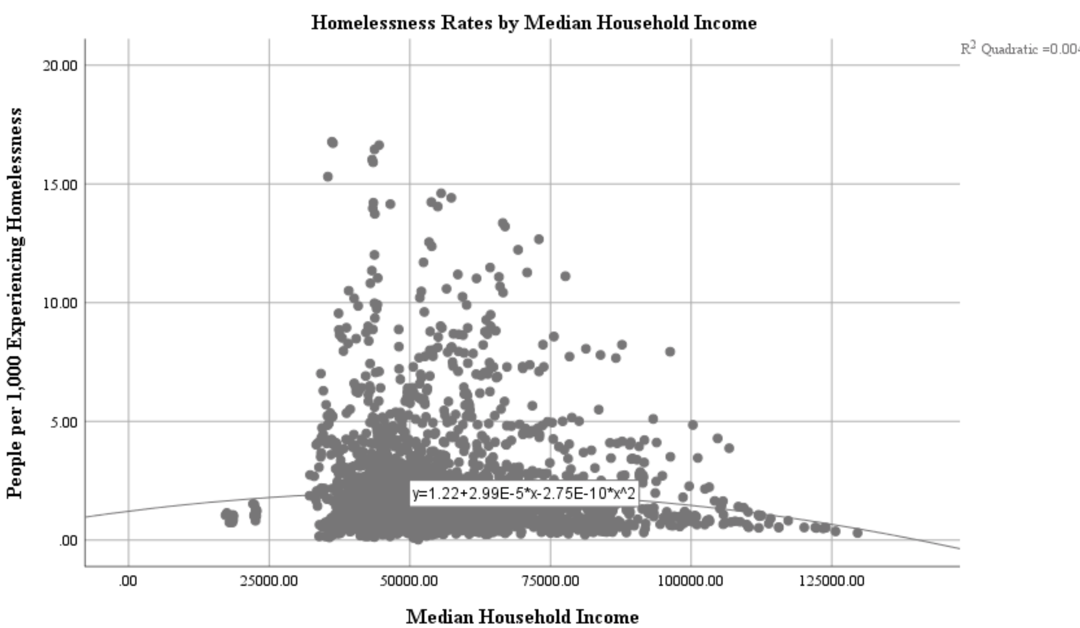

Figure 43: Homelessness rates by median household income quadratic regression

Table 31: ANOVA table regressing homelessness rates by median household income

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.094	1	23.094	5.764	.016[b]
	Residual	12577.030	3139	4.007		
	Total	12600.124	3140			
2	Regression	52.477	2	26.239	6.562	.001[c]
	Residual	12547.647	3138	3.999		
	Total	12600.124	3140			
3	Regression	55.127	3	18.376	4.595	.003[d]
	Residual	12544.997	3137	3.999		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Median Household Income

c. Predictors: (Constant), Median Household Income, medinc2

d. Predictors: (Constant), Median Household Income, medinc2, medinc3

Table 32: Coefficient table regressing homelessness rates by median household income

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.295	.139		16.524	.000
	Median Household Income	-5.861E-6	.000	-.043	-2.401	.016
2	(Constant)	1.218	.421		2.892	.004
	Median Household Income	2.992E-5	.000	.219	2.229	.026
	medinc2	-2.749E-10	.000	-.266	-2.711	.007
3	(Constant)	1.965	1.010		1.946	.052
	Median Household Income	-7.170E-6	.000	-.052	-.151	.880
	medinc2	3.019E-10	.000	.292	.422	.673
	medinc3	-2.793E-15	.000	-.296	-.814	.416

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 33: Model fit results regressing homelessness rates by median gross rent

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.230[a]	.053	.053	1.94965	.053	175.848	1	3139	.000
2	.249[b]	.062	.062	1.94057	.009	30.423	1	3138	.000
3	.251[c]	.063	.062	1.94020	.001	2.202	1	3137	.138

a. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units

b. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units, medren2

c. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units, medren2, medren3

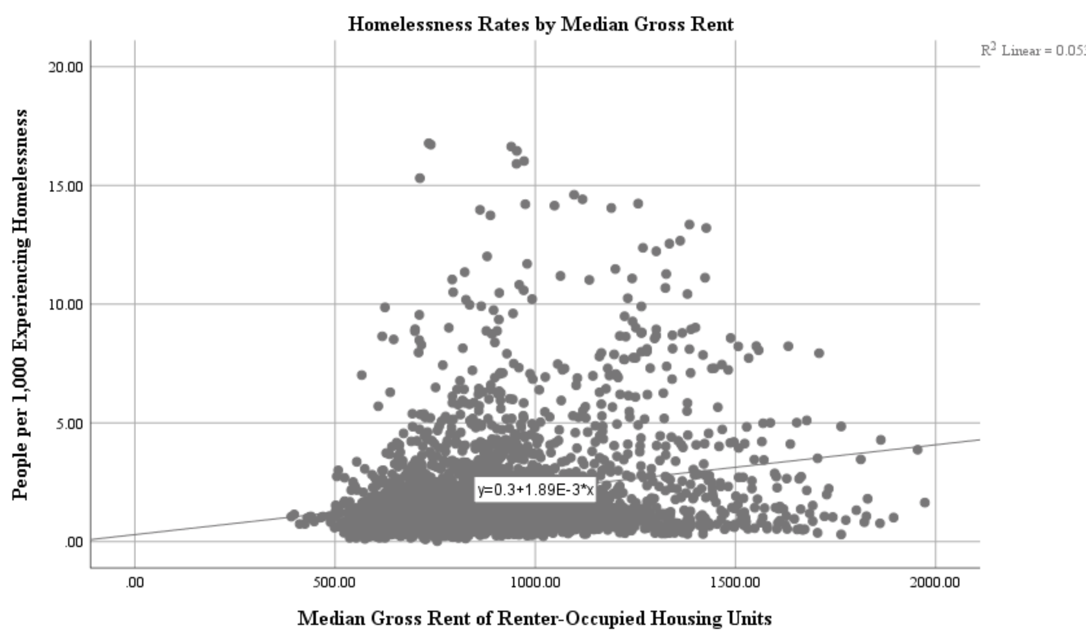

Figure 44: Homelessness rates by median gross rent linear regression

Table 34: ANOVA table regressing homelessness rates by median gross rent

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	668.420	1	668.420	175.848	.000[b]
	Residual	11931.704	3139	3.801		
	Total	12600.124	3140			
2	Regression	782.986	2	391.493	103.960	.000[c]
	Residual	11817.138	3138	3.766		
	Total	12600.124	3140			
3	Regression	791.273	3	263.758	70.067	.000[d]
	Residual	11808.851	3137	3.764		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units

c. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units, medren2

d. Predictors: (Constant), Median Gross Rent of Renter-Occupied Housing Units, medren2, medren3

Table 35: Coefficient table regressing homelessness rates by median gross rent

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.295	.131		2.252	.024
	Median Gross Rent of Renter-Occupied Housing Units	.002	.000	.230	13.261	.000
2	(Constant)	-1.874	.414		-4.522	.000
	Median Gross Rent of Renter-Occupied Housing Units	.006	.001	.788	7.681	.000
	medren2	-2.238E-6	.000	-.566	-5.516	.000
3	(Constant)	-.181	1.214		-.150	.881
	Median Gross Rent of Renter-Occupied Housing Units	.001	.004	.146	.328	.743
	medren2	2.922E-6	.000	.739	.834	.404
	medren3	-1.581E-9	.000	-.681	-1.484	.138

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 36: Model fit results regressing homelessness rates by median home value

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.344[a]	.118	.118	1.88138	.118	420.768	1	3139	.000
2	.344[b]	.118	.118	1.88168	.000	.003	1	3138	.959
3	.346[c]	.120	.119	1.88007	.002	6.368	1	3137	.012
4	.350[d]	.123	.121	1.87766	.003	9.080	1	3136	.003

a. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units

b. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2

c. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2, medval3

d. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2, medval3, medval4

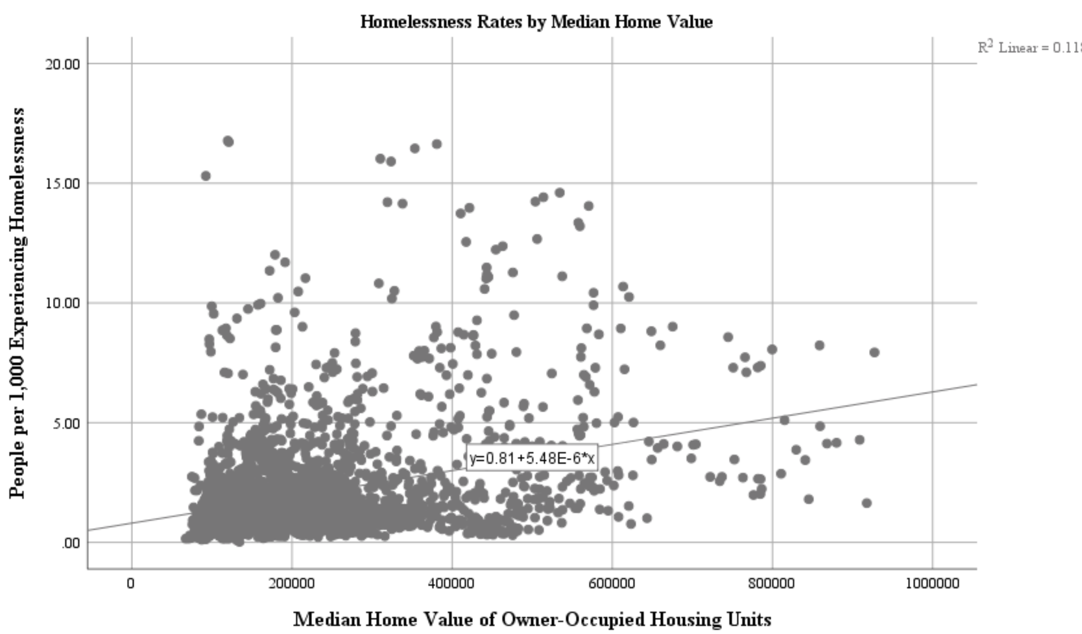

Figure 45: Homelessness rates by median home value linear regression

Table 37: ANOVA table regressing homelessness rates by median home value

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1489.348	1	1489.348	420.768	.000[b]
	Residual	11110.776	3139	3.540		
	Total	12600.124	3140			
2	Regression	1489.357	2	744.678	210.319	.000[c]
	Residual	11110.767	3138	3.541		
	Total	12600.124	3140			
3	Regression	1511.864	3	503.955	142.575	.000[d]
	Residual	11088.260	3137	3.535		
	Total	12600.124	3140			
4	Regression	1543.878	4	385.969	109.477	.000[e]
	Residual	11056.246	3136	3.526		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units

c. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2

d. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2, medval3

e. Predictors: (Constant), Median Home Value of Owner-Occupied Housing Units, medval2, medval3, medval4

Table 38: Coefficient table regressing homelessness rates by median home value

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.805	.066		12.182	.000
	Median Home Value of Owner-Occupied Housing Units	5.479E-6	.000	.344	20.513	.000
2	(Constant)	.800	.123		6.527	.000
	Median Home Value of Owner-Occupied Housing Units	5.522E-6	.000	.346	6.283	.000
	medval2	-6.293E-14	.000	-.003	-.051	.959
3	(Constant)	1.280	.226		5.657	.000
	Median Home Value of Owner-Occupied Housing Units	2.478E-10	.000	.000	.000	1.000
	medval2	1.666E-11	.000	.747	2.472	.013
	medval3	-1.373E-17	.000	-.435	-2.523	.012
4	(Constant)	.217	.419		.517	.605
	Median Home Value of Owner-Occupied Housing Units	1.619E-5	.000	1.016	2.760	.006
	medval2	-6.044E-11	.000	-2.711	-2.285	.022
	medval3	1.240E-16	.000	3.930	2.694	.007
	medval4	-8.014E-23	.000	-1.926	-3.013	.003

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 39: Model fit results regressing homelessness rates by percentage of renters in a family with children

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.082[a]	.007	.006	1.95246	.007	18.832	1	2793	.000
2	.138[b]	.019	.018	1.94052	.012	35.474	1	2792	.000
3	.146[c]	.021	.020	1.93874	.002	6.122	1	2791	.013

a. Predictors: (Constant), Percentage of Renters in a Family with Children

b. Predictors: (Constant), Percentage of Renters in a Family with Children, renfam2

c. Predictors: (Constant), Percentage of Renters in a Family with Children, renfam2, renfam3

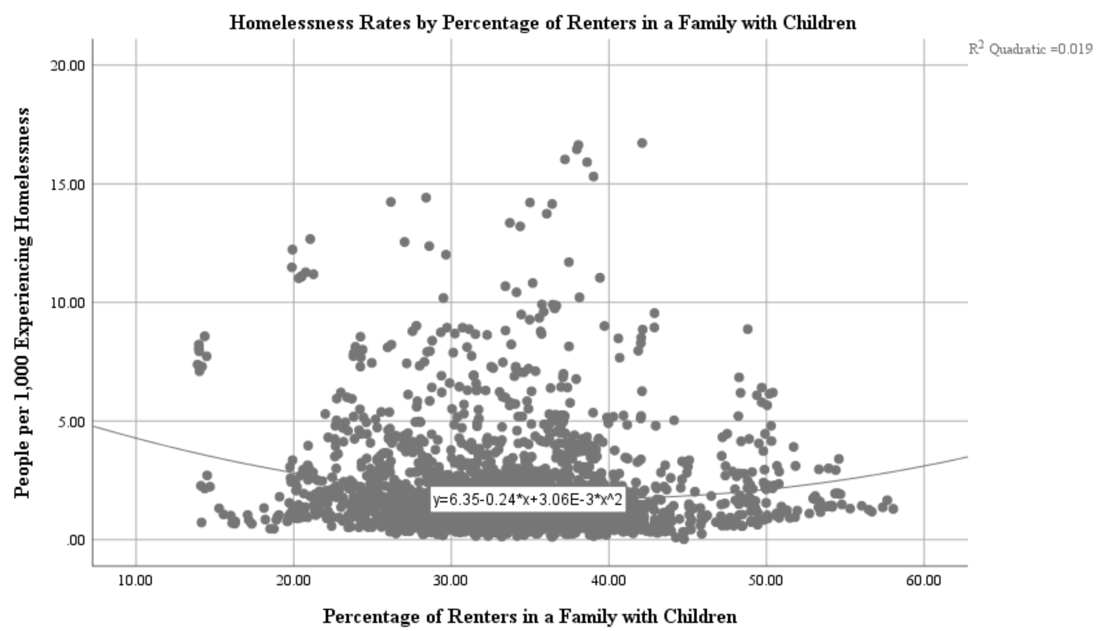

Figure 46: Homelessness rates by percentage of renters in a family with children quadratic regression

Table 40: ANOVA table regressing homelessness rates by percentage of renters in a family with children

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71.791	1	71.791	18.832	.000[b]
	Residual	10647.162	2793	3.812		
	Total	10718.953	2794			
2	Regression	205.371	2	102.685	27.269	.000[c]
	Residual	10513.582	2792	3.766		
	Total	10718.953	2794			
3	Regression	228.380	3	76.127	20.253	.000[d]
	Residual	10490.573	2791	3.759		
	Total	10718.953	2794			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Renters in a Family with Children

c. Predictors: (Constant), Percentage of Renters in a Family with Children, renfam2

d. Predictors: (Constant), Percentage of Renters in a Family with Children, renfam2, renfam3

Table 41: Coefficient table regressing homelessness rates by percentage of renters in a family with children

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.778	.197		14.111	.000
	Percentage of Renters in a Family with Children	-.025	.006	-.082	-4.340	.000
2	(Constant)	6.350	.631		10.065	.000
	Percentage of Renters in a Family with Children	-.238	.036	-.784	-6.568	.000
	renfam2	.003	.001	.711	5.956	.000
3	(Constant)	10.489	1.787		5.868	.000
	Percentage of Renters in a Family with Children	-.625	.161	-2.061	-3.891	.000
	renfam2	.015	.005	3.384	3.114	.002
	renfam3	.000	.000	-1.426	-2.474	.013

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 42: Model fit results regressing homelessness rates by percentage of renter-occupied housing units

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.380[a]	.145	.144	1.85290	.145	531.037	1	3139	.000
2	.397[b]	.158	.157	1.83885	.013	49.139	1	3138	.000
3	.402[c]	.162	.161	1.83477	.004	14.994	1	3137	.000

a. Predictors: (Constant), Percentage of Renter-Occupied Housing Units

b. Predictors: (Constant), Percentage of Renter-Occupied Housing Units, renocc2

c. Predictors: (Constant), Percentage of Renter-Occupied Housing Units, renocc2, renocc3

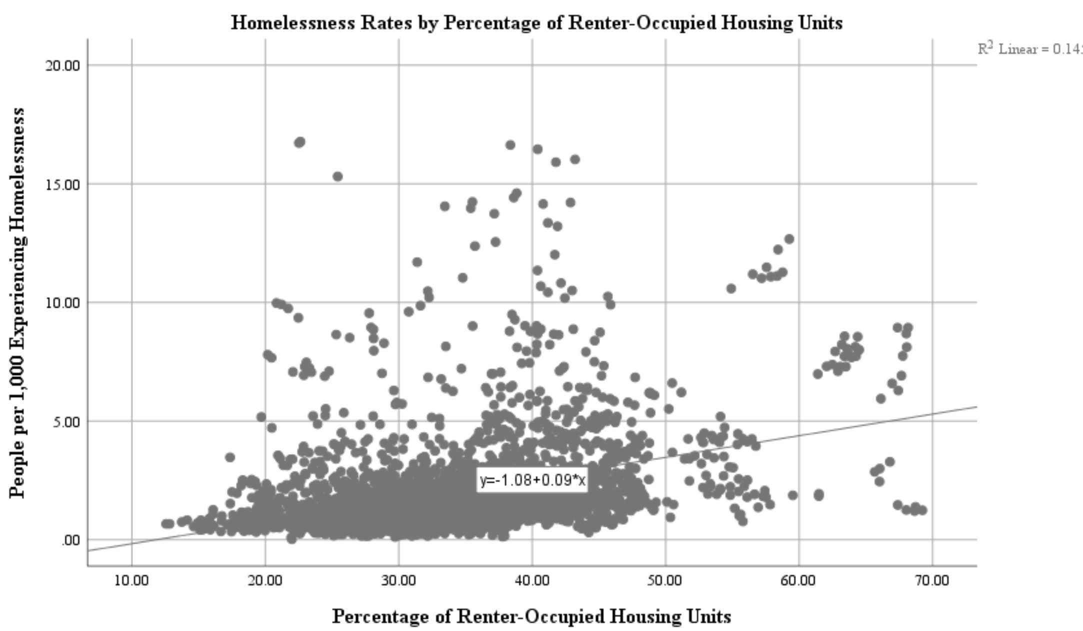

Figure 47: Homelessness rates by percentage of renter-occupied housing units linear regression

Table 43: ANOVA table regressing homelessness rates by percentage of renter-occupied housing units

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1823.177	1	1823.177	531.037	.000[b]
	Residual	10776.947	3139	3.433		
	Total	12600.124	3140			
2	Regression	1989.334	2	994.667	294.160	.000[c]
	Residual	10610.790	3138	3.381		
	Total	12600.124	3140			
3	Regression	2039.810	3	679.937	201.979	.000[d]
	Residual	10560.314	3137	3.366		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Renter-Occupied Housing Units

c. Predictors: (Constant), Percentage of Renter-Occupied Housing Units, renocc2

d. Predictors: (Constant), Percentage of Renter-Occupied Housing Units, renocc2, renocc3

Table 44: Coefficient table regressing homelessness rates by percentage of renter-occupied housing units

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-1.079	.137		-7.905	.000
	Percentage of Renter-Occupied Housing Units	.091	.004	.380	23.044	.000
2	(Constant)	1.448	.385		3.759	.000
	Percentage of Renter-Occupied Housing Units	-.053	.021	-.222	-2.535	.011
	renocc2	.002	.000	.613	7.010	.000
3	(Constant)	5.272	1.060		4.975	.000
	Percentage of Renter-Occupied Housing Units	-.379	.087	-1.583	-4.370	.000
	renocc2	.011	.002	3.371	4.697	.000
	renocc3	-7.212E-5	.000	-1.445	-3.872	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 45: Model fit results regressing homelessness rates by percentage of renters identifying as white, non-Hispanic

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.135[a]	.018	.018	1.98518	.018	58.248	1	3139	.000
2	.158[b]	.025	.024	1.97852	.007	22.167	1	3138	.000
3	.158[c]	.025	.024	1.97883	.000	.000	1	3137	1.000

a. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic

b. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic, renwhi2

c. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic, renwhi2, renwhi3

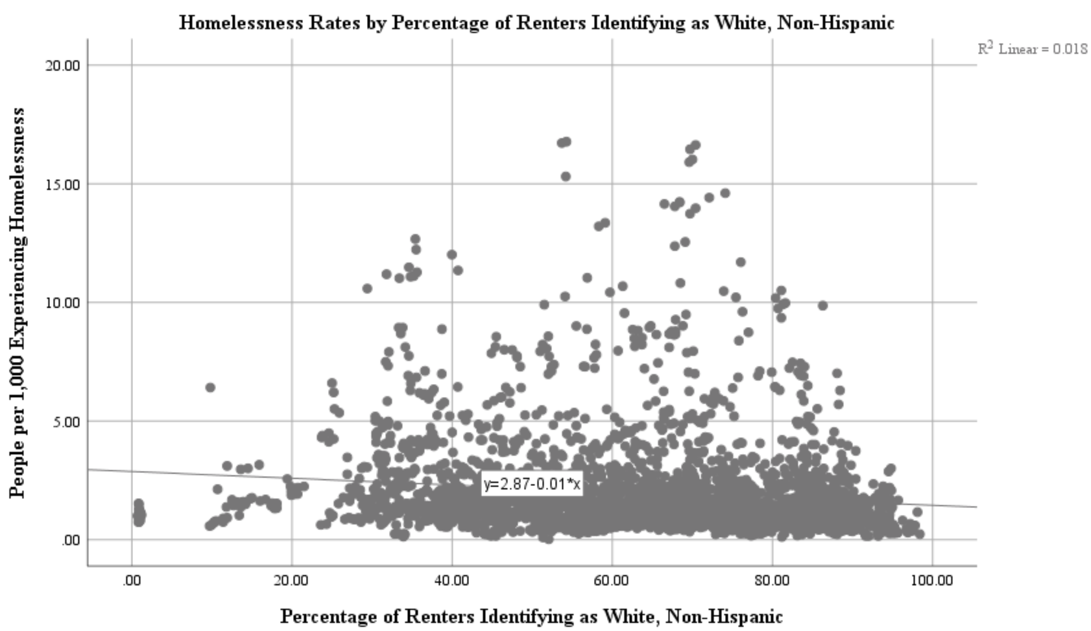

Figure 48: Homelessness rates by percentage of renters identifying as white, non-Hispanic linear regression

Table 46: ANOVA table regressing homelessness rates by percentage of renters identifying as white, non-Hispanic

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	229.551	1	229.551	58.248	.000[b]
	Residual	12370.573	3139	3.941		
	Total	12600.124	3140			
2	Regression	316.326	2	158.163	40.404	.000[c]
	Residual	12283.798	3138	3.915		
	Total	12600.124	3140			
3	Regression	316.326	3	105.442	26.927	.000[d]
	Residual	12283.798	3137	3.916		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic

c. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic, renwhi2

d. Predictors: (Constant), Percentage of Renters Identifying as White, Non-Hispanic, renwhi2, renwhi3

Table 47: Coefficient table regressing homelessness rates by percentage of renters identifying as white, non-Hispanic

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.873	.123		23.332	.000
	Percentage of Renters Identifying as White, Non-Hispanic	-.014	.002	-.135	-7.632	.000
2	(Constant)	1.735	.271		6.396	.000
	Percentage of Renters Identifying as White, Non-Hispanic	.029	.009	.277	3.104	.002
	renwhi2	.000	.000	-.420	-4.708	.000
3	(Constant)	1.735	.391		4.436	.000
	Percentage of Renters Identifying as White, Non-Hispanic	.029	.024	.277	1.227	.220
	renwhi2	.000	.000	-.421	-.788	.431
	renwhi3	1.379E-9	.000	.000	.000	1.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 48: Model fit results regressing homelessness rates by percentage of renters without any college education

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.154[a]	.024	.023	1.97974	.024	75.842	1	3139	.000
2	.154[b]	.024	.023	1.98005	.000	.008	1	3138	.927
3	.216[c]	.047	.046	1.95673	.023	76.246	1	3137	.000

a. Predictors: (Constant), Percentage of Renters Without any College Education

b. Predictors: (Constant), Percentage of Renters Without any College Education, renedu2

c. Predictors: (Constant), Percentage of Renters Without any College Education, renedu2, renedu3

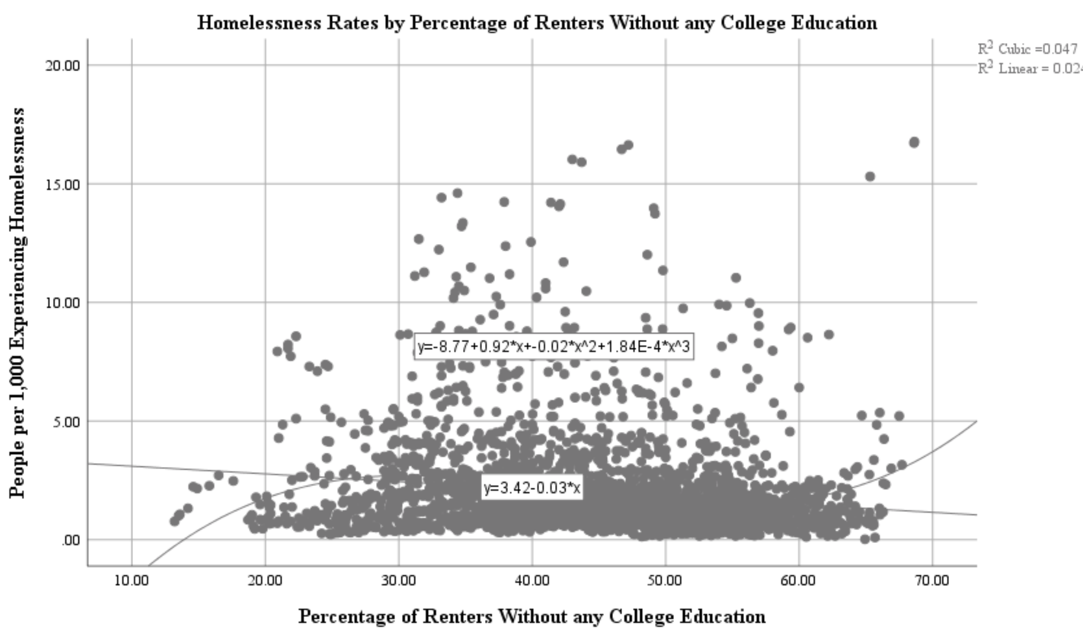

Figure 49: Homelessness rates by percentage of renters without any college education cubic and linear regressions

Table 49: ANOVA table regressing homelessness rates by percentage of renters without any college education

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	297.251	1	297.251	75.842	.000[b]
	Residual	12302.873	3139	3.919		
	Total	12600.124	3140			
2	Regression	297.284	2	148.642	37.913	.000[c]
	Residual	12302.840	3138	3.921		
	Total	12600.124	3140			
3	Regression	589.214	3	196.405	51.297	.000[d]
	Residual	12010.910	3137	3.829		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Renters Without any College Education

c. Predictors: (Constant), Percentage of Renters Without any College Education, renedu2

d. Predictors: (Constant), Percentage of Renters Without any College Education, renedu2, renedu3

Table 50: Coefficient table regressing homelessness rates by percentage of renters without any college education

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.421	.170		20.125	.000
	Percentage of Renters Without any College Education	-.032	.004	-.154	-8.709	.000
2	(Constant)	3.373	.558		6.048	.000
	Percentage of Renters Without any College Education	-.030	.026	-.142	-1.159	.247
	renedu2	-2.712E-5	.000	-.011	-.092	.927
3	(Constant)	-8.765	1.495		-5.862	.000
	Percentage of Renters Without any College Education	.922	.112	4.372	8.232	.000
	renedu2	-.024	.003	-9.809	-8.691	.000
	renedu3	.000	.000	5.371	8.732	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 51: Model fit results regressing homelessness rates by unemployment rate

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.178[a]	.032	.031	1.97166	.032	102.236	1	3139	.000
2	.184[b]	.034	.033	1.96950	.002	7.880	1	3138	.005
3	.203[c]	.041	.040	1.96241	.007	23.725	1	3137	.000

a. Predictors: (Constant), Unemployment Rate

b. Predictors: (Constant), Unemployment Rate, unemp2

c. Predictors: (Constant), Unemployment Rate, unemp2, unemp3

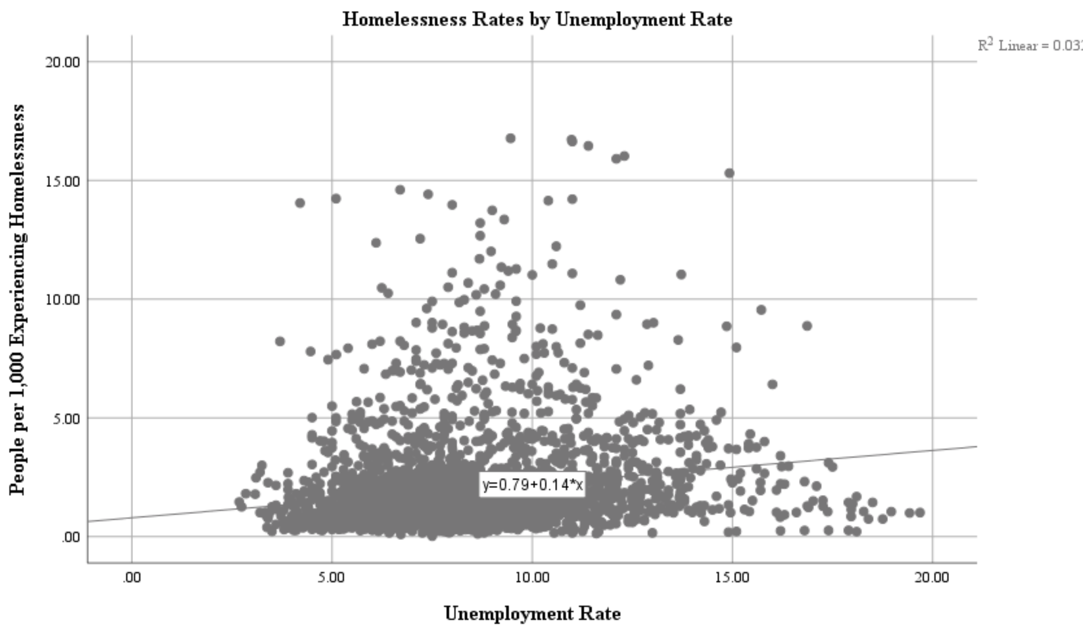

Figure 50: Homelessness rates by unemployment rate linear regression

Table 52: ANOVA table regressing homelessness rates by unemployment rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	397.435	1	397.435	102.236	.000[b]
	Residual	12202.689	3139	3.887		
	Total	12600.124	3140			
2	Regression	428.002	2	214.001	55.170	.000[c]
	Residual	12172.122	3138	3.879		
	Total	12600.124	3140			
3	Regression	519.370	3	173.123	44.955	.000[d]
	Residual	12080.754	3137	3.851		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Unemployment Rate

c. Predictors: (Constant), Unemployment Rate, unemp2

d. Predictors: (Constant), Unemployment Rate, unemp2, unemp3

Table 53: Coefficient table regressing homelessness rates by unemployment rate

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.793	.122		6.511	.000
	Unemployment Rate	.142	.014	.178	10.111	.000
2	(Constant)	-.017	.313		-.054	.957
	Unemployment Rate	.329	.068	.411	4.834	.000
	unemp2	-.010	.004	-.239	-2.807	.005
3	(Constant)	3.300	.749		4.405	.000
	Unemployment Rate	-.821	.245	-1.027	-3.343	.001
	unemp2	.112	.025	2.723	4.435	.000
	unemp3	-.004	.001	-1.584	-4.871	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 54: Model fit results regressing homelessness rates by poverty rate

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.127[a]	.016	.016	1.94318	.016	45.742	1	2793	.000
2	.164[b]	.027	.026	1.93286	.011	30.894	1	2792	.000
3	.164[c]	.027	.026	1.93310	.000	.325	1	2791	.569
4	.164[d]	.027	.026	1.93339	.000	.156	1	2790	.692

a. Predictors: (Constant), Poverty Rate

b. Predictors: (Constant), Poverty Rate, pov2

c. Predictors: (Constant), Poverty Rate, pov2, pov3

d. Predictors: (Constant), Poverty Rate, pov2, pov3, pov4

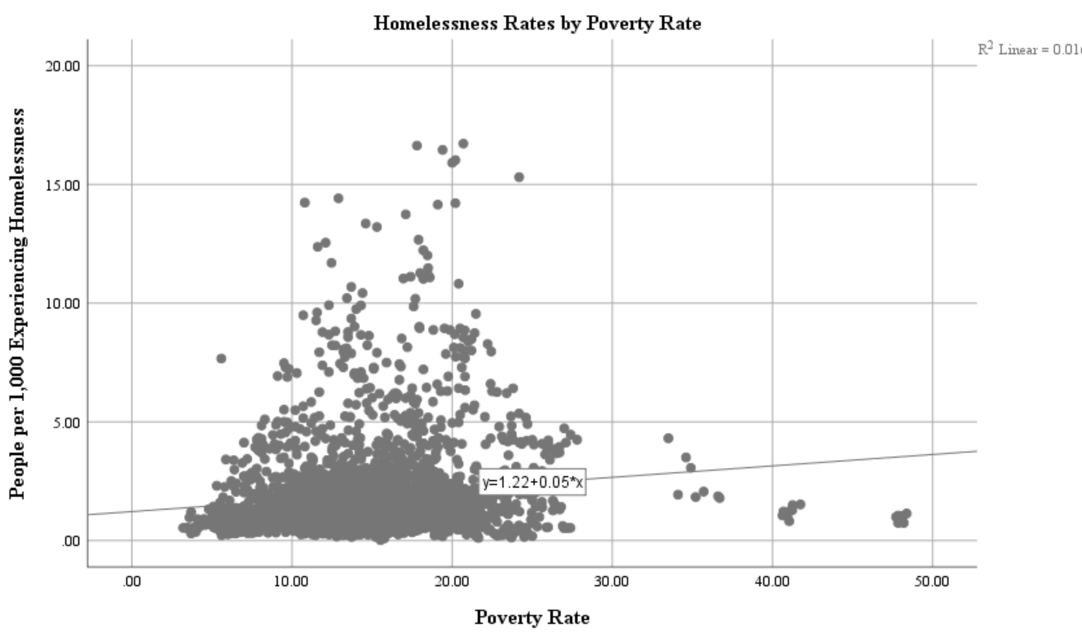

Figure 51: Homelessness rates by poverty rate linear regression

Table 55: ANOVA table regressing homelessness rates by poverty rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	172.718	1	172.718	45.742	.000[b]
	Residual	10546.235	2793	3.776		
	Total	10718.953	2794			
2	Regression	288.139	2	144.069	38.563	.000[c]
	Residual	10430.814	2792	3.736		
	Total	10718.953	2794			
3	Regression	289.353	3	96.451	25.811	.000[d]
	Residual	10429.600	2791	3.737		
	Total	10718.953	2794			
4	Regression	289.938	4	72.485	19.391	.000[e]
	Residual	10429.015	2790	3.738		
	Total	10718.953	2794			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Poverty Rate

c. Predictors: (Constant), Poverty Rate, pov2

d. Predictors: (Constant), Poverty Rate, pov2, pov3

e. Predictors: (Constant), Poverty Rate, pov2, pov3, pov4

Table 56: Coefficient table regressing homelessness rates by poverty rate

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.224	.112		10.930	.000
	Poverty Rate	.048	.007	.127	6.763	.000
2	(Constant)	.357	.192		1.860	.063
	Poverty Rate	.156	.021	.412	7.549	.000
	pov2	-.003	.001	-.303	-5.558	.000
3	(Constant)	.539	.372		1.446	.148
	Poverty Rate	.122	.063	.322	1.926	.054
	pov2	-.001	.003	-.120	-.368	.713
	pov3	-2.607E-5	.000	-.104	-.570	.569
4	(Constant)	.333	.639		.521	.603
	Poverty Rate	.176	.152	.466	1.164	.245
	pov2	-.006	.012	-.595	-.478	.633
	pov3	.000	.000	.516	.327	.744
	pov4	-1.681E-6	.000	-.289	-.396	.692

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 57: Model fit results regressing homelessness rates by eviction filing rate

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.053[a]	.003	.002	1.96953	.003	6.508	1	2345	.011
2	.087[b]	.008	.007	1.96527	.005	11.178	1	2344	.001
3	.091[c]	.008	.007	1.96486	.001	1.962	1	2343	.161
4	.092[d]	.009	.007	1.96509	.000	.459	1	2342	.498

a. Predictors: (Constant), Eviction Filing Rate

b. Predictors: (Constant), Eviction Filing Rate, evic2

c. Predictors: (Constant), Eviction Filing Rate, evic2, evic3

d. Predictors: (Constant), Eviction Filing Rate, evic2, evic3, evic4

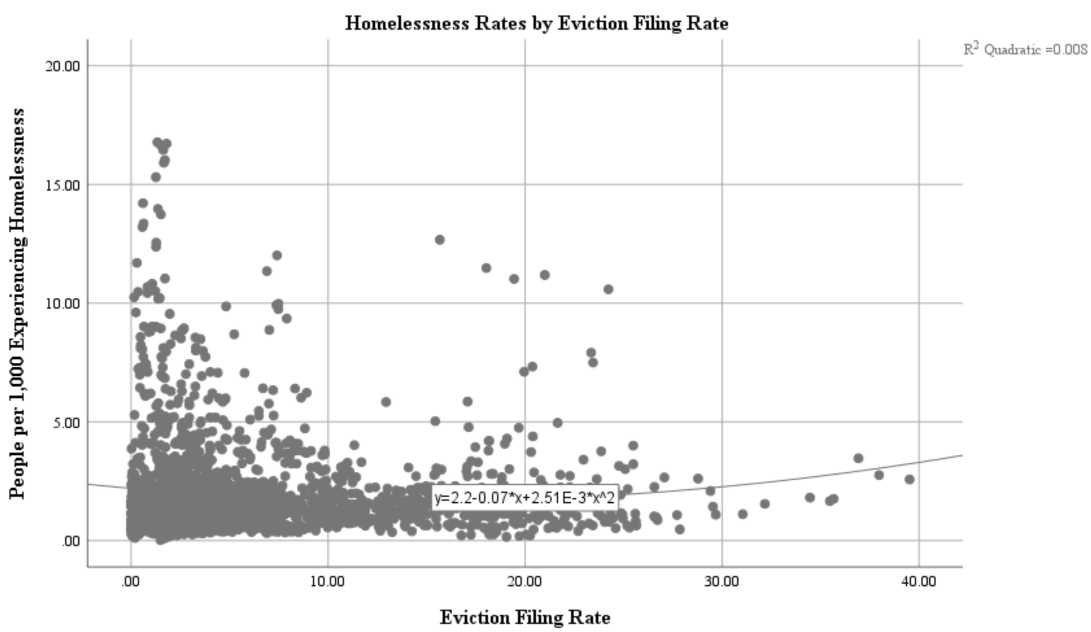

Figure 52: Homelessness rates by eviction filing rate quadratic regression

Table 58: ANOVA table regressing homelessness rates by eviction filing rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.243	1	25.243	6.508	.011[b]
	Residual	9096.346	2345	3.879		
	Total	9121.590	2346			
2	Regression	68.416	2	34.208	8.857	.000[c]
	Residual	9053.174	2344	3.862		
	Total	9121.590	2346			
3	Regression	75.989	3	25.330	6.561	.000[d]
	Residual	9045.600	2343	3.861		
	Total	9121.590	2346			
4	Regression	77.761	4	19.440	5.034	.000[e]
	Residual	9043.828	2342	3.862		
	Total	9121.590	2346			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Eviction Filing Rate

c. Predictors: (Constant), Eviction Filing Rate, evic2

d. Predictors: (Constant), Eviction Filing Rate, evic2, evic3

e. Predictors: (Constant), Eviction Filing Rate, evic2, evic3, evic4

Table 59: Coefficient table regressing homelessness rates by eviction filing rate

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.046	.057		35.708	.000
	Eviction Filing Rate	-.017	.007	-.053	-2.551	.011
2	(Constant)	2.200	.073		29.967	.000
	Eviction Filing Rate	-.073	.018	-.225	-4.053	.000
	evic2	.003	.001	.185	3.343	.001
3	(Constant)	2.269	.089		25.642	.000
	Eviction Filing Rate	-.113	.033	-.346	-3.366	.001
	evic2	.006	.003	.472	2.226	.026
	evic3	-9.156E-5	.000	-.182	-1.401	.161
4	(Constant)	2.233	.104		21.567	.000
	Eviction Filing Rate	-.081	.057	-.249	-1.415	.157
	evic2	.001	.008	.074	.118	.906
	evic3	.000	.000	.384	.454	.650
	evic4	-4.455E-6	.000	-.271	-.677	.498

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 60: Model fit results regressing homelessness rates by percentage of rent-burdened households

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.285[a]	.081	.081	1.92049	.081	277.258	1	3139	.000
2	.287[b]	.082	.082	1.91974	.001	3.445	1	3138	.064

a. Predictors: (Constant), Percentage of Rent-Burdened Households

b. Predictors: (Constant), Percentage of Rent-Burdened Households, burd2

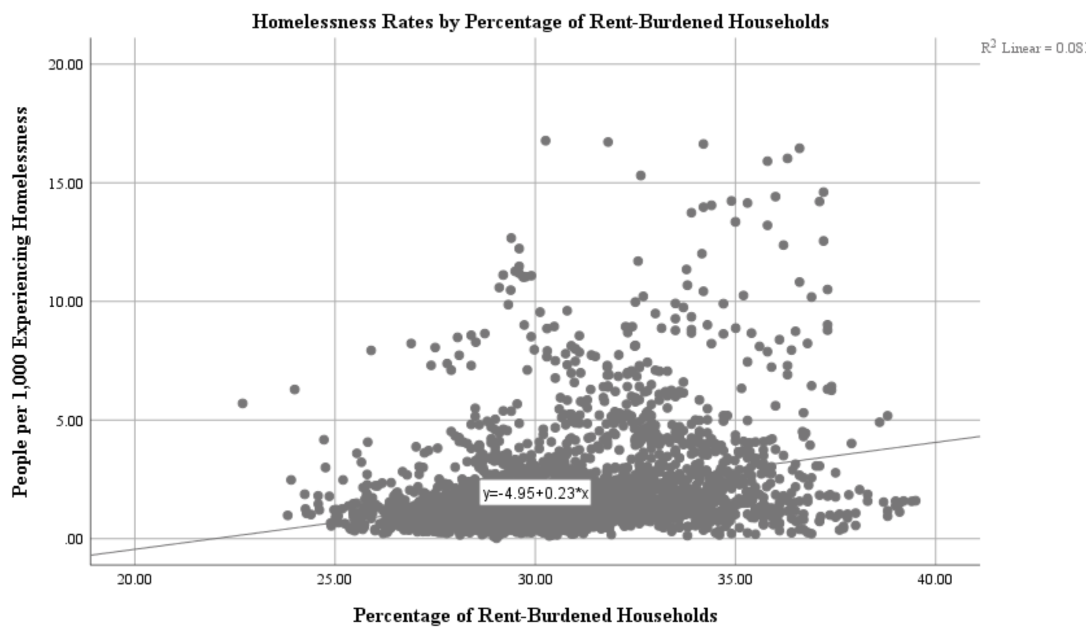

Figure 53: Homelessness rates by percentage of rent-burdened households linear regression

Table 61: ANOVA table regressing homelessness rates by percentage of rent-burdened households

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1022.607	1	1022.607	277.258	.000[b]
	Residual	11577.517	3139	3.688		
	Total	12600.124	3140			
2	Regression	1035.304	2	517.652	140.460	.000[c]
	Residual	11564.820	3138	3.685		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Percentage of Rent-Burdened Households

c. Predictors: (Constant), Percentage of Rent-Burdened Households, burd2

Table 62: Coefficients table regressing homelessness rates by percentage of rent-burdened households

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-4.954	.417		-11.868	.000
	Percentage of Rent-Burdened Households	.225	.014	.285	16.651	.000
2	(Constant)	1.949	3.742		.521	.602
	Percentage of Rent-Burdened Households	-.218	.239	-.276	-.911	.362
	burd2	.007	.004	.561	1.856	.064

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 63: Model fit results regressing homelessness rates by Gini index

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.268[a]	.072	.071	1.88739	.072	216.052	1	2793	.000
2	.277[b]	.077	.076	1.88244	.005	15.710	1	2792	.000

a. Predictors: (Constant), Gini Index

b. Predictors: (Constant), Gini Index, gini2

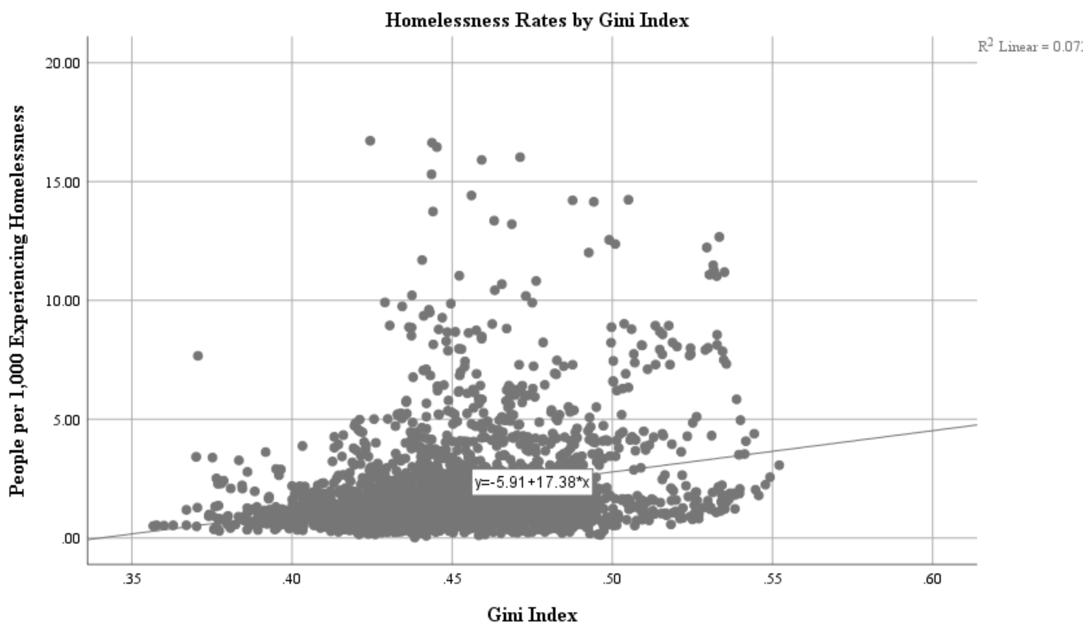

Figure 54: Homelessness rates by Gini Index linear regression

Table 64: ANOVA table regressing homelessness rates by Gini index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	769.629	1	769.629	216.052	.000[b]
	Residual	9949.324	2793	3.562		
	Total	10718.953	2794			
2	Regression	825.299	2	412.649	116.450	.000[c]
	Residual	9893.654	2792	3.544		
	Total	10718.953	2794			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Gini Index

c. Predictors: (Constant), Gini Index, gini2

Table 65: Coefficient table regressing homelessness rates by Gini index

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-5.911	.535		-11.044	.000
	Gini Index	17.383	1.183	.268	14.699	.000
2	(Constant)	14.455	5.166		2.798	.005
	Gini Index	-72.365	22.674	-1.116	-3.192	.001
	gini2	98.430	24.834	1.385	3.964	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 66: Model fit results regressing homelessness rates by vacancy rate

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.129[a]	.017	.016	1.98673	.017	53.244	1	3139	.000
2	.150[b]	.022	.022	1.98130	.006	18.245	1	3138	.000
3	.165[c]	.027	.026	1.97673	.005	15.524	1	3137	.000
4	.177[d]	.031	.030	1.97280	.004	13.510	1	3136	.000

a. Predictors: (Constant), Vacancy Rate

b. Predictors: (Constant), Vacancy Rate, vac2

c. Predictors: (Constant), Vacancy Rate, vac2, vac3

d. Predictors: (Constant), Vacancy Rate, vac2, vac3, vac4

Figure 55: Homelessness rates by vacancy rate linear regression

Table 67: ANOVA table regressing homelessness rates by vacancy rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	210.159	1	210.159	53.244	.000[b]
	Residual	12389.965	3139	3.947		
	Total	12600.124	3140			
2	Regression	281.782	2	140.891	35.891	.000[c]
	Residual	12318.342	3138	3.926		
	Total	12600.124	3140			
3	Regression	342.442	3	114.147	29.213	.000[d]
	Residual	12257.682	3137	3.907		
	Total	12600.124	3140			
4	Regression	395.020	4	98.755	25.374	.000[e]
	Residual	12205.104	3136	3.892		
	Total	12600.124	3140			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Vacancy Rate

c. Predictors: (Constant), Vacancy Rate, vac2

d. Predictors: (Constant), Vacancy Rate, vac2, vac3

e. Predictors: (Constant), Vacancy Rate, vac2, vac3, vac4

Table 68: Coefficients table regressing homelessness rates by vacancy rate

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.482	.076		19.501	.000
	Vacancy Rate	.039	.005	.129	7.297	.000
2	(Constant)	1.982	.139		14.224	.000
	Vacancy Rate	-.032	.017	-.103	-1.808	.071
	vac2	.002	.000	.245	4.271	.000
3	(Constant)	1.132	.256		4.415	.000
	Vacancy Rate	.148	.049	.487	3.036	.002
	vac2	-.008	.003	-1.058	-3.154	.002
	vac3	.000	.000	.766	3.940	.000
4	(Constant)	2.645	.485		5.458	.000
	Vacancy Rate	-.282	.127	-.925	-2.223	.026
	vac2	.030	.011	3.819	2.791	.005
	vac3	-.001	.000	-5.481	-3.204	.001
	vac4	1.478E-5	.000	2.777	3.676	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 69: Model fit summary regressing homelessness rates by mean temperature

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.301[a]	.090	.090	1.85850	.090	301.778	1	3037	.000
2	.315[b]	.099	.098	1.85004	.009	28.826	1	3036	.000
3	.324[c]	.105	.104	1.84428	.006	20.006	1	3035	.000
4	.329[d]	.108	.107	1.84097	.004	11.926	1	3034	.001

a. Predictors: (Constant), Mean Temperature in January in Fahrenheit

b. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2

c. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2, temp3

d. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2, temp3, temp4

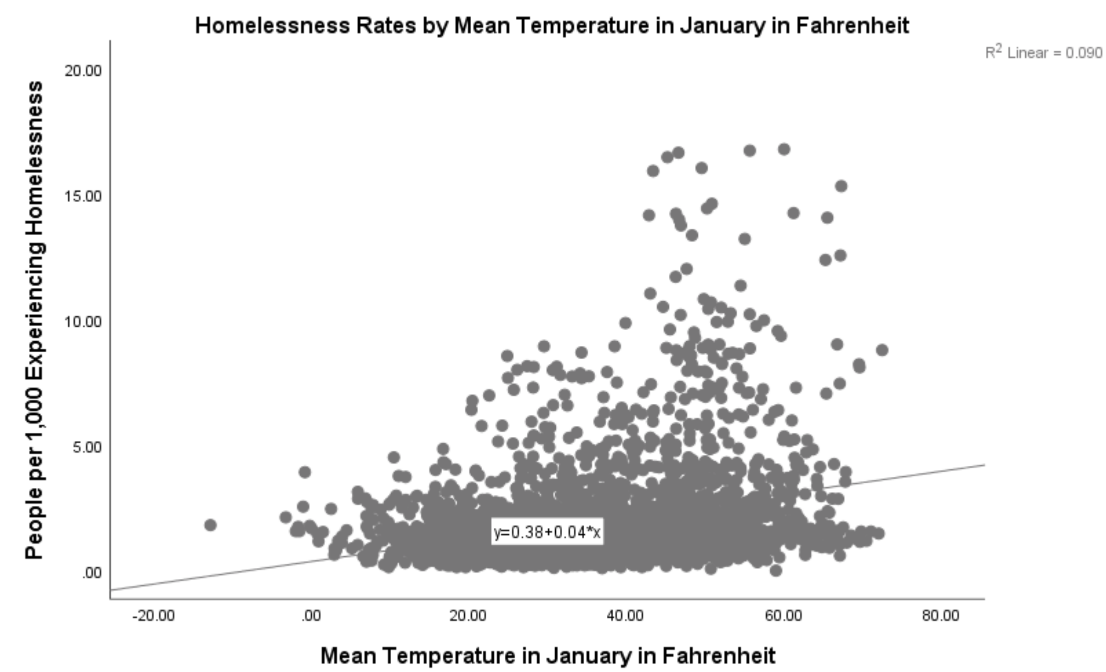

Figure 56: Homelessness rates by mean temperature in January linear regression

Table 70: ANOVA table regressing homelessness rates by mean temperature

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1042.345	1	1042.345	301.778	.000[b]
	Residual	10489.841	3037	3.454		
	Total	11532.186	3038			
2	Regression	1141.008	2	570.504	166.685	.000[c]
	Residual	10391.178	3036	3.423		
	Total	11532.186	3038			
3	Regression	1209.055	3	403.018	118.487	.000[d]
	Residual	10323.131	3035	3.401		
	Total	11532.186	3038			
4	Regression	1249.474	4	312.368	92.167	.000[e]
	Residual	10282.713	3034	3.389		
	Total	11532.186	3038			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Mean Temperature in January in Fahrenheit

c. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2

d. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2, temp3

e. Predictors: (Constant), Mean Temperature in January in Fahrenheit, temp2, temp3, temp4

Table 71: Coefficients table regressing homelessness rates by mean temperature

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.381	.096		3.960	.000
	Mean Temperature in January in Fahrenheit	.045	.003	.301	17.372	.000
2	(Constant)	1.309	.198		6.625	.000
	Mean Temperature in January in Fahrenheit	-.014	.011	-.092	-1.220	.223
	temp2	.001	.000	.403	5.369	.000
3	(Constant)	2.238	.286		7.818	.000
	Mean Temperature in January in Fahrenheit	-.121	.027	-.814	-4.573	.000
	temp2	.004	.001	2.145	5.409	.000
	temp3	-3.256E-5	.000	-1.054	-4.473	.000
4	(Constant)	1.817	.311		5.850	.000
	Mean Temperature in January in Fahrenheit	-.011	.041	-.075	-.271	.786
	temp2	-.003	.002	-1.319	-1.223	.221
	temp3	.000	.000	3.955	2.691	.007
	temp4	-1.133E-6	.000	-2.304	-3.453	.001

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 72: Model fit results regressing homelessness rates by total precipitation

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.160[a]	.026	.025	1.92041	.026	79.918	1	3029	.000
2	.211[b]	.045	.044	1.90201	.019	59.892	1	3028	.000
3	.224[c]	.050	.049	1.89689	.005	17.364	1	3027	.000
4	.224[d]	.050	.049	1.89717	.000	.130	1	3026	.719

a. Predictors: (Constant), Total Precipitation in January in Inches

b. Predictors: (Constant), Total Precipitation in January in Inches, precip2

c. Predictors: (Constant), Total Precipitation in January in Inches, precip2, precip3

d. Predictors: (Constant), Total Precipitation in January in Inches, precip2, precip3, precip4

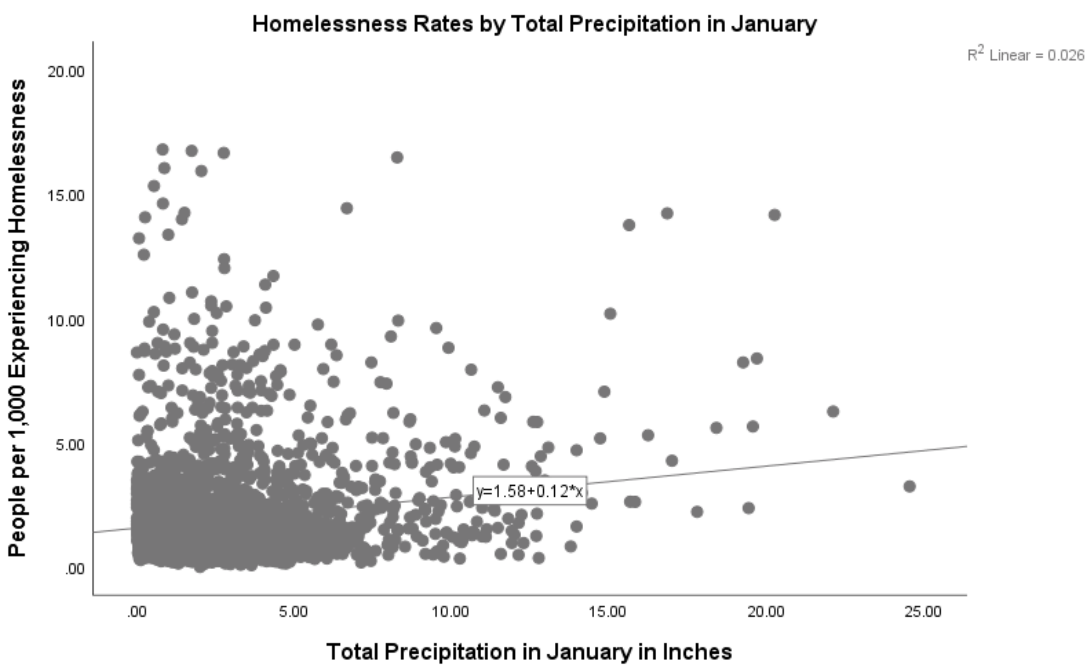

Figure 57: Homelessness rates by total precipitation in January linear regression

Table 73: ANOVA table regressing homelessness rates by total precipitation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	294.736	1	294.736	79.918	.000[b]
	Residual	11170.915	3029	3.688		
	Total	11465.651	3030			
2	Regression	511.405	2	255.702	70.682	.000[c]
	Residual	10954.246	3028	3.618		
	Total	11465.651	3030			
3	Regression	573.883	3	191.294	53.164	.000[d]
	Residual	10891.768	3027	3.598		
	Total	11465.651	3030			
4	Regression	574.350	4	143.587	39.894	.000[e]
	Residual	10891.301	3026	3.599		
	Total	11465.651	3030			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Total Precipitation in January in Inches

c. Predictors: (Constant), Total Precipitation in January in Inches, precip2

d. Predictors: (Constant), Total Precipitation in January in Inches, precip2, precip3

e. Predictors: (Constant), Total Precipitation in January in Inches, precip2, precip3, precip4

Table 74: Coefficients table regressing homelessness rates by total precipitation

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.581	.053		29.562	.000
	Total Precipitation in January in Inches	.124	.014	.160	8.940	.000
2	(Constant)	1.950	.071		27.375	.000
	Total Precipitation in January in Inches	-.090	.031	-.116	-2.909	.004
	precip2	.017	.002	.309	7.739	.000
3	(Constant)	2.165	.088		24.654	.000
	Total Precipitation in January in Inches	-.280	.055	-.361	-5.086	.000
	precip2	.051	.008	.916	6.064	.000
	precip3	-.001	.000	-.409	-4.167	.000
4	(Constant)	2.185	.104		21.017	.000
	Total Precipitation in January in Inches	-.306	.091	-.395	-3.355	.001
	precip2	.059	.023	1.055	2.539	.011
	precip3	-.002	.002	-.622	-1.038	.299
	precip4	1.868E-5	.000	.109	.360	.719

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 75: Model fit results regressing homelessness rates by Housing First index

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.003[a]	.000	.000	2.00441	.000	.032	1	3134	.859
2	.094[b]	.009	.008	1.99594	.009	27.627	1	3133	.000
3	.094[c]	.009	.008	1.99625	.000	.045	1	3132	.831

a. Predictors: (Constant), Housing First index

b. Predictors: (Constant), Housing First index, hf2

c. Predictors: (Constant), Housing First index, hf2, hf3

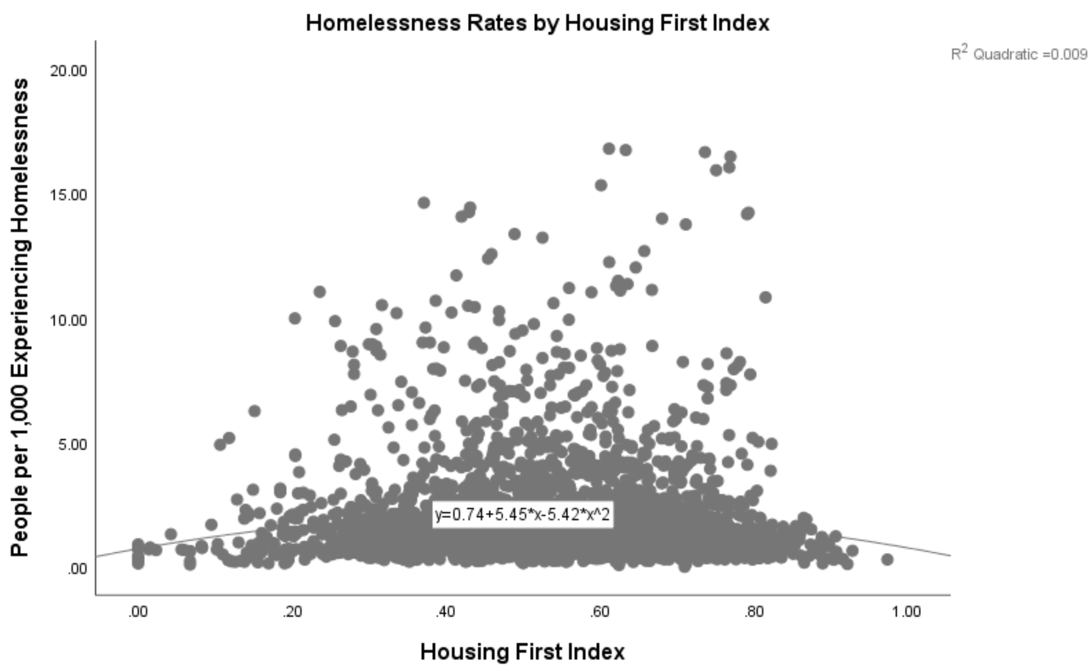

Figure 58: Homelessness rates by Housing First index quadratic regression

Table 76: ANOVA table regressing homelessness rates by Housing First index

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.128	1	.128	.032	.859[b]
	Residual	12591.294	3134	4.018		
	Total	12591.421	3135			
2	Regression	110.189	2	55.094	13.830	.000[c]
	Residual	12481.233	3133	3.984		
	Total	12591.421	3135			
3	Regression	110.369	3	36.790	9.232	.000[d]
	Residual	12481.052	3132	3.985		
	Total	12591.421	3135			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), Housing First index

c. Predictors: (Constant), Housing First index, hf2

d. Predictors: (Constant), Housing First index, hf2, hf3

Table 77: Coefficients table regressing homelessness rates by Housing First index

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.994	.126		15.775	.000
	Housing First index	-.040	.226	-.003	-.178	.859
2	(Constant)	.744	.269		2.764	.006
	Housing First index	5.454	1.069	.432	5.101	.000
	hf2	-5.422	1.032	-.445	-5.256	.000
3	(Constant)	.677	.414		1.636	.102
	Housing First index	6.012	2.829	.476	2.125	.034
	hf2	-6.716	6.165	-.551	-1.089	.276
	hf3	.893	4.196	.064	.213	.831

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Table 78: Model fit results regressing homelessness rates by HUD CoC funding

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.390[a]	.152	.152	1.83842	.152	553.701	1	3089	.000
2	.400[b]	.160	.159	1.83023	.008	28.696	1	3088	.000
3	.402[c]	.161	.161	1.82884	.002	5.707	1	3087	.017
4	.405[d]	.164	.163	1.82666	.002	8.365	1	3086	.004

a. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person

b. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2

c. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2, fund3

d. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2, fund3, fund4

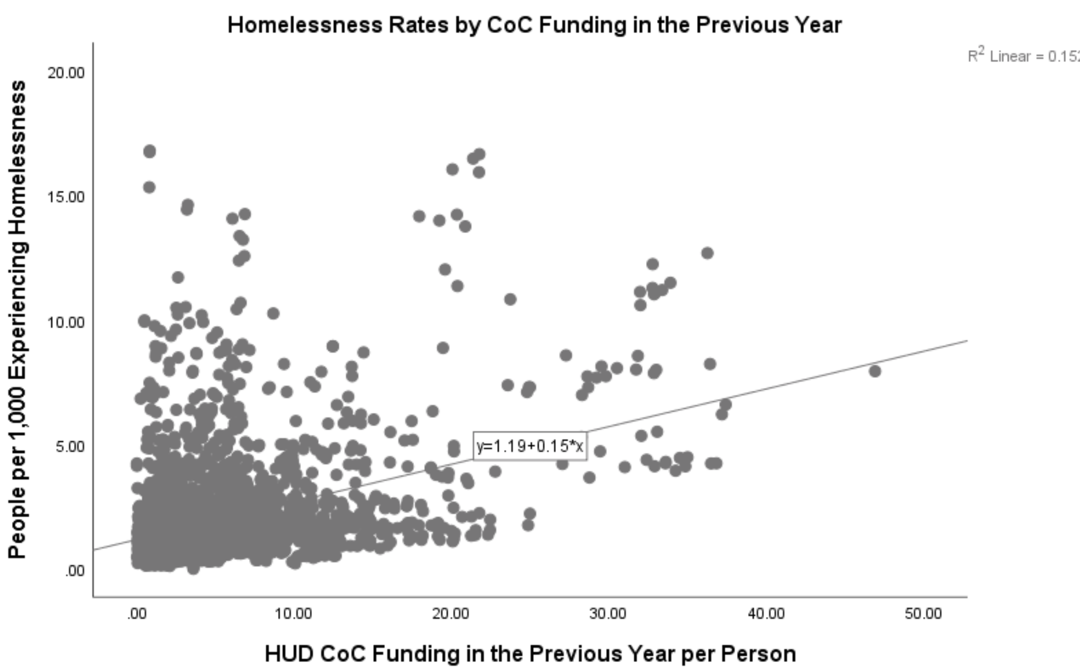

Figure 59: Homelessness rates by CoC funding in the previous year linear regression

Table 79: ANOVA table regressing homelessness rates by HUD CoC funding

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1871.392	1	1871.392	553.701	.000[b]
	Residual	10440.172	3089	3.380		
	Total	12311.564	3090			
2	Regression	1967.515	2	983.758	293.680	.000[c]
	Residual	10344.049	3088	3.350		
	Total	12311.564	3090			
3	Regression	1986.604	3	662.201	197.988	.000[d]
	Residual	10324.960	3087	3.345		
	Total	12311.564	3090			
4	Regression	2014.516	4	503.629	150.936	.000[e]
	Residual	10297.048	3086	3.337		
	Total	12311.564	3090			

a. Dependent Variable: People per 1,000 Experiencing Homelessness

b. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person

c. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2

d. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2, fund3

e. Predictors: (Constant), HUD CoC Funding in the Previous Year per Person, fund2, fund3, fund4

Table 80: Coefficients table regressing homelessness rates by HUD CoC funding

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.191	.047		25.473	.000
	HUD CoC Funding in the Previous Year per Person	.151	.006	.390	23.531	.000
2	(Constant)	1.415	.063		22.628	.000
	HUD CoC Funding in the Previous Year per Person	.078	.015	.201	5.143	.000
	fund2	.003	.001	.209	5.357	.000
3	(Constant)	1.529	.079		19.414	.000
	HUD CoC Funding in the Previous Year per Person	.019	.029	.050	.673	.501
	fund2	.009	.002	.615	3.528	.000
	fund3	.000	.000	-.279	-2.389	.017
4	(Constant)	1.373	.095		14.400	.000
	HUD CoC Funding in the Previous Year per Person	.124	.046	.321	2.687	.007
	fund2	-.007	.006	-.518	-1.208	.227
	fund3	.001	.000	1.406	2.366	.018
	fund4	-9.960E-6	.000	-.822	-2.892	.004

a. Dependent Variable: People per 1,000 Experiencing Homelessness

Appendix 5: Model Testing Results

Table 81: Autoregressive residual covariance matrix for yearcoded repeating variable

Residual Covariance (R) Matrix[a]

	[yearcoded = 1.00]	[yearcoded = 2.00]	[yearcoded = 3.00]	[yearcoded = 4.00]	[yearcoded = 5.00]	[yearcoded = 6.00]	[yearcoded = 7.00]
[yearcoded = 1.00]	2.158026	1.881578	1.640544	1.430387	1.247151	1.087388	.948092
[yearcoded = 2.00]	1.881578	2.158026	1.881578	1.640544	1.430387	1.247151	1.087388
[yearcoded = 3.00]	1.640544	1.881578	2.158026	1.881578	1.640544	1.430387	1.247151
[yearcoded = 4.00]	1.430387	1.640544	1.881578	2.158026	1.881578	1.640544	1.430387
[yearcoded = 5.00]	1.247151	1.430387	1.640544	1.881578	2.158026	1.881578	1.640544
[yearcoded = 6.00]	1.087388	1.247151	1.430387	1.640544	1.881578	2.158026	1.881578
[yearcoded = 7.00]	.948092	1.087388	1.247151	1.430387	1.640544	1.881578	2.158026

First-Order Autoregressive

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 82: Information criteria for Model 1 measuring main effects of all variables

Information Criteria[a]

-2 Restricted Log Likelihood	5117.713
Akaike's Information Criterion (AIC)	5123.713
Hurvich and Tsai's Criterion (AICC)	5123.725
Bozdogan's Criterion (CAIC)	5143.484
Schwarz's Bayesian Criterion (BIC)	5140.484

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 83: Type III tests of fixed effects for Model 1 measuring main effects of all variables

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	6859.020	.103	.748
coccat	2	311.003	4.061	.018
inczon	1	320.766	1.049	.307
pop	0	.	.	.
bach	1	810.553	3.016	.083
medinc	1	803.556	.468	.494
medren	1	922.549	18.395	.000
medval	1	828.139	10.432	.001
renfam	1	666.197	.540	.463
renocc	1	545.749	.164	.686
renwhi	1	585.687	3.854	.050
renedu	1	746.652	5.821	.016
unemp	1	1647.906	1.409	.235
pov	1	1320.456	.779	.378
evic	1	1422.967	.114	.736
burd	1	1729.809	6.754	.009
gini	1	1002.101	.046	.830
vac	1	452.685	2.584	.109
temp	1	1837.697	2.424	.120
precip	1	1696.294	1.837	.176
hf	1	1977.624	.299	.584
fund	1	753.774	24.652	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	633.257	.508	.476
evic2	1	1880.448	.146	.702
hf2	1	1966.959	1.150	.284
yearcoded	1	1339.173	23.222	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 84: Fixed effects estimates for Model 1 measuring main effects of all variables

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	1.626141	5.523480	6636.718	.294	.768	-9.201654	12.453937
[coccat=1]	.743383	.368418	307.441	2.018	.044	.018444	1.468322
[coccat=2]	.001605	.329376	316.705	.005	.996	-.646438	.649647
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.206832	.201961	320.766	-1.024	.307	-.604169	.190504
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-7.1892E-7	2.06991E-7	310.007	-3.473	.001	-1.12621E-6	-3.11637E-7
bach	-.038692	.022279	810.553	-1.737	.083	-.082423	.005040
medinc	-2.8937E-5	4.22782E-5	803.556	-.684	.494	-.000112	5.40513E-5
medren	.004398	.001025	922.549	4.289	.000	.002385	.006410
medval	4.1306E-6	1.27893E-6	828.139	3.230	.001	1.62036E-6	6.64102E-6
renfam	.051218	.069706	666.197	.735	.463	-.085652	.188089
renocc	.007266	.017937	545.749	.405	.686	-.027968	.042499
renwhi	.014115	.007190	585.687	1.963	.050	-5.96438E-6	.028235
renedu	-.032513	.013476	746.652	-2.413	.016	-.058969	-.006058
unemp	.031997	.026951	1647.906	1.187	.235	-.020865	.084858
pov	.035939	.040715	1320.456	.883	.378	-.043935	.115813
evic	.007692	.022786	1422.967	.338	.736	-.037005	.052390
burd	-.078772	.030310	1729.809	-2.599	.009	-.138220	-.019323
gini	.827676	3.861156	1002.101	.214	.830	-6.749202	8.404555
vac	.024776	.015413	452.685	1.607	.109	-.005514	.055065
temp	.004907	.003151	1837.697	1.557	.120	-.001274	.011087
precip	-.011155	.008231	1696.294	-1.355	.176	-.027299	.004989
hf	.562213	1.027655	1977.624	.547	.584	-1.453188	2.577614
fund	.080640	.016241	753.774	4.965	.000	.048757	.112524
pop2	7.911E-14	2.4860E-14	308.876	3.182	.002	3.0196E-14	1.2802E-13
medinc2	-2.874E-10	2.5053E-10	629.693	-1.147	.252	-7.7940E-10	2.0457E-10
renfam2	-.000700	.000982	633.257	-.713	.476	-.002629	.001229
evic2	-.000287	.000749	1880.448	-.383	.702	-.001755	.001182
hf2	-1.022895	.953825	1966.959	-1.072	.284	-2.893509	.847719
yearcoded	-.139791	.029008	1339.173	-4.819	.000	-.196697	-.082884

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 85: Information criteria for Model 2 removing gini

Information Criteria[a]

-2 Restricted Log Likelihood	5122.298
Akaike's Information Criterion (AIC)	5126.298
Hurvich and Tsai's Criterion (AICC)	5126.304
Bozdogan's Criterion (CAIC)	5139.480
Schwarz's Bayesian Criterion (BIC)	5137.480

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 86: Type III tests of fixed effects for Model 2 removing gini

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	858.376	.483	.487
inczon	1	322.018	1.068	.302
coccat	2	310.346	4.075	.018
pop	0	.	.	.
bach	1	648.554	3.389	.066
medinc	1	809.849	.513	.474
medren	1	922.176	18.399	.000
medval	1	777.154	11.255	.001
renfam	1	660.682	.572	.450
renocc	1	546.508	.166	.684
renwhi	1	555.609	3.884	.049
renedu	1	637.635	6.039	.014
unemp	1	1648.679	1.411	.235
pov	1	1321.576	.853	.356
evic	1	1424.129	.108	.743
burd	1	1732.914	6.713	.010
vac	1	447.438	2.748	.098
temp	1	1843.563	2.446	.118
precip	1	1696.426	1.830	.176
hf	1	1978.566	.293	.588
fund	1	758.594	24.964	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	622.168	.551	.458
evic2	1	1883.307	.145	.704

hf2	1	1967.651	1.142	.285
yearcoded	1	1311.031	25.039	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 87: Fixed effects estimates for Model 2 removing gini

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	1.907563	2.989405	838.768	.638	.524	-3.960031	7.775156
[inczon=0]	-.208400	.201651	322.018	-1.033	.302	-.605120	.188320
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.750463	.366460	306.311	2.048	.041	.029365	1.471562
[coccat=2]	.009978	.326671	315.213	.031	.976	-.632753	.652708
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.14421E-7	2.05754E-7	308.807	-3.472	.001	-1.11927E-6	-3.09562E-7
bach	-.036486	.019818	648.554	-1.841	.066	-.075402	.002430
medinc	-3.00508E-5	4.19735E-5	809.849	-.716	.474	-.000112	5.233890E-5
medren	.004396	.001025	922.176	4.289	.000	.002384	.006407
medval	4.190620E-6	1.24913E-6	777.154	3.355	.001	1.738549E-6	6.642692E-6
renfam	.052503	.069408	660.682	.756	.450	-.083785	.188790
renocc	.007308	.017921	546.508	.408	.684	-.027894	.042509
renwhi	.013751	.006978	555.609	1.971	.049	4.516017E-5	.027456
renedu	-.031681	.012892	637.635	-2.457	.014	-.056998	-.006365
unemp	.032005	.026941	1648.679	1.188	.235	-.020837	.084846
pov	.037186	.040272	1321.576	.923	.356	-.041817	.116190
evic	.007470	.022751	1424.129	.328	.743	-.037159	.052099
burd	-.078370	.030247	1732.914	-2.591	.010	-.137694	-.019045
vac	.025243	.015228	447.438	1.658	.098	-.004684	.055169
temp	.004927	.003150	1843.563	1.564	.118	-.001251	.011104
precip	-.011134	.008230	1696.426	-1.353	.176	-.027276	.005007
hf	.556092	1.026889	1978.566	.542	.588	-1.457805	2.569989
fund	.080918	.016195	758.594	4.996	.000	.049125	.112710
pop2	7.86203E-14	2.4733E-14	307.157	3.179	.002	2.99523E-14	1.27288E-13
medinc2	-2.8883E-10	2.5024E-10	626.396	-1.154	.249	-7.8024E-10	2.02585E-10
renfam2	-.000724	.000975	622.168	-.742	.458	-.002639	.001192
evic2	-.000285	.000748	1883.307	-.380	.704	-.001752	.001183
hf2	-1.018889	.953330	1967.651	-1.069	.285	-2.888531	.850754
yearcoded	-.137819	.027542	1311.031	-5.004	.000	-.191850	-.083787

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 88: Information criteria for Model 3 adding inczon * gini interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	5112.382
Akaike's Information Criterion (AIC)	5116.382
Hurvich and Tsai's Criterion (AICC)	5116.388
Bozdogan's Criterion (CAIC)	5129.562
Schwarz's Bayesian Criterion (BIC)	5127.562

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 89: Type III tests of fixed effects for Model 3 adding inczon * gini interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	821.793	.313	.576
inczon	1	545.271	.218	.641
coccat	2	309.384	4.017	.019
pop	0	.	.	.
bach	1	805.087	3.110	.078
medinc	1	814.394	.574	.449
medren	1	916.386	17.939	.000
medval	1	834.274	10.158	.001
renfam	1	664.252	.558	.455
renocc	1	541.821	.155	.694
renwhi	1	586.157	3.650	.057
renedu	1	745.521	6.059	.014
unemp	1	1649.571	1.343	.247
pov	1	1314.204	.792	.374
evic	1	1419.282	.105	.746
burd	1	1746.575	6.510	.011
vac	1	450.352	2.538	.112
temp	1	1837.088	2.425	.120
precip	1	1695.448	1.841	.175
hf	1	1976.750	.288	.592
fund	1	748.994	24.489	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	631.713	.529	.467
evic2	1	1876.625	.140	.708

hf2	1	1966.200	1.127	.288
yearcoded	1	1332.298	23.069	.000
inczon * gini	2	718.713	.181	.834

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 90: Fixed effects estimates for Model 3 adding inczon * gini interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	1.049835	3.421242	755.317	.307	.759	-5.666439	7.766108
[inczon=0]	1.034062	2.215126	545.271	.467	.641	-3.317165	5.385288
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.743894	.368245	305.771	2.020	.044	.019278	1.468510
[coccat=2]	.007511	.329397	314.975	.023	.982	-.640587	.655608
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.058659E-7	2.081809E-7	310.349	-3.391	.001	-1.115490E-6	-2.962414E-7
bach	-.039340	.022308	805.087	-1.763	.078	-.083130	.004449
medinc	-3.232463E-5	4.268087E-5	814.394	-.757	.449	-.000116	5.145285E-5
medren	.004355	.001028	916.386	4.235	.000	.002337	.006372
medval	4.084599E-6	1.281562E-6	834.274	3.187	.001	1.569134E-6	6.600063E-6
renfam	.052093	.069708	664.252	.747	.455	-.084781	.188967
renocc	.007053	.017935	541.821	.393	.694	-.028178	.042283
renwhi	.013779	.007213	586.157	1.910	.057	-.000387	.027945
renedu	-.033382	.013561	745.521	-2.462	.014	-.060005	-.006759
unemp	.031272	.026984	1649.571	1.159	.247	-.021655	.084199
pov	.036247	.040718	1314.204	.890	.374	-.043633	.116128
evic	.007398	.022792	1419.282	.325	.746	-.037312	.052107
burd	-.077536	.030389	1746.575	-2.551	.011	-.137139	-.017933
vac	.024554	.015412	450.352	1.593	.112	-.005734	.054842
temp	.004909	.003152	1837.088	1.557	.120	-.001274	.011091
precip	-.011172	.008233	1695.448	-1.357	.175	-.027320	.004977
hf	.551450	1.028047	1976.750	.536	.592	-1.464720	2.567621
fund	.080398	.016246	748.994	4.949	.000	.048504	.112292
pop2	7.728713E-14	2.50577E-14	309.619	3.084	.002	2.798212E-14	1.265921E-13
medinc2	-2.57821E-10	2.55852E-10	654.649	-1.008	.314	-7.60211E-10	2.44569E-10
renfam2	-.000715	.000982	631.713	-.728	.467	-.002644	.001214
evic2	-.000280	.000749	1876.625	-.374	.708	-.001749	.001189
hf2	-1.013185	.954198	1966.200	-1.062	.288	-2.884531	.858160

yearcoded	-.139366	.029016	1332.298	-4.803	.000	-.196289	-.082444
[inczon=0] * gini	-.287419	4.338840	959.590	-.066	.947	-8.802128	8.227291
[inczon=1] * gini	2.467155	4.838609	718.919	.510	.610	-7.032337	11.966646

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 91: Information criteria for Model 4 adding coccat * gini interaction

Information Criteria[a]

-2 Restricted Log Likelihood	5103.325
Akaike's Information Criterion (AIC)	5107.325
Hurvich and Tsai's Criterion (AICC)	5107.331
Bozdogan's Criterion (CAIC)	5120.504
Schwarz's Bayesian Criterion (BIC)	5118.504

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 92: Type III tests of fixed effects for Model 4 adding coccat * gini interaction

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	765.047	.002	.968
inczon	1	319.073	1.053	.306
coccat	2	532.163	.653	.521
pop	0	.	.	.
bach	1	801.793	3.079	.080
medinc	1	799.070	.459	.498
medren	1	918.671	17.572	.000
medval	1	822.203	10.426	.001
renfam	1	666.796	.721	.396
renocc	1	547.614	.217	.641
renwhi	1	582.998	3.905	.049
renedu	1	744.557	6.524	.011
unemp	1	1638.611	1.348	.246
pov	1	1315.617	.600	.439
evic	1	1412.195	.118	.731
burd	1	1726.639	6.339	.012
vac	1	451.325	2.709	.100
temp	1	1836.695	2.454	.117
precip	1	1695.319	1.829	.176
hf	1	1975.925	.313	.576
fund	1	759.144	23.090	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	630.619	.634	.426
evic2	1	1874.421	.153	.696

hf2	1	1966.318	1.165	.281
yearcoded	1	1319.671	23.237	.000
coccat * gini	3	645.694	.615	.605

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 93: Fixed effects estimates for Model 4 adding coccat * gini interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	-.549985	6.059427	670.969	-.091	.928	-12.447705	11.347735
[inczon=0]	-.206973	.201726	319.073	-1.026	.306	-.603854	.189908
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-1.094950	5.946213	553.302	-.184	.854	-12.774862	10.584962
[coccat=2]	2.599959	5.106646	590.786	.509	.611	-7.429430	12.629348
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.059128E-7	2.068568E-7	308.370	-3.413	.001	-1.112942E-6	-2.988834E-7
bach	-.039045	.022252	801.793	-1.755	.080	-.082724	.004634
medinc	-2.864934E-5	4.228225E-5	799.070	-.678	.498	-.000112	5.434805E-5
medren	.004308	.001028	918.671	4.192	.000	.002291	.006324
medval	4.132776E-6	1.279918E-6	822.203	3.229	.001	1.620485E-6	6.645067E-6
renfam	.059327	.069845	666.796	.849	.396	-.077816	.196470
renocc	.008386	.017986	547.614	.466	.641	-.026944	.043716
renwhi	.014222	.007197	582.998	1.976	.049	8.713853E-5	.028356
renedu	-.034597	.013545	744.557	-2.554	.011	-.061187	-.008007
unemp	.031287	.026944	1638.611	1.161	.246	-.021560	.084135
pov	.031617	.040811	1315.617	.775	.439	-.048446	.111679
evic	.007834	.022771	1412.195	.344	.731	-.036836	.052503
burd	-.076410	.030348	1726.639	-2.518	.012	-.135932	-.016888
vac	.025357	.015405	451.325	1.646	.100	-.004917	.055631
temp	.004939	.003153	1836.695	1.566	.117	-.001245	.011122
precip	-.011139	.008236	1695.319	-1.352	.176	-.027293	.005016
hf	.576151	1.029992	1975.925	.559	.576	-1.443835	2.596136
fund	.078568	.016350	759.144	4.805	.000	.046470	.110665
pop2	7.55962E-14	2.49863E-14	308.852	3.026	.003	2.64312E-14	1.24761E-13
medinc2	-2.90236E-10	2.50575E-10	626.639	-1.158	.247	-7.82306E-10	2.01832E-10
renfam2	-.000782	.000983	630.619	-.796	.426	-.002712	.001147
evic2	-.000293	.000749	1874.421	-.391	.696	-.001761	.001175
hf2	-1.030999	.955343	1966.318	-1.079	.281	-2.904591	.842593
yearcoded	-.140427	.029131	1319.671	-4.821	.000	-.197575	-.083279

[coccat=1] * gini	9.202982	7.707563	551.714	1.194	.233	-5.936777	24.342741
[coccat=2] * gini	-.235590	3.937730	968.957	-.060	.952	-7.963052	7.491871
[coccat=3] * gini	5.698489	11.996953	641.467	.475	.635	-17.859556	29.256534

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 94: Information criteria for Model 21 adding gini * hf interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	5104.665
Akaike's Information Criterion (AIC)	5108.665
Hurvich and Tsai's Criterion (AICC)	5108.671
Bozdogan's Criterion (CAIC)	5121.845
Schwarz's Bayesian Criterion (BIC)	5119.845

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 95: Type III tests of fixed effects for Model 21 adding gini * hf interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	880.455	.622	.431
inczon	1	320.257	1.042	.308
coccat	2	311.205	3.879	.022
pop	0	.	.	.
bach	1	803.696	2.478	.116
medinc	1	813.309	.555	.457
medren	1	923.838	18.948	.000
medval	1	817.850	10.662	.001
renfam	1	665.983	.423	.516
renocc	1	549.408	.096	.756
renwhi	1	587.121	3.283	.071
renedu	1	730.259	5.385	.021
unemp	1	1650.557	1.501	.221
pov	1	1313.197	.883	.348
evic	1	1425.128	.147	.701
burd	1	1729.257	6.877	.009
vac	1	455.182	2.322	.128
temp	1	1837.875	2.389	.122
precip	1	1696.618	1.646	.200
hf	1	1648.346	1.267	.260
fund	1	771.272	26.934	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	630.977	.424	.515
evic2	1	1886.152	.235	.628

hf2	1	1910.449	2.611	.106
yearcoded	1	1351.521	22.217	.000
gini * hf	1	1588.479	1.351	.245
gini * hf2	1	1890.754	2.953	.086

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 96: Fixed effects estimates for Model 21 adding gini * hf interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	2.233044	3.020365	861.996	.739	.460	-3.695085	8.161174
[inczon=0]	-.206180	.201990	320.257	-1.021	.308	-.603575	.191215
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.705063	.368709	308.550	1.912	.057	-.020440	1.430566
[coccat=2]	-.025791	.329185	317.703	-.078	.938	-.673450	.621867
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.039148E-7	2.069620E-7	309.041	-3.401	.001	-1.111148E-6	-2.966818E-7
bach	-.034615	.021990	803.696	-1.574	.116	-.077779	.008550
medinc	-3.141696E-5	4.217935E-5	813.309	-.745	.457	-.000114	5.137626E-5
medren	.004463	.001025	923.838	4.353	.000	.002451	.006476
medval	4.159867E-6	1.273953E-6	817.850	3.265	.001	1.659265E-6	6.660470E-6
renfam	.045389	.069767	665.983	.651	.516	-.091602	.182379
renocc	.005571	.017952	549.408	.310	.756	-.029691	.040833
renwhi	.012982	.007165	587.121	1.812	.071	-.001090	.027054
renedu	-.031090	.013398	730.259	-2.321	.021	-.057394	-.004787
unemp	.033006	.026937	1650.557	1.225	.221	-.019827	.085840
pov	.038212	.040666	1313.197	.940	.348	-.041565	.117990
evic	.008736	.022762	1425.128	.384	.701	-.035915	.053388
burd	-.079420	.030286	1729.257	-2.622	.009	-.138821	-.020019
vac	.023472	.015403	455.182	1.524	.128	-.006797	.053742
temp	.004866	.003148	1837.875	1.546	.122	-.001308	.011039
precip	-.010555	.008227	1696.618	-1.283	.200	-.026691	.005581
hf	-8.146859	7.236424	1648.346	-1.126	.260	-22.340411	6.046693
fund	.084935	.016366	771.272	5.190	.000	.052808	.117061
pop2	7.766000E-14	2.486717E-14	307.858	3.123	.002	2.872888E-14	1.265911E-13
medinc2	-2.869738E-10	2.505918E-10	627.922	-1.145	.253	-7.790732E-10	2.051256E-10
renfam2	-.000640	.000983	630.977	-.651	.515	-.002570	.001290

evic2	-.000363	.000749	1886.152	-.485	.628	-.001832	.001106
hf2	14.264418	8.827970	1910.449	1.616	.106	-3.049054	31.577890
yearcoded	-.135554	.028759	1351.521	-4.713	.000	-.191971	-.079138
gini * hf	18.546846	15.959503	1588.479	1.162	.245	-12.757057	49.850749
gini * hf2	-33.330962	19.395476	1890.754	-1.718	.086	-71.369745	4.707822

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 97: Information criteria for Model 24 removing evic

Information Criteria[a]

-2 Restricted Log Likelihood	5102.639
Akaike's Information Criterion (AIC)	5106.639
Hurvich and Tsai's Criterion (AICC)	5106.645
Bozdogan's Criterion (CAIC)	5119.822
Schwarz's Bayesian Criterion (BIC)	5117.822

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 98: Type III tests of fixed effects for Model 24 removing evic

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	853.017	.523	.470
inczon	1	321.528	1.052	.306
coccat	2	309.352	4.161	.016
pop	0	.	.	.
bach	1	637.159	3.345	.068
medinc	1	810.103	.542	.462
medren	1	920.021	18.501	.000
medval	1	755.674	11.321	.001
renfam	1	653.185	.589	.443
renocc	1	547.264	.151	.698
renwhi	1	493.350	4.197	.041
renedu	1	634.575	5.995	.015
unemp	1	1572.607	1.510	.219
pov	1	1266.642	.808	.369
burd	1	1734.324	6.673	.010
vac	1	435.264	2.661	.104
temp	1	1856.445	2.496	.114
precip	1	1697.344	1.831	.176
hf	1	1980.516	.294	.588
fund	1	755.492	25.088	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	610.599	.577	.448
hf2	1	1969.468	1.144	.285
yearcoded	1	1316.086	24.955	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 99: Fixed effects estimates for Model 24 removing evic

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	1.977640	2.979387	833.433	.664	.507	-3.870343	7.825623
[inczon=0]	-.206028	.200884	321.528	-1.026	.306	-.601241	.189186
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.759296	.365347	304.481	2.078	.039	.040371	1.478220
[coccat=2]	.013780	.326140	314.778	.042	.966	-.627909	.655469
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.132101E-7	2.049724E-7	306.642	-3.480	.001	-1.116541E-6	-3.098796E-7
bach	-.035996	.019682	637.159	-1.829	.068	-.074646	.002654
medinc	-3.084698E-5	4.189878E-5	810.103	-.736	.462	-.000113	5.139600E-5
medren	.004401	.001023	920.021	4.301	.000	.002393	.006409
medval	4.153871E-6	1.234579E-6	755.674	3.365	.001	1.730259E-6	6.577484E-6
renfam	.052953	.068977	653.185	.768	.443	-.082491	.188397
renocc	.006946	.017872	547.264	.389	.698	-.028161	.042052
renwhi	.013451	.006565	493.350	2.049	.041	.000551	.026351
renedu	-.031492	.012862	634.575	-2.448	.015	-.056749	-.006235
unemp	.032652	.026568	1572.607	1.229	.219	-.019460	.084764
pov	.035803	.039837	1266.642	.899	.369	-.042350	.113956
burd	-.078047	.030213	1734.324	-2.583	.010	-.137304	-.018790
vac	.024573	.015063	435.264	1.631	.104	-.005032	.054178
temp	.004950	.003133	1856.445	1.580	.114	-.001194	.011095
precip	-.011129	.008224	1697.344	-1.353	.176	-.027258	.005001
hf	.556283	1.026406	1980.516	.542	.588	-1.456666	2.569232
fund	.080959	.016163	755.492	5.009	.000	.049229	.112689
pop2	7.852766E-14	2.46744E-14	306.159	3.183	.002	2.997477E-14	1.270806E-13
medinc2	-2.85862E-10	2.49711E-10	631.231	-1.145	.253	-7.76229E-10	2.045035E-10
renfam2	-.000734	.000967	610.599	-.760	.448	-.002632	.001164
hf2	-1.019180	.952890	1969.468	-1.070	.285	-2.887958	.849598
yearcoded	-.137352	.027495	1316.086	-4.996	.000	-.191291	-.083413

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 100: Information criteria for Model 45 removing renocc

Information Criteria[a]	
-2 Restricted Log Likelihood	6545.698
Akaike's Information Criterion (AIC)	6549.698
Hurvich and Tsai's Criterion (AICC)	6549.702
Bozdogan's Criterion (CAIC)	6563.439
Schwarz's Bayesian Criterion (BIC)	6561.439

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 101: Type III tests of fixed effects for Model 45 removing renocc

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1116.982	3.506	.061
inczon	1	376.766	2.557	.111
coccat	2	367.762	4.937	.008
pop	0	.	.	.
bach	1	823.679	11.374	.001
medinc	1	1124.670	.143	.705
medren	1	1071.900	13.835	.000
medval	1	899.543	40.561	.000
renfam	1	784.191	.000	.988
renwhi	1	585.361	.968	.326
renedu	1	847.895	14.862	.000
unemp	1	2023.764	.393	.531
pov	1	1408.741	1.713	.191
burd	1	2241.307	4.442	.035
vac	1	490.377	2.074	.151
temp	1	2525.336	3.607	.058
precip	1	2315.761	.131	.717
hf	1	2605.326	3.382	.066
fund	1	903.709	18.390	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	732.033	.035	.851
hf2	1	2602.020	5.501	.019
yearcoded	1	1515.123	23.509	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 102: Fixed effects estimates for Model 45 removing renocc

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	4.170769	2.308064	1083.461	1.807	.071	-.358013	8.699550
[inczon=0]	-.282972	.176973	376.766	-1.599	.111	-.630951	.065007
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.748136	.344982	360.639	2.169	.031	.069708	1.426565
[coccat=2]	-.017133	.310948	374.213	-.055	.956	-.628558	.594291
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.472261E-7	1.886218E-7	362.596	-3.962	.000	-1.118156E-6	-3.762961E-7
bach	-.056484	.016748	823.679	-3.373	.001	-.089358	-.023610
medinc	-1.303725E-5	3.441816E-5	1124.670	-.379	.705	-8.056828E-5	5.449377E-5
medren	.002994	.000805	1071.900	3.720	.000	.001415	.004573
medval	6.373217E-6	1.000697E-6	899.543	6.369	.000	4.409243E-6	8.337190E-6
renfam	-.000866	.059636	784.191	-.015	.988	-.117932	.116199
renwhi	.005312	.005399	585.361	.984	.326	-.005293	.015917
renedu	-.043351	.011245	847.895	-3.855	.000	-.065422	-.021280
unemp	.014400	.022959	2023.764	.627	.531	-.030625	.059425
pov	.041000	.031321	1408.741	1.309	.191	-.020442	.102441
burd	-.050741	.024076	2241.307	-2.108	.035	-.097955	-.003527
vac	.016709	.011604	490.377	1.440	.151	-.006090	.039508
temp	.005179	.002727	2525.336	1.899	.058	-.000168	.010526
precip	-.002402	.006631	2315.761	-.362	.717	-.015405	.010600
hf	1.572970	.855274	2605.326	1.839	.066	-.104115	3.250054
fund	.057326	.013368	903.709	4.288	.000	.031090	.083562
pop2	8.146299E-14	2.28432E-14	360.985	3.566	.000	3.654052E-14	1.263855E-13
medinc2	-3.57139E-10	2.02525E-10	872.808	-1.763	.078	-7.54633E-10	4.035510E-11
renfam2	-.000158	.000844	732.033	-.187	.851	-.001815	.001498
hf2	-1.867677	.796329	2602.020	-2.345	.019	-3.429179	-.306175
yearcoded	-.114866	.023690	1515.123	-4.849	.000	-.161335	-.068397

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 103: Information criteria for Model 50 adding renocc * medinc interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6615.417
Akaike's Information Criterion (AIC)	6619.417
Hurvich and Tsai's Criterion (AICC)	6619.422
Bozdogan's Criterion (CAIC)	6633.157
Schwarz's Bayesian Criterion (BIC)	6631.157

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 104: Type III tests of fixed effects for Model 50 adding renocc * medinc interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1107.256	3.724	.054
inczon	1	372.980	1.588	.208
coccat	2	364.076	4.253	.015
pop	0	.	.	.
bach	1	788.516	11.224	.001
medinc	1	1032.278	2.456	.117
medren	1	1130.052	14.112	.000
medval	1	968.391	43.452	.000
renfam	1	796.033	.065	.799
renwhi	1	567.637	2.235	.135
renedu	1	833.537	12.672	.000
unemp	1	2014.625	.613	.434
pov	1	1521.812	.838	.360
burd	1	2508.877	5.318	.021
vac	1	495.429	2.751	.098
temp	1	2513.022	3.504	.061
precip	1	2319.971	.079	.778
hf	1	2606.167	3.215	.073
fund	1	856.531	19.972	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	732.207	.003	.955
hf2	1	2602.516	5.269	.022
yearcoded	1	1461.397	22.625	.000

medinc * renocc	0	.	.	.
renocc * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 105: Fixed effects estimates for Model 50 adding renocc & medinc interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	4.347970	2.339241	1072.257	1.859	.063	-.242039	8.937979
[inczon=0]	-.222939	.176920	372.980	-1.260	.208	-.570826	.124947
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.695526	.341734	359.316	2.035	.043	.023475	1.367577
[coccat=2]	-.013667	.307455	371.273	-.044	.965	-.618240	.590905
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.778096E-7	1.889143E-7	362.585	-3.588	.000	-1.049315E-6	-3.063043E-7
bach	-.056158	.016763	788.516	-3.350	.001	-.089063	-.023254
medinc	-6.107715E-5	3.897385E-5	1032.278	-1.567	.117	-.000138	1.539986E-5
medren	.003201	.000852	1130.052	3.757	.000	.001529	.004873
medval	6.798069E-6	1.031295E-6	968.391	6.592	.000	4.774238E-6	8.821900E-6
renfam	-.015415	.060435	796.033	-.255	.799	-.134046	.103216
renwhi	.008496	.005682	567.637	1.495	.135	-.002665	.019657
renedu	-.040141	.011276	833.537	-3.560	.000	-.062273	-.018008
unemp	.017937	.022902	2014.625	.783	.434	-.026977	.062852
pov	.029919	.032681	1521.812	.915	.360	-.034185	.094023
burd	-.059020	.025593	2508.877	-2.306	.021	-.109206	-.008834
vac	.020310	.012245	495.429	1.659	.098	-.003748	.044368
temp	.005115	.002733	2513.022	1.872	.061	-.000243	.010474
precip	-.001870	.006639	2319.971	-.282	.778	-.014889	.011149
hf	1.532378	.854685	2606.167	1.793	.073	-.143551	3.208308
fund	.060275	.013487	856.531	4.469	.000	.033803	.086747
pop2	7.17998E-14	2.29997E-14	362.062	3.122	.002	2.65699E-14	1.17029E-13
medinc2	2.49045E-10	3.02010E-10	724.537	.825	.410	-3.43874E-10	8.41965E-10
renfam2	4.816458E-5	.000851	732.207	.057	.955	-.001622	.001718
hf2	-1.827069	.795995	2602.516	-2.295	.022	-3.387916	-.266222
yearcoded	-.112494	.023650	1461.397	-4.757	.000	-.158886	-.066102
medinc * renocc	1.298502E-6	5.782189E-7	631.404	2.246	.025	1.630369E-7	2.433967E-6
renocc*medinc2	-1.87060E-11	6.60921E-12	642.368	-2.830	.005	-3.16849E-11	-5.72841E-12

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 106: Information criteria for Model 62 adding renocc * hf interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6540.710
Akaike's Information Criterion (AIC)	6544.710
Hurvich and Tsai's Criterion (AICC)	6544.715
Bozdogan's Criterion (CAIC)	6558.450
Schwarz's Bayesian Criterion (BIC)	6556.450

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 107: Type III tests of fixed effects for Model 62 adding renocc * hf interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1101.999	3.801	.051
inczon	1	375.569	2.650	.104
coccat	2	366.234	5.233	.006
pop	0	.	.	.
bach	1	800.208	10.592	.001
medinc	1	1108.939	.246	.620
medren	1	1173.583	15.078	.000
medval	1	914.049	40.452	.000
renfam	1	790.692	.016	.900
renwhi	1	592.356	.855	.355
renedu	1	845.962	14.933	.000
unemp	1	2013.547	.436	.509
pov	1	1578.951	2.033	.154
burd	1	2433.495	4.557	.033
vac	1	513.495	.924	.337
temp	1	2512.942	3.498	.062
precip	1	2316.159	.085	.771
hf	1	1513.141	.527	.468
fund	1	952.560	23.076	.000
pop2	0	.	.	.
medinc2	0	.	.	.
renfam2	1	731.044	.011	.915
hf2	1	1986.031	2.887	.089

yearcoded	1	1480.980	22.378	.000
renocc * hf	1	1116.453	2.154	.143
renocc * hf2	1	1665.789	6.792	.009

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 108: Fixed effects estimates for Model 62 adding renocc * hf interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	4.397914	2.324846	1068.700	1.892	.059	-.163866	8.959695
[inczon=0]	-.287563	.176639	375.569	-1.628	.104	-.634887	.059762
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.738453	.343283	360.550	2.151	.032	.063365	1.413541
[coccat=2]	-.059382	.309286	373.268	-.192	.848	-.667544	.548779
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.282665E-7	1.888141E-7	363.390	-3.857	.000	-1.099572E-6	-3.569610E-7
bach	-.054579	.016770	800.208	-3.255	.001	-.087498	-.021660
medinc	-1.699864E-5	3.428388E-5	1108.939	-.496	.620	-8.426724E-5	5.026996E-5
medren	.003269	.000842	1173.583	3.883	.000	.001617	.004921
medval	6.427512E-6	1.010589E-6	914.049	6.360	.000	4.444169E-6	8.410856E-6
renfam	-.007519	.059896	790.692	-.126	.900	-.125093	.110056
renwhi	.005193	.005615	592.356	.925	.355	-.005834	.016220
renedu	-.043553	.011271	845.962	-3.864	.000	-.065675	-.021431
unemp	.015114	.022881	2013.547	.661	.509	-.029760	.059987
pov	.046906	.032900	1578.951	1.426	.154	-.017626	.111439
burd	-.053232	.024937	2433.495	-2.135	.033	-.102132	-.004332
vac	.011736	.012210	513.495	.961	.337	-.012252	.035724
temp	.005101	.002727	2512.942	1.870	.062	-.000247	.010449
precip	-.001929	.006624	2316.159	-.291	.771	-.014919	.011062
hf	-1.478815	2.036926	1513.141	-.726	.468	-5.474313	2.516682
fund	.065478	.013631	952.560	4.804	.000	.038729	.092228
pop2	7.857862E-14	2.28956E-14	361.899	3.432	.001	3.355336E-14	1.236039E-13
medinc2	-3.62595E-10	2.04594E-10	924.921	-1.772	.077	-7.64117E-10	3.892711E-11
renfam2	-8.983819E-5	.000844	731.044	-.106	.915	-.001747	.001567
hf2	3.847674	2.264345	1986.031	1.699	.089	-.593066	8.288415
yearcoded	-.111763	.023626	1480.980	-4.731	.000	-.158106	-.065419
renocc * hf	.085694	.058392	1116.453	1.468	.143	-.028876	.200263
renocc * hf2	-.171087	.065648	1665.789	-2.606	.009	-.299848	-.042327

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 109: Information criteria for Model 65 removing renfam

Information Criteria[a]	
-2 Restricted Log Likelihood	6522.660
Akaike's Information Criterion (AIC)	6526.660
Hurvich and Tsai's Criterion (AICC)	6526.665
Bozdogan's Criterion (CAIC)	6540.401
Schwarz's Bayesian Criterion (BIC)	6538.401

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 110: Type III tests of fixed effects for Model 65 removing renfam

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1043.836	4.477	.035
inczon	1	376.549	2.684	.102
coccat	2	366.746	5.371	.005
pop	0	.	.	.
bach	1	663.866	10.033	.002
medinc	1	1034.146	.382	.537
medren	1	1168.096	14.313	.000
medval	1	918.117	41.087	.000
renwhi	1	528.889	1.938	.164
renedu	1	843.079	14.807	.000
unemp	1	2008.031	.310	.578
pov	1	1407.189	1.625	.203
burd	1	2400.480	4.161	.041
vac	1	509.998	1.239	.266
temp	1	2517.001	3.455	.063
precip	1	2317.289	.070	.792
hf	1	1501.363	.644	.422
fund	1	853.135	27.610	.000
pop2	0	.	.	.
medinc2	0	.	.	.
hf2	1	1983.460	3.072	.080
yearcoded	1	1426.635	21.905	.000
renocc * hf	1	1098.124	2.498	.114
renocc * hf2	1	1661.268	7.203	.007

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 111: Fixed effects estimates for Model 65 removing renfam

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.932061	1.937938	1000.043	2.029	.043	.129169	7.734952
[inczon=0]	-.288589	.176155	376.549	-1.638	.102	-.634959	.057781
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.753021	.341144	361.877	2.207	.028	.082147	1.423895
[coccat=2]	-.048626	.308162	374.930	-.158	.875	-.654568	.557317
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.315078E-7	1.879995E-7	365.136	-3.891	.000	-1.101205E-6	-3.618102E-7
bach	-.046945	.014821	663.866	-3.167	.002	-.076047	-.017843
medinc	-2.094065E-5	3.387484E-5	1034.146	-.618	.537	-8.741191E-5	4.553062E-5
medren	.003134	.000828	1168.096	3.783	.000	.001509	.004759
medval	6.463353E-6	1.008342E-6	918.117	6.410	.000	4.484430E-6	8.442276E-6
renwhi	.007237	.005198	528.889	1.392	.164	-.002976	.017449
renedu	-.043272	.011246	843.079	-3.848	.000	-.065345	-.021200
unemp	.012621	.022678	2008.031	.557	.578	-.031853	.057096
pov	.040768	.031986	1407.189	1.275	.203	-.021977	.103514
burd	-.050545	.024779	2400.480	-2.040	.041	-.099135	-.001955
vac	.013417	.012053	509.998	1.113	.266	-.010263	.037097
temp	.005069	.002727	2517.001	1.859	.063	-.000278	.010416
precip	-.001748	.006622	2317.289	-.264	.792	-.014734	.011237
hf	-1.622359	2.021155	1501.363	-.803	.422	-5.586945	2.342227
fund	.069012	.013134	853.135	5.254	.000	.043233	.094790
pop2	7.920646E-14	2.28176E-14	363.138	3.471	.001	3.433506E-14	1.240779E-13
medinc2	-3.53577E-10	2.03701E-10	902.835	-1.736	.083	-7.53360E-10	4.620516E-11
hf2	3.952964	2.255433	1983.460	1.753	.080	-.470302	8.376230
yearcoded	-.108670	.023219	1426.635	-4.680	.000	-.154216	-.063123
renocc * hf	.091228	.057725	1098.124	1.580	.114	-.022035	.204492
renocc * hf2	-.175215	.065284	1661.268	-2.684	.007	-.303263	-.047167

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 112: Information criteria for Model 84 removing precip

Information Criteria[a]

-2 Restricted Log Likelihood	6514.533
Akaike's Information Criterion (AIC)	6518.533
Hurvich and Tsai's Criterion (AICC)	6518.537
Bozdogan's Criterion (CAIC)	6532.275
Schwarz's Bayesian Criterion (BIC)	6530.275

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 113: Type III tests of fixed effects for Model 84 removing precip

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1046.570	4.420	.036
inczon	1	377.082	2.697	.101
coccat	2	367.063	5.378	.005
pop	0	.	.	.
bach	1	663.393	9.967	.002
medinc	1	1037.884	.364	.546
medren	1	1166.278	14.431	.000
medval	0	.	.	.
renwhi	1	528.840	1.965	.162
renedu	1	842.239	14.746	.000
unemp	1	1999.449	.336	.562
pov	1	1408.426	1.633	.202
burd	1	2400.444	4.188	.041
vac	1	510.360	1.263	.262
temp	1	2521.466	3.391	.066
hf	1	1503.083	.674	.412
fund	1	853.672	27.617	.000
pop2	0	.	.	.
medinc2	0	.	.	.
hf2	1	1985.683	3.136	.077
yearcoded	1	1428.148	22.247	.000
renocc * hf	1	1099.333	2.536	.112
renocc * hf2	1	1662.538	7.271	.007

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 114: Fixed effects estimates for Model 84 removing precip

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.895140	1.932368	1002.210	2.016	.044	.103190	7.687091
[inczon=0]	-.289186	.176083	377.082	-1.642	.101	-.635414	.057043
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.752877	.341033	362.270	2.208	.028	.082224	1.423531
[coccat=2]	-.049100	.308058	375.264	-.159	.873	-.654837	.556637
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.308587E-7	1.879231E-7	365.538	-3.889	.000	-1.100405E-6	-3.613126E-7
bach	-.046625	.014768	663.393	-3.157	.002	-.075622	-.017627
medinc	-2.040573E-5	3.380304E-5	1037.884	-.604	.546	-8.673581E-5	4.592436E-5
medren	.003143	.000827	1166.278	3.799	.000	.001520	.004767
medval	6.413091E-6	9.899162E-7	913.255	6.478	.000	4.470316E-6	8.355866E-6
renwhi	.007282	.005194	528.840	1.402	.162	-.002922	.017486
renedu	-.043096	.011223	842.239	-3.840	.000	-.065123	-.021068
unemp	.013107	.022599	1999.449	.580	.562	-.031214	.057427
pov	.040859	.031977	1408.426	1.278	.202	-.021868	.103586
burd	-.050685	.024768	2400.444	-2.046	.041	-.099254	-.002116
vac	.013531	.012041	510.360	1.124	.262	-.010125	.037187
temp	.004987	.002708	2521.466	1.841	.066	-.000324	.010298
hf	-1.655346	2.016741	1503.083	-.821	.412	-5.611272	2.300580
fund	.069002	.013130	853.672	5.255	.000	.043231	.094774
pop2	7.919169E-14	2.28102E-14	363.530	3.472	.001	3.433509E-14	1.240483E-13
medinc2	-3.56670E-10	2.03301E-10	906.035	-1.754	.080	-7.55666E-10	4.232626E-11
hf2	3.986779	2.251261	1985.683	1.771	.077	-.428301	8.401860
yearcoded	-.109150	.023141	1428.148	-4.717	.000	-.154545	-.063755
renocc * hf	.091831	.057664	1099.333	1.592	.112	-.021314	.204975
renocc * hf2	-.175872	.065222	1662.538	-2.697	.007	-.303797	-.047946

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 115: Information criteria for Model 102 removing unemp

Information Criteria[a]

-2 Restricted Log Likelihood	6542.904
Akaike's Information Criterion (AIC)	6546.904
Hurvich and Tsai's Criterion (AICC)	6546.909
Bozdogan's Criterion (CAIC)	6560.653
Schwarz's Bayesian Criterion (BIC)	6558.653

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 116: Type III tests of fixed effects for Model 102 removing unemp

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1075.410	4.050	.044
inczon	1	377.119	2.788	.096
coccat	2	366.765	5.443	.005
pop	0	.	.	.
bach	1	627.907	11.924	.001
medinc	1	1041.223	.198	.656
medren	1	1245.362	15.785	.000
medval	0	.	.	.
renwhi	1	538.048	2.250	.134
renedu	1	843.573	16.194	.000
pov	1	1620.216	3.076	.080
burd	1	2386.811	4.255	.039
vac	1	509.455	1.379	.241
temp	1	2528.979	3.267	.071
hf	1	1490.177	.583	.445
fund	1	850.180	27.284	.000
pop2	0	.	.	.
medinc2	0	.	.	.
hf2	1	1974.894	2.971	.085
yearcoded	1	1766.658	31.280	.000
renocc * hf	1	1091.990	2.399	.122
renocc * hf2	1	1655.565	7.088	.008

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 117: Fixed effects estimates for Model 102 removing unemp

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.675016	1.914129	1027.374	1.920	.055	-.081033	7.431065
[inczon=0]	-.293252	.175614	377.119	-1.670	.096	-.638558	.052053
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.774246	.340232	362.372	2.276	.023	.105169	1.443323
[coccat=2]	-.025563	.307082	374.706	-.083	.934	-.629382	.578256
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.210015E-7	1.874189E-7	365.292	-3.847	.000	-1.089557E-6	-3.524461E-7
bach	-.049622	.014370	627.907	-3.453	.001	-.077842	-.021402
medinc	-1.489229E-5	3.342889E-5	1041.223	-.445	.656	-8.048797E-5	5.070338E-5
medren	.003228	.000813	1245.362	3.973	.000	.001634	.004822
medval	6.295051E-6	9.498994E-7	1039.363	6.627	.000	4.431112E-6	8.158990E-6
renwhi	.007770	.005180	538.048	1.500	.134	-.002406	.017945
renedu	-.044871	.011150	843.573	-4.024	.000	-.066757	-.022985
pov	.052340	.029844	1620.216	1.754	.080	-.006196	.110877
burd	-.050422	.024443	2386.811	-2.063	.039	-.098354	-.002489
vac	.014113	.012020	509.455	1.174	.241	-.009501	.037727
temp	.004910	.002716	2528.979	1.808	.071	-.000416	.010236
hf	-1.540210	2.017216	1490.177	-.764	.445	-5.497095	2.416675
fund	.068400	.013095	850.180	5.223	.000	.042698	.094102
pop2	7.823612E-14	2.27541E-14	363.300	3.438	.001	3.348971E-14	1.229825E-13
medinc2	-3.78383E-10	2.02109E-10	905.919	-1.872	.062	-7.75039E-10	1.827364E-11
hf2	3.885492	2.254086	1974.894	1.724	.085	-.535145	8.306130
yearcoded	-.116595	.020847	1766.658	-5.593	.000	-.157483	-.075708
renocc * hf	.089347	.057685	1091.990	1.549	.122	-.023838	.202533
renocc * hf2	-.173894	.065315	1655.565	-2.662	.008	-.302003	-.045784

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 118: Information criteria for Model 119 removing medinc

Information Criteria[a]

-2 Restricted Log Likelihood	6504.198
Akaike's Information Criterion (AIC)	6508.198
Hurvich and Tsai's Criterion (AICC)	6508.203
Bozdogan's Criterion (CAIC)	6521.948
Schwarz's Bayesian Criterion (BIC)	6519.948

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 119: Type III tests of fixed effects for Model 119 removing medinc

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	984.043	7.064	.008
inczon	1	374.362	4.177	.042
coccat	2	362.226	6.038	.003
pop	0	.	.	.
bach	1	566.920	38.784	.000
medren	1	1291.687	1.050	.306
medval	0	.	.	.
renwhi	1	517.055	3.118	.078
renedu	1	837.137	23.988	.000
pov	1	1184.668	7.434	.006
burd	1	2165.696	.298	.585
vac	1	442.241	9.551	.002
temp	1	2579.779	5.335	.021
hf	1	1532.747	6.221	.013
fund	1	868.915	22.923	.000
pop2	0	.	.	.
hf2	1	2039.367	8.755	.003
yearcoded	1	1755.105	42.082	.000
renocc * hf	1	1049.049	13.638	.000
renocc * hf2	1	1684.436	16.971	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 120: Fixed effects estimates for Model 119 removing medinc

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.352458	1.375845	894.532	2.437	.015	.652199	6.052718
[inczon=0]	-.367112	.179617	374.362	-2.044	.042	-.720298	-.013927
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.963730	.348353	358.962	2.767	.006	.278660	1.648800
[coccat=2]	.141471	.314161	369.605	.450	.653	-.476296	.759237
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.079172E-7	1.914875E-7	356.864	-3.175	.002	-9.845029E-7	-2.313315E-7
bach	-.081513	.013089	566.920	-6.228	.000	-.107221	-.055804
medren	.000642	.000626	1291.687	1.025	.306	-.000587	.001871
medval	5.871492E-6	9.593658E-7	1055.730	6.120	.000	3.989011E-6	7.753972E-6
renwhi	.009276	.005253	517.055	1.766	.078	-.001044	.019597
renedu	-.054717	.011172	837.137	-4.898	.000	-.076645	-.032789
pov	.066609	.024430	1184.668	2.727	.006	.018678	.114540
burd	-.012724	.023291	2165.696	-.546	.585	-.058399	.032952
vac	.035065	.011346	442.241	3.090	.002	.012766	.057365
temp	.006232	.002698	2579.779	2.310	.021	.000941	.011523
hf	-4.823383	1.933914	1532.747	-2.494	.013	-8.616781	-1.029986
fund	.063659	.013296	868.915	4.788	.000	.037563	.089756
pop2	6.86214E-14	2.33380E-14	356.526	2.940	.003	2.272397E-14	1.145189E-13
hf2	6.546338	2.212491	2039.367	2.959	.003	2.207360	10.885316
yearcoded	-.125518	.019349	1755.105	-6.487	.000	-.163467	-.087568
renocc * hf	.199988	.054154	1049.049	3.693	.000	.093726	.306250
renocc * hf2	-.261987	.063596	1684.436	-4.120	.000	-.386723	-.137252

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 121: Information criteria for Model 122 adding pop * medinc interaction*

Information Criteria[a]	
-2 Restricted Log Likelihood	6791.405
Akaike's Information Criterion (AIC)	6795.405
Hurvich and Tsai's Criterion (AICC)	6795.410
Bozdogan's Criterion (CAIC)	6809.152
Schwarz's Bayesian Criterion (BIC)	6807.152

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 122: Type III tests of fixed effects for Model 122 adding pop * medinc interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	956.595	4.356	.037
inczon	1	374.011	3.046	.082
coccat	2	372.415	5.626	.004
pop	1	763.971	5.214	.023
bach	1	585.131	30.601	.000
medren	1	1239.719	4.293	.038
medval	0	.	.	.
renwhi	1	517.278	3.147	.077
renedu	1	838.192	20.611	.000
pov	1	1417.453	11.817	.001
burd	1	2343.625	1.578	.209
vac	1	444.798	7.370	.007
temp	1	2567.800	4.866	.027
hf	1	1590.193	2.997	.084
fund	1	853.250	26.842	.000
pop2	0	.	.	.
hf2	1	2059.937	5.680	.017
yearcoded	1	1730.465	46.356	.000
renocc * hf	1	1151.451	7.208	.007
renocc * hf2	1	1737.925	11.465	.001
pop * medinc	0	.	.	.
pop * medinc2	0	.	.	.
medinc * pop2	0	.	.	.
pop2 * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 123: Fixed effects estimates for Model 122 adding pop * medinc interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.635092	1.389876	864.085	1.896	.058	-.092836	5.363019
[inczon=0]	-.313140	.179429	374.011	-1.745	.082	-.665956	.039675
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.903681	.355281	373.689	2.544	.011	.205080	1.602281
[coccat=2]	.093858	.321120	382.705	.292	.770	-.537522	.725239
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-3.960482E-6	1.734423E-6	763.971	-2.283	.023	-7.365282E-6	-5.556819E-7
bach	-.073449	.013277	585.131	-5.532	.000	-.099526	-.047371
medren	.001398	.000675	1239.719	2.072	.038	7.430328E-5	.002721
medval	6.038826E-6	9.713118E-7	1070.628	6.217	.000	4.132935E-6	7.944717E-6
renwhi	.009290	.005237	517.278	1.774	.077	-.000999	.019578
renedu	-.050875	.011206	838.192	-4.540	.000	-.072871	-.028879
pov	.091739	.026687	1417.453	3.438	.001	.039388	.144090
burd	-.030121	.023979	2343.625	-1.256	.209	-.077143	.016900
vac	.031107	.011458	444.798	2.715	.007	.008588	.053626
temp	.005964	.002704	2567.800	2.206	.027	.000663	.011266
hf	-3.427219	1.979656	1590.193	-1.731	.084	-7.310228	.455791
fund	.069115	.013340	853.250	5.181	.000	.042932	.095299
pop2	9.95547E-13	6.34477E-13	1065.921	1.569	.117	-2.49418E-13	2.240513E-12
hf2	5.342444	2.241645	2059.937	2.383	.017	.946318	9.738571
yearcoded	-.135644	.019923	1730.465	-6.809	.000	-.174719	-.096569
renocc * hf	.150959	.056227	1151.451	2.685	.007	.040640	.261279
renocc * hf2	-.219755	.064902	1737.925	-3.386	.001	-.347049	-.092462
pop * medinc	1.21219E-10	5.24051E-11	834.079	2.313	.021	1.835833E-11	2.240811E-10
pop * medinc2	-1.08159E-15	4.07763E-16	922.221	-2.653	.008	-1.88184E-15	-2.81341E-16
medinc * pop2	-3.40856E-17	2.16264E-17	1123.509	-1.576	.115	-7.65183E-17	8.347157E-18
pop2 * medinc2	3.09848E-22	1.86616E-22	1195.566	1.660	.097	-5.62836E-23	6.759797E-22

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 124: Information criteria for Model 124 adding medinc * medren interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6552.442
Akaike's Information Criterion (AIC)	6556.442
Hurvich and Tsai's Criterion (AICC)	6556.446
Bozdogan's Criterion (CAIC)	6570.190
Schwarz's Bayesian Criterion (BIC)	6568.190

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 125: Type III tests of fixed effects for Model 124 adding medinc * medren interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	852.263	.610	.435
inczon	1	377.255	2.096	.149
coccat	2	367.558	5.079	.007
pop	0	.	.	.
bach	1	605.668	9.990	.002
medren	1	953.433	31.290	.000
medval	0	.	.	.
renwhi	1	523.517	3.491	.062
renedu	1	809.718	12.965	.000
pov	1	1313.767	3.111	.078
burd	1	2421.152	8.580	.003
vac	1	494.869	.188	.665
temp	1	2531.297	2.102	.147
hf	1	1494.886	.148	.700
fund	1	823.365	31.778	.000
pop2	0	.	.	.
hf2	1	1959.888	2.090	.148
yearcoded	1	1730.941	32.432	.000
renocc * hf	1	1086.965	1.145	.285
renocc * hf2	1	1636.739	5.349	.021
medinc * medren	0	.	.	.
medren * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 126: Fixed effects estimates for Model 124 adding medinc * medren interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.963199	1.367818	799.091	.704	.482	-1.721741	3.648139
[inczon=0]	-.246588	.170344	377.255	-1.448	.149	-.581531	.088355
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.678949	.329980	363.469	2.058	.040	.030039	1.327859
[coccat=2]	-.079344	.297473	374.122	-.267	.790	-.664273	.505584
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.19822E-7	1.810207E-7	364.316	-3.976	.000	-1.075799E-6	-3.638458E-7
bach	-.043229	.013677	605.668	-3.161	.002	-.070090	-.016368
medren	.011423	.002042	953.433	5.594	.000	.007416	.015431
medval	6.978933E-6	9.457942E-7	1073.163	7.379	.000	5.123117E-6	8.834748E-6
renwhi	.009352	.005006	523.517	1.868	.062	-.000482	.019186
renedu	-.039540	.010981	809.718	-3.601	.000	-.061096	-.017985
pov	.047517	.026938	1313.767	1.764	.078	-.005330	.100363
burd	-.072622	.024792	2421.152	-2.929	.003	-.121238	-.024006
vac	.005067	.011681	494.869	.434	.665	-.017884	.028017
temp	.003944	.002720	2531.297	1.450	.147	-.001390	.009277
hf	-.760853	1.977095	1494.886	-.385	.700	-4.639028	3.117323
fund	.072404	.012844	823.365	5.637	.000	.047193	.097615
pop2	7.59309E-14	2.19893E-14	362.990	3.453	.001	3.26883E-14	1.19173E-13
hf2	3.216780	2.225220	1959.888	1.446	.148	-1.147266	7.580826
yearcoded	-.112892	.019823	1730.941	-5.695	.000	-.151772	-.074012
renocc * hf	.060303	.056344	1086.965	1.070	.285	-.050253	.170859
renocc * hf2	-.148934	.064396	1636.739	-2.313	.021	-.275241	-.022627
medinc * medren	-1.59748E-7	3.886288E-8	975.923	-4.111	.000	-2.360132E-7	-8.348429E-8
medren*medinc2	5.94686E-13	2.11004E-13	972.317	2.818	.005	1.80608E-13	1.00876E-12

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 127: Information criteria for Model 125 adding medinc * medval interaction*

Information Criteria[a]	
-2 Restricted Log Likelihood	6549.851
Akaike's Information Criterion (AIC)	6553.851
Hurvich and Tsai's Criterion (AICC)	6553.856
Bozdogan's Criterion (CAIC)	6567.600
Schwarz's Bayesian Criterion (BIC)	6565.600

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 128: Type III tests of fixed effects for Model 125 adding medinc * medval interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	845.920	.340	.560
inczon	1	382.656	.814	.367
coccat	2	372.881	5.443	.005
pop	0	.	.	.
bach	1	582.444	13.241	.000
medren	1	1163.845	23.117	.000
medval	1	1040.850	55.838	.000
renwhi	1	524.055	4.473	.035
renedu	1	787.379	15.048	.000
pov	1	1313.910	14.065	.000
burd	1	2362.361	10.352	.001
vac	1	463.599	1.289	.257
temp	1	2593.208	2.821	.093
hf	1	1550.848	.033	.856
fund	1	796.202	41.629	.000
pop2	0	.	.	.
hf2	1	2001.588	.701	.403
yearcoded	1	1699.567	35.013	.000
renocc * hf	1	1130.133	.225	.636
renocc * hf2	1	1691.249	2.805	.094
medinc * medval	0	.	.	.
medval * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 129: Fixed effects estimates for Model 125 adding medinc * medval interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.559136	1.337505	790.112	.418	.676	-2.066348	3.184620
[inczon=0]	-.150460	.166742	382.656	-.902	.367	-.478306	.177387
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.780096	.319618	368.617	2.441	.015	.151592	1.408601
[coccat=2]	.041190	.288395	380.996	.143	.887	-.525855	.608235
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.920855E-7	1.755308E-7	368.958	-3.373	.001	-9.372517E-7	-2.469193E-7
bach	-.046710	.012836	582.444	-3.639	.000	-.071921	-.021499
medren	.003250	.000676	1163.845	4.808	.000	.001923	.004576
medval	3.697498E-5	4.948150E-6	1040.850	7.472	.000	2.726549E-5	4.668447E-5
renwhi	.010346	.004892	524.055	2.115	.035	.000736	.019956
renedu	-.041361	.010662	787.379	-3.879	.000	-.062291	-.020431
pov	.093487	.024928	1313.910	3.750	.000	.044584	.142390
burd	-.077909	.024215	2362.361	-3.217	.001	-.125394	-.030425
vac	.012258	.010795	463.599	1.136	.257	-.008955	.033471
temp	.004517	.002689	2593.208	1.680	.093	-.000756	.009790
hf	.353554	1.954149	1550.848	.181	.856	-3.479500	4.186608
fund	.081945	.012701	796.202	6.452	.000	.057014	.106876
pop2	5.57066E-14	2.14325E-14	370.171	2.599	.010	1.35617E-14	9.78514E-14
hf2	1.854333	2.214878	2001.588	.837	.403	-2.489374	6.198040
yearcoded	-.113607	.019200	1699.567	-5.917	.000	-.151265	-.075950
renocc * hf	.026268	.055418	1130.133	.474	.636	-.082465	.135001
renocc * hf2	-.107203	.064012	1691.249	-1.675	.094	-.232754	.018349
medinc * medval	-6.24685E-10	1.14401E-10	1000.842	-5.460	.000	-8.49179E-10	-4.00191E-10
medval*medinc2	2.68310E-15	6.53710E-16	1051.848	4.104	.000	1.40037E-15	3.96583E-15

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 130: Information criteria for Model 126 adding medinc * renwhi interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6571.396
Akaike's Information Criterion (AIC)	6575.396
Hurvich and Tsai's Criterion (AICC)	6575.401
Bozdogan's Criterion (CAIC)	6589.145
Schwarz's Bayesian Criterion (BIC)	6587.145

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 131: Type III tests of fixed effects for Model 126 adding medinc * renwhi interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	969.090	2.670	.103
inczon	1	376.607	2.635	.105
coccat	2	365.573	5.742	.004
pop	0	.	.	.
bach	1	614.615	19.980	.000
medren	1	1313.630	6.918	.009
medval	0	.	.	.
renwhi	1	741.001	.487	.486
renedu	1	861.431	17.780	.000
pov	1	1510.941	9.828	.002
burd	1	2354.652	2.070	.150
vac	1	472.781	5.078	.025
temp	1	2569.130	4.810	.028
hf	1	1523.079	2.043	.153
fund	1	861.325	25.482	.000
pop2	0	.	.	.
hf2	1	2024.881	4.877	.027
yearcoded	1	1718.301	41.885	.000
renocc * hf	1	1105.008	5.411	.020
renocc * hf2	1	1697.695	10.313	.001
medinc * renwhi	0	.	.	.
renwhi * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 132: Fixed effects estimates for Model 126 adding medinc * renwhi interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	2.079370	1.412168	892.002	1.472	.141	-.692189	4.850929
[inczon=0]	-.290950	.179223	376.607	-1.623	.105	-.643354	.061454
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.868570	.346278	360.120	2.508	.013	.187588	1.549551
[coccat=2]	.047284	.313683	374.683	.151	.880	-.569515	.664084
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.001548E-7	1.920340E-7	365.089	-3.646	.000	-1.077786E-6	-3.225233E-7
bach	-.063375	.014178	614.615	-4.470	.000	-.091219	-.035532
medren	.001916	.000729	1313.630	2.630	.009	.000487	.003346
medval	6.015638E-6	9.568300E-7	1039.533	6.287	.000	4.138099E-6	7.893176E-6
renwhi	-.010800	.015483	741.001	-.698	.486	-.041195	.019595
renedu	-.047566	.011280	861.431	-4.217	.000	-.069707	-.025426
pov	.087397	.027879	1510.941	3.135	.002	.032712	.142082
burd	-.034572	.024029	2354.652	-1.439	.150	-.081693	.012549
vac	.026381	.011707	472.781	2.253	.025	.003376	.049386
temp	.005924	.002701	2569.130	2.193	.028	.000627	.011220
hf	-2.864622	2.004345	1523.079	-1.429	.153	-6.796191	1.066946
fund	.066820	.013237	861.325	5.048	.000	.040840	.092801
pop2	7.68318E-14	2.32800E-14	362.436	3.300	.001	3.10508E-14	1.22612E-13
hf2	4.964873	2.248074	2024.881	2.209	.027	.556094	9.373653
yearcoded	-.132690	.020503	1718.301	-6.472	.000	-.172902	-.092477
renocc * hf	.132868	.057122	1105.008	2.326	.020	.020789	.244947
renocc * hf2	-.208869	.065040	1697.695	-3.211	.001	-.336437	-.081301
medinc * renwhi	9.675904E-7	4.537043E-7	822.674	2.133	.033	7.703619E-8	1.858145E-6
renwhi*medinc2	-1.05562E-11	3.39710E-12	820.421	-3.107	.002	-1.72243E-11	-3.88824E-12

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 133: Information criteria for Model 127 adding medinc * renedu interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6571.481
Akaike's Information Criterion (AIC)	6575.481
Hurvich and Tsai's Criterion (AICC)	6575.486
Bozdogan's Criterion (CAIC)	6589.230
Schwarz's Bayesian Criterion (BIC)	6587.230

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 134: Type III tests of fixed effects for Model 127 adding medinc * renedu interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	958.768	3.117	.078
inczon	1	375.296	3.694	.055
coccat	2	364.745	5.690	.004
pop	0	.	.	.
bach	1	608.630	21.727	.000
medren	1	1249.013	6.917	.009
medval	0	.	.	.
renwhi	1	531.923	2.280	.132
renedu	1	946.531	5.962	.015
pov	1	1710.192	4.868	.027
burd	1	2353.514	1.113	.292
vac	1	488.117	3.290	.070
temp	1	2551.307	4.425	.036
hf	1	1544.773	1.859	.173
fund	1	863.141	24.525	.000
pop2	0	.	.	.
hf2	1	2025.009	4.567	.033
yearcoded	1	1780.903	34.527	.000
renocc * hf	1	1142.548	5.081	.024
renocc * hf2	1	1712.275	9.795	.002
medinc * renedu	0	.	.	.
renedu * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 135: Fixed effects estimates for Model 127 adding medinc * renedu interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.292077	1.410453	883.738	1.625	.105	-.476151	5.060306
[inczon=0]	-.343699	.178819	375.296	-1.922	.055	-.695312	.007915
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.857618	.346098	360.597	2.478	.014	.176995	1.538242
[coccat=2]	.039736	.312431	373.482	.127	.899	-.574608	.654080
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.963734E-7	1.913839E-7	364.388	-3.639	.000	-1.072729E-6	-3.200178E-7
bach	-.064856	.013914	608.630	-4.661	.000	-.092181	-.037531
medren	.001931	.000734	1249.013	2.630	.009	.000491	.003372
medval	5.994227E-6	9.547048E-7	1044.166	6.279	.000	4.120869E-6	7.867586E-6
renwhi	.007941	.005259	531.923	1.510	.132	-.002391	.018272
renedu	-.060088	.024608	946.531	-2.442	.015	-.108381	-.011795
pov	.064413	.029195	1710.192	2.206	.027	.007151	.121674
burd	-.025173	.023863	2353.514	-1.055	.292	-.071967	.021622
vac	.021806	.012022	488.117	1.814	.070	-.001815	.045427
temp	.005690	.002705	2551.307	2.104	.036	.000386	.010995
hf	-2.760570	2.024667	1544.773	-1.363	.173	-6.731957	1.210817
fund	.065527	.013232	863.141	4.952	.000	.039557	.091497
pop2	7.64942E-14	2.32215E-14	361.939	3.294	.001	3.08280E-14	1.22160E-13
hf2	4.842355	2.265920	2025.009	2.137	.033	.398577	9.286132
yearcoded	-.121582	.020691	1780.903	-5.876	.000	-.162164	-.081000
renocc * hf	.130629	.057950	1142.548	2.254	.024	.016928	.244330
renocc * hf2	-.205757	.065743	1712.275	-3.130	.002	-.334703	-.076812
medinc * renedu	1.056058E-6	7.105381E-7	897.518	1.486	.138	-3.384520E-7	2.450567E-6
renedu*medinc2	-1.47271E-11	5.83451E-12	842.331	-2.524	.012	-2.61790E-11	-3.27524E-12

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 136: Information criteria for Model 128 adding medinc * pov interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6556.349
Akaike's Information Criterion (AIC)	6560.349
Hurvich and Tsai's Criterion (AICC)	6560.353
Bozdogan's Criterion (CAIC)	6574.098
Schwarz's Bayesian Criterion (BIC)	6572.098

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 137: Type III tests of fixed effects for Model 128 adding medinc * pov interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	933.477	1.092	.296
inczon	1	377.836	2.174	.141
coccat	2	363.200	5.522	.004
pop	0	.	.	.
bach	1	622.696	20.224	.000
medren	1	1173.783	11.814	.001
medval	0	.	.	.
renwhi	1	519.072	5.090	.024
renedu	1	841.350	14.636	.000
pov	1	771.910	4.031	.045
burd	1	2361.943	3.278	.070
vac	1	471.300	3.678	.056
temp	1	2557.363	4.122	.042
hf	1	1574.388	1.885	.170
fund	1	829.335	31.107	.000
pop2	0	.	.	.
hf2	1	2038.227	4.494	.034
yearcoded	1	1789.253	37.538	.000
renocc * hf	1	1151.200	5.102	.024
renocc * hf2	1	1723.350	9.604	.002
medinc * pov	1	1132.128	16.237	.000
pov * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 138: Fixed effects estimates for Model 128 adding medinc * pov interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	1.294006	1.422899	867.000	.909	.363	-1.498724	4.086736
[inczon=0]	-.261414	.177301	377.836	-1.474	.141	-.610035	.087206
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.821879	.340424	359.516	2.414	.016	.152407	1.491351
[coccat=2]	.025252	.306927	370.098	.082	.934	-.578288	.628792
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.527653E-7	1.868220E-7	359.790	-3.494	.001	-1.020166E-6	-2.853651E-7
bach	-.061068	.013579	622.696	-4.497	.000	-.087734	-.034401
medren	.002646	.000770	1173.783	3.437	.001	.001135	.004156
medval	6.418933E-6	9.526470E-7	1064.767	6.738	.000	4.549654E-6	8.288211E-6
renwhi	.011644	.005161	519.072	2.256	.024	.001505	.021783
renedu	-.043129	.011273	841.350	-3.826	.000	-.065257	-.021002
pov	-.118026	.058786	771.910	-2.008	.045	-.233427	-.002626
burd	-.043767	.024175	2361.943	-1.810	.070	-.091173	.003640
vac	.022182	.011567	471.300	1.918	.056	-.000546	.044911
temp	.005494	.002706	2557.363	2.030	.042	.000188	.010800
hf	-2.700150	1.966854	1574.388	-1.373	.170	-6.558079	1.157780
fund	.073645	.013204	829.335	5.577	.000	.047727	.099563
pop2	6.954577E-14	2.272134E-14	358.226	3.061	.002	2.486179E-14	1.142298E-13
hf2	4.725247	2.229008	2038.227	2.120	.034	.353875	9.096618
yearcoded	-.127061	.020739	1789.253	-6.127	.000	-.167736	-.086387
renocc * hf	.126076	.055818	1151.200	2.259	.024	.016559	.235593
renocc * hf2	-.199709	.064442	1723.350	-3.099	.002	-.326103	-.073316
medinc * pov	9.881022E-6	2.452150E-6	1132.128	4.030	.000	5.069752E-6	1.469229E-5
pov * medinc2	-1.115757E-10	2.433721E-11	1290.497	-4.585	.000	-1.593206E-10	-6.383091E-11

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 139: Information criteria for Model 129 adding medinc * burd interaction*

Information Criteria[a]	
-2 Restricted Log Likelihood	6555.636
Akaike's Information Criterion (AIC)	6559.636
Hurvich and Tsai's Criterion (AICC)	6559.641
Bozdogan's Criterion (CAIC)	6573.385
Schwarz's Bayesian Criterion (BIC)	6571.385

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 140: Type III tests of fixed effects for Model 129 adding medinc * burd interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	911.344	1.583	.209
inczon	1	374.587	2.974	.085
coccat	2	363.776	5.359	.005
pop	0	.	.	.
bach	1	627.470	12.573	.000
medren	1	1164.639	16.153	.000
medval	0	.	.	.
renwhi	1	530.489	2.620	.106
renedu	1	846.441	14.564	.000
pov	1	1641.195	4.949	.026
burd	1	1647.991	.243	.622
vac	1	512.056	1.328	.250
temp	1	2524.471	3.185	.074
hf	1	1478.531	.391	.532
fund	1	844.752	27.526	.000
pop2	0	.	.	.
hf2	1	1954.228	2.548	.111
yearcoded	1	1814.500	34.294	.000
renocc * hf	1	1090.961	1.881	.171
renocc * hf2	1	1639.004	6.274	.012
medinc * burd	1	1030.324	.137	.711
burd * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 141: Fixed effects estimates for Model 129 adding medinc * burd interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	1.604093	1.393811	846.370	1.151	.250	-1.131639	4.339824
[inczon=0]	-.302578	.175442	374.587	-1.725	.085	-.647553	.042397
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.774047	.339344	359.550	2.281	.023	.106698	1.441395
[coccat=2]	-.015802	.306039	371.388	-.052	.959	-.617587	.585984
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.228696E-7	1.869683E-7	362.249	-3.866	.000	-1.090549E-6	-3.551901E-7
bach	-.050496	.014241	627.470	-3.546	.000	-.078462	-.022531
medren	.003333	.000829	1164.639	4.019	.000	.001706	.004961
medval	6.290463E-6	9.481405E-7	1043.959	6.635	.000	4.429984E-6	8.150941E-6
renwhi	.008346	.005156	530.489	1.619	.106	-.001783	.018475
renedu	-.042763	.011205	846.441	-3.816	.000	-.064757	-.020770
pov	.064294	.028900	1641.195	2.225	.026	.007609	.120979
burd	-.021544	.043671	1647.991	-.493	.622	-.107200	.064113
vac	.013867	.012032	512.056	1.153	.250	-.009772	.037507
temp	.004856	.002721	2524.471	1.785	.074	-.000480	.010192
hf	-1.268679	2.029812	1478.531	-.625	.532	-5.250297	2.712938
fund	.068598	.013075	844.752	5.247	.000	.042935	.094261
pop2	7.827590E-14	2.269918E-14	360.254	3.448	.001	3.363636E-14	1.229154E-13
hf2	3.612328	2.263207	1954.228	1.596	.111	-.826225	8.050880
yearcoded	-.120501	.020577	1814.500	-5.856	.000	-.160858	-.080144
renocc * hf	.079808	.058194	1090.961	1.371	.171	-.034377	.193994
renocc * hf2	-.164490	.065669	1639.004	-2.505	.012	-.293295	-.035685
medinc * burd	3.810254E-7	1.029536E-6	1030.324	.370	.711	-1.639200E-6	2.401251E-6
burd * medinc2	-1.866524E-11	6.587901E-12	881.393	-2.833	.005	-3.159504E-11	-5.735434E-12

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 142: Information criteria for Model 130 adding medinc * vac interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6559.869
Akaike's Information Criterion (AIC)	6563.869
Hurvich and Tsai's Criterion (AICC)	6563.874
Bozdogan's Criterion (CAIC)	6577.618
Schwarz's Bayesian Criterion (BIC)	6575.618

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 143: Type III tests of fixed effects for Model 130 adding medinc * vac interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	978.910	3.333	.068
inczon	1	376.142	2.675	.103
coccat	2	365.972	5.583	.004
pop	0	.	.	.
bach	1	616.222	23.652	.000
medren	1	1423.419	7.585	.006
medval	0	.	.	.
renwhi	1	523.468	3.242	.072
renedu	1	851.613	19.400	.000
pov	1	1534.098	6.527	.011
burd	1	2360.745	1.771	.183
vac	1	867.835	1.534	.216
temp	1	2568.086	4.323	.038
hf	1	1578.628	3.292	.070
fund	1	856.029	25.731	.000
pop2	0	.	.	.
hf2	1	2059.226	6.297	.012
yearcoded	1	1755.922	39.856	.000
renocc * hf	1	1132.374	7.889	.005
renocc * hf2	1	1730.240	12.766	.000
medinc * vac	1	961.169	6.762	.009
vac * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 144: Fixed effects estimates for Model 130 adding medinc * vac interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.347813	1.390763	896.835	1.688	.092	-.381716	5.077342
[inczon=0]	-.290980	.177907	376.142	-1.636	.103	-.640798	.058838
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.800572	.344546	362.782	2.324	.021	.123013	1.478131
[coccat=2]	-.018239	.311654	375.635	-.059	.953	-.631044	.594566
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.190135E-7	1.901573E-7	365.027	-3.781	.000	-1.092955E-6	-3.450722E-7
bach	-.065442	.013456	616.222	-4.863	.000	-.091868	-.039016
medren	.001895	.000688	1423.419	2.754	.006	.000545	.003245
medval	6.176346E-6	9.530435E-7	1033.186	6.481	.000	4.306225E-6	8.046468E-6
renwhi	.009365	.005201	523.468	1.801	.072	-.000853	.019582
renedu	-.049141	.011157	851.613	-4.405	.000	-.071039	-.027243
pov	.071732	.028078	1534.098	2.555	.011	.016656	.126807
burd	-.031701	.023818	2360.745	-1.331	.183	-.078408	.015005
vac	-.095019	.076715	867.835	-1.239	.216	-.245588	.055550
temp	.005614	.002700	2568.086	2.079	.038	.000319	.010910
hf	-3.544358	1.953493	1578.628	-1.814	.070	-7.376072	.287356
fund	.066912	.013191	856.029	5.073	.000	.041022	.092803
pop2	7.839020E-14	2.307199E-14	361.721	3.398	.001	3.301813E-14	1.237623E-13
hf2	5.574422	2.221432	2059.226	2.509	.012	1.217935	9.930910
yearcoded	-.127574	.020208	1755.922	-6.313	.000	-.167208	-.087940
renocc * hf	.155100	.055222	1132.374	2.809	.005	.046751	.263449
renocc * hf2	-.229056	.064108	1730.240	-3.573	.000	-.354792	-.103319
medinc * vac	6.578615E-6	2.529785E-6	961.169	2.600	.009	1.614077E-6	1.154315E-5
vac * medinc2	-7.789349E-11	2.222740E-11	1115.007	-3.504	.000	-1.215057E-10	-3.428124E-11

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 145: Information criteria for Model 132 adding medinc * hf interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6603.937
Akaike's Information Criterion (AIC)	6607.937
Hurvich and Tsai's Criterion (AICC)	6607.941
Bozdogan's Criterion (CAIC)	6621.684
Schwarz's Bayesian Criterion (BIC)	6619.684

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 146: Type III tests of fixed effects for Model 132 adding medinc * hf interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	945.312	3.200	.074
inczon	1	368.348	3.082	.080
coccat	2	357.120	5.672	.004
pop	0	.	.	.
bach	1	638.426	21.134	.000
medren	1	1454.157	8.994	.003
medval	0	.	.	.
renwhi	1	519.455	3.069	.080
renedu	1	833.044	19.053	.000
pov	1	1650.952	8.434	.004
burd	1	2419.057	2.938	.087
vac	1	492.445	3.637	.057
temp	1	2543.228	4.580	.032
hf	1	1549.892	3.262	.071
fund	1	837.930	26.411	.000
pop2	0	.	.	.
hf2	1	2067.783	5.883	.015
yearcoded	1	1814.730	39.470	.000
renocc * hf	1	1120.877	4.940	.026
renocc * hf2	1	1685.018	10.349	.001
medinc * hf	1	1477.479	3.773	.052
medinc * hf2	1	1975.790	4.337	.037
hf * medinc2	0	.	.	.
medinc2 * hf2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 147: Fixed effects estimates for Model 132 adding medinc * hf interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.264449	1.391422	869.004	1.627	.104	-.466491	4.995389
[inczon=0]	-.310666	.176954	368.348	-1.756	.080	-.658632	.037300
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.861643	.342094	353.495	2.519	.012	.188846	1.534439
[coccat=2]	.057952	.308472	364.434	.188	.851	-.548656	.664561
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.732020E-7	1.887162E-7	356.354	-3.567	.000	-1.044339E-6	-3.020646E-7
bach	-.063234	.013755	638.426	-4.597	.000	-.090245	-.036223
medren	.002251	.000751	1454.157	2.999	.003	.000779	.003723
medval	5.959137E-6	9.600909E-7	1057.094	6.207	.000	4.075237E-6	7.843038E-6
renwhi	.009110	.005200	519.455	1.752	.080	-.001106	.019326
renedu	-.048602	.011135	833.044	-4.365	.000	-.070457	-.026747
pov	.082035	.028248	1650.952	2.904	.004	.026630	.137441
burd	-.041570	.024254	2419.057	-1.714	.087	-.089131	.005991
vac	.022477	.011786	492.445	1.907	.057	-.000681	.045634
temp	.005802	.002711	2543.228	2.140	.032	.000486	.011119
hf	-10.061591	5.571077	1549.892	-1.806	.071	-20.989235	.866052
fund	.067900	.013212	837.930	5.139	.000	.041967	.093833
pop2	7.39970E-14	2.29541E-14	355.135	3.224	.001	2.885400E-14	1.191402E-13
hf2	16.789217	6.922060	2067.783	2.425	.015	3.214282	30.364151
yearcoded	-.129237	.020571	1814.730	-6.283	.000	-.169582	-.088892
renocc * hf	.126201	.056783	1120.877	2.223	.026	.014788	.237614
renocc * hf2	-.208547	.064827	1685.018	-3.217	.001	-.335697	-.081396
medinc * hf	.000303	.000156	1477.479	1.942	.052	-2.989829E-6	.000609
medinc * hf2	-.000424	.000204	1975.790	-2.083	.037	-.000823	-2.470244E-5
hf * medinc2	-3.009604E-9	1.111687E-9	1322.890	-2.707	.007	-5.190467E-9	-8.28741E-10
medinc2 * hf2	3.682995E-9	1.512114E-9	1817.664	2.436	.015	7.173309E-10	6.648659E-9

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 148: Information criteria for Model 133 adding medinc * fund interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6562.545
Akaike's Information Criterion (AIC)	6566.545
Hurvich and Tsai's Criterion (AICC)	6566.549
Bozdogan's Criterion (CAIC)	6580.294
Schwarz's Bayesian Criterion (BIC)	6578.294

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 149: Type III tests of fixed effects for Model 133 adding medinc * fund interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	957.665	4.630	.032
inczon	1	374.375	2.506	.114
coccat	2	362.998	5.439	.005
pop	0	.	.	.
bach	1	564.804	38.087	.000
medren	1	1272.533	3.159	.076
medval	0	.	.	.
renwhi	1	513.837	4.265	.039
renedu	1	821.403	23.279	.000
pov	1	1299.363	13.343	.000
burd	1	2244.577	1.417	.234
vac	1	442.724	9.349	.002
temp	1	2583.038	5.139	.023
hf	1	1562.299	3.904	.048
fund	1	928.388	2.073	.150
pop2	0	.	.	.
hf2	1	2053.962	6.703	.010
yearcoded	1	1766.790	45.406	.000
renocc * hf	1	1086.310	9.426	.002
renocc * hf2	1	1710.207	13.733	.000
medinc * fund	1	1093.832	6.913	.009
fund * medinc2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 150: Fixed effects estimates for Model 133 adding medinc * fund interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.670148	1.372539	874.553	1.945	.052	-.023707	5.364003
[inczon=0]	-.282274	.178307	374.375	-1.583	.114	-.632883	.068335
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.884656	.343970	359.782	2.572	.011	.208211	1.561100
[coccat=2]	.105859	.309802	370.041	.342	.733	-.503335	.715053
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.924213E-7	1.890843E-7	359.016	-3.133	.002	-9.642734E-7	-2.205693E-7
bach	-.079882	.012944	564.804	-6.171	.000	-.105305	-.054458
medren	.001127	.000634	1272.533	1.777	.076	-.000117	.002370
medval	6.531240E-6	9.872575E-7	1133.350	6.616	.000	4.594182E-6	8.468298E-6
renwhi	.010747	.005204	513.837	2.065	.039	.000523	.020971
renedu	-.053412	.011070	821.403	-4.825	.000	-.075141	-.031683
pov	.092357	.025284	1299.363	3.653	.000	.042755	.141958
burd	-.028063	.023577	2244.577	-1.190	.234	-.074297	.018171
vac	.034325	.011226	442.724	3.058	.002	.012262	.056388
temp	.006106	.002694	2583.038	2.267	.023	.000824	.011388
hf	-3.826815	1.936847	1562.299	-1.976	.048	-7.625909	-.027721
fund	-.136927	.095094	928.388	-1.440	.150	-.323550	.049697
pop2	6.416077E-14	2.30598E-14	359.209	2.782	.006	1.881153E-14	1.095100E-13
hf2	5.725348	2.211370	2053.962	2.589	.010	1.388586	10.062110
yearcoded	-.132699	.019693	1766.790	-6.738	.000	-.171323	-.094075
renocc * hf	.166942	.054377	1086.310	3.070	.002	.060247	.273637
renocc * hf2	-.235802	.063630	1710.207	-3.706	.000	-.360602	-.111002
medinc * fund	7.667060E-6	2.916012E-6	1093.832	2.629	.009	1.945451E-6	1.338867E-5
fund * medinc2	-6.37810E-11	2.02370E-11	1332.346	-3.152	.002	-1.03480E-10	-2.40812E-11

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 151: Information criteria for Model 134 adding medinc * yearcoded interaction*

Information Criteria[a]	
-2 Restricted Log Likelihood	6566.855
Akaike's Information Criterion (AIC)	6570.855
Hurvich and Tsai's Criterion (AICC)	6570.859
Bozdogan's Criterion (CAIC)	6584.603
Schwarz's Bayesian Criterion (BIC)	6582.603

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 152: Type III tests of fixed effects for Model 134 adding medinc * yearcoded interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	972.595	4.911	.027
inczon	1	373.680	3.386	.067
coccat	2	362.524	5.801	.003
pop	0	.	.	.
bach	1	588.533	35.388	.000
medren	1	1279.397	1.438	.231
medval	0	.	.	.
renwhi	1	519.493	3.596	.058
renedu	1	835.292	22.680	.000
pov	1	1412.772	13.926	.000
burd	1	2290.118	.858	.354
vac	1	452.944	9.537	.002
temp	1	2573.840	5.309	.021
hf	1	1584.499	3.967	.047
fund	1	860.810	23.961	.000
pop2	0	.	.	.
hf2	1	2072.832	6.550	.011
yearcoded	1	1878.093	14.937	.000
renocc * hf	1	1115.112	9.548	.002
renocc * hf2	1	1728.872	13.476	.000
medinc * yearcoded	1	1813.655	9.675	.002
medinc2 * yearcoded	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 153: Fixed effects estimates for Model 134 adding medinc * yearcoded interaction

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	2.804722	1.396521	889.579	2.008	.045	.063862	5.545581
[inczon=0]	-.330741	.179734	373.680	-1.840	.067	-.684157	.022676
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.941061	.347434	359.328	2.709	.007	.257803	1.624320
[coccat=2]	.138048	.313812	369.557	.440	.660	-.479033	.755130
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.19839E-7	1.91098E-7	358.096	-3.244	.001	-9.95655E-7	-2.44023E-7
bach	-.078547	.013204	588.533	-5.949	.000	-.104480	-.052615
medren	.000837	.000698	1279.397	1.199	.231	-.000533	.002208
medval	6.172096E-6	9.69017E-7	1025.121	6.369	.000	4.270611E-6	8.073580E-6
renwhi	.009950	.005247	519.493	1.896	.058	-.000358	.020258
renedu	-.053543	.011243	835.292	-4.762	.000	-.075611	-.031475
pov	.098148	.026301	1412.772	3.732	.000	.046555	.149741
burd	-.021982	.023731	2290.118	-.926	.354	-.068519	.024554
vac	.035385	.011458	452.944	3.088	.002	.012867	.057902
temp	.006212	.002696	2573.840	2.304	.021	.000926	.011499
hf	-3.895937	1.956175	1584.499	-1.992	.047	-7.732900	-.058973
fund	.065369	.013354	860.810	4.895	.000	.039158	.091580
pop2	6.84472E-14	2.3272E-14	357.233	2.941	.003	2.26792E-14	1.14215E-13
hf2	5.693711	2.224647	2072.832	2.559	.011	1.330935	10.056488
yearcoded	-.534461	.138288	1878.093	-3.865	.000	-.805674	-.263247
renocc * hf	.170222	.055089	1115.112	3.090	.002	.062133	.278311
renocc * hf2	-.235185	.064065	1728.872	-3.671	.000	-.360839	-.109531
medinc * yearcoded	1.235730E-5	3.97276E-6	1813.655	3.111	.002	4.565631E-6	2.014897E-5
medinc2 * yearcoded	-8.7904E-11	2.7536E-11	1824.373	-3.192	.001	-1.4191E-10	-3.3897E-11

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 154: Information criteria for Model 135 removing burd

Information Criteria[a]

-2 Restricted Log Likelihood	6498.810
Akaike's Information Criterion (AIC)	6502.810
Hurvich and Tsai's Criterion (AICC)	6502.815
Bozdogan's Criterion (CAIC)	6516.561
Schwarz's Bayesian Criterion (BIC)	6514.561

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 155: Type III tests of fixed effects for Model 135 removing burd

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	887.019	6.856	.009
inczon	1	372.049	3.992	.046
coccat	2	360.604	6.083	.003
pop	0	.	.	.
bach	1	563.148	38.647	.000
medren	1	1170.144	.800	.371
medval	0	.	.	.
renwhi	1	523.214	3.084	.080
renedu	1	833.008	23.868	.000
pov	1	1030.524	7.741	.005
vac	1	446.843	9.430	.002
temp	1	2582.354	5.370	.021
hf	1	1491.068	6.764	.009
fund	1	874.045	23.022	.000
pop2	0	.	.	.
hf2	1	2024.655	9.229	.002
yearcoded	1	1661.592	44.233	.000
renocc * hf	1	1031.913	14.447	.000
renocc * hf2	1	1679.789	17.625	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 156: Fixed effects estimates for Model 135 removing burd

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.131270	1.315059	813.743	2.381	.017	.549963	5.712578
[inczon=0]	-.355458	.177911	372.049	-1.998	.046	-.705296	-.005620
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.945704	.346063	360.318	2.733	.007	.265147	1.626261
[coccat=2]	.113853	.309303	362.042	.368	.713	-.494404	.722110
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.100333E-7	1.909559E-7	361.572	-3.195	.002	-9.855571E-7	-2.345095E-7
bach	-.080971	.013025	563.148	-6.217	.000	-.106554	-.055388
medren	.000525	.000588	1170.144	.894	.371	-.000627	.001678
medval	5.919344E-6	9.539859E-7	1050.821	6.205	.000	4.047410E-6	7.791278E-6
renwhi	.009202	.005240	523.214	1.756	.080	-.001092	.019495
renedu	-.054420	.011139	833.008	-4.885	.000	-.076284	-.032556
pov	.060745	.021833	1030.524	2.782	.005	.017903	.103588
vac	.034714	.011304	446.843	3.071	.002	.012498	.056931
temp	.006253	.002698	2582.354	2.317	.021	.000962	.011544
hf	-4.971713	1.911653	1491.068	-2.601	.009	-8.721527	-1.221899
fund	.063694	.013275	874.045	4.798	.000	.037640	.089748
pop2	6.86170E-14	2.32793E-14	361.346	2.948	.003	2.283709E-14	1.143970E-13
hf2	6.676000	2.197537	2024.655	3.038	.002	2.366330	10.985670
yearcoded	-.122312	.018391	1661.592	-6.651	.000	-.158383	-.086241
renocc * hf	.203803	.053618	1031.913	3.801	.000	.098589	.309016
renocc * hf2	-.265436	.063227	1679.789	-4.198	.000	-.389448	-.141425

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 157: Information criteria for Model 141 adding medval * burd interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6524.730
Akaike's Information Criterion (AIC)	6528.730
Hurvich and Tsai's Criterion (AICC)	6528.735
Bozdogan's Criterion (CAIC)	6542.480
Schwarz's Bayesian Criterion (BIC)	6540.480

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 158: Type III tests of fixed effects adding medval * burd interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	870.418	8.552	.004
inczon	1	375.900	2.825	.094
coccat	2	361.086	6.378	.002
pop	0	.	.	.
bach	1	572.550	34.607	.000
medren	1	1154.472	.094	.760
medval	1	1337.048	.002	.964
renwhi	1	516.915	2.897	.089
renedu	1	817.352	23.596	.000
pov	1	1055.431	3.631	.057
vac	1	440.255	9.211	.003
temp	1	2585.655	5.472	.019
hf	1	1487.777	7.786	.005
fund	1	847.771	24.937	.000
pop2	0	.	.	.
hf2	1	2004.482	10.112	.001
yearcoded	1	1638.989	37.085	.000
renocc * hf	1	1017.199	15.836	.000
renocc * hf2	1	1652.094	18.791	.000
medval * burd	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 159: Fixed effects estimates for Model 141 adding medval * burd interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.559247	1.320525	801.219	2.695	.007	.967150	6.151344
[inczon=0]	-.298441	.177573	375.900	-1.681	.094	-.647601	.050719
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.882171	.342673	358.304	2.574	.010	.208268	1.556074
[coccat=2]	.014430	.308674	366.288	.047	.963	-.592567	.621426
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.127592E-7	1.885128E-7	357.813	-3.250	.001	-9.834914E-7	-2.420270E-7
bach	-.076722	.013042	572.550	-5.883	.000	-.102338	-.051106
medren	.000185	.000605	1154.472	.306	.760	-.001002	.001372
medval	-1.309192E-7	2.920383E-6	1337.048	-.045	.964	-5.859951E-6	5.598113E-6
renwhi	.008833	.005189	516.915	1.702	.089	-.001362	.019028
renedu	-.053714	.011058	817.352	-4.858	.000	-.075419	-.032009
pov	.043968	.023073	1055.431	1.906	.057	-.001306	.089242
vac	.033930	.011180	440.255	3.035	.003	.011957	.055902
temp	.006312	.002698	2585.655	2.339	.019	.001021	.011603
hf	-5.330299	1.910207	1487.777	-2.790	.005	-9.077284	-1.583313
fund	.065861	.013189	847.771	4.994	.000	.039975	.091748
pop2	6.682861E-14	2.299212E-14	357.758	2.907	.004	2.161192E-14	1.120453E-13
hf2	6.980433	2.195102	2004.482	3.180	.001	2.675513	11.285353
yearcoded	-.114016	.018723	1638.989	-6.090	.000	-.150739	-.077293
renocc * hf	.212564	.053415	1017.199	3.979	.000	.107748	.317379
renocc * hf2	-.273326	.063054	1652.094	-4.335	.000	-.397000	-.149652
medval * burd	1.997317E-7	9.125471E-8	1334.543	2.189	.029	2.071343E-8	3.787500E-7

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 160: Information criteria for Model 150 removing medren

Information Criteria[a]

-2 Restricted Log Likelihood	6486.568
Akaike's Information Criterion (AIC)	6490.568
Hurvich and Tsai's Criterion (AICC)	6490.573
Bozdogan's Criterion (CAIC)	6504.320
Schwarz's Bayesian Criterion (BIC)	6502.320

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 161: Type III tests of fixed effects for Model 150 removing medren

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	737.155	11.404	.001
inczon	1	375.552	5.025	.026
coccat	2	360.392	5.945	.003
pop	0	.	.	.
bach	1	576.206	37.998	.000
medval	0	.	.	.
renwhi	1	434.444	2.330	.128
renedu	1	817.899	26.027	.000
pov	1	902.463	7.016	.008
vac	1	442.591	9.879	.002
temp	1	2586.171	5.431	.020
hf	1	1486.460	6.417	.011
fund	1	870.768	22.613	.000
pop2	0	.	.	.
hf2	1	2019.339	8.847	.003
yearcoded	1	1811.159	55.362	.000
renocc * hf	1	1033.016	14.043	.000
renocc * hf2	1	1679.445	17.201	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 162: Fixed effects estimates for Model 150 removing medren

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	3.636592	1.188484	683.169	3.060	.002	1.303072	5.970112
[inczon=0]	-.389735	.173858	375.552	-2.242	.026	-.731593	-.047878
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.962887	.345800	360.014	2.785	.006	.282845	1.642929
[coccat=2]	.153862	.306276	360.196	.502	.616	-.448451	.756175
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.946172E-7	1.903056E-7	362.748	-3.125	.002	-9.688581E-7	-2.203763E-7
bach	-.080117	.012997	576.206	-6.164	.000	-.105644	-.054589
medval	6.448734E-6	7.482612E-7	659.010	8.618	.000	4.979471E-6	7.917997E-6
renwhi	.007369	.004828	434.444	1.526	.128	-.002120	.016858
renedu	-.056063	.010989	817.899	-5.102	.000	-.077633	-.034493
pov	.056462	.021316	902.463	2.649	.008	.014628	.098296
vac	.035458	.011281	442.591	3.143	.002	.013286	.057630
temp	.006287	.002698	2586.171	2.330	.020	.000997	.011577
hf	-4.825482	1.904925	1486.460	-2.533	.011	-8.562108	-1.088855
fund	.063078	.013265	870.768	4.755	.000	.037044	.089113
pop2	6.697828E-14	2.322309E-14	361.672	2.884	.004	2.130903E-14	1.126475E-13
hf2	6.514962	2.190307	2019.339	2.974	.003	2.219466	10.810459
yearcoded	-.113029	.015191	1811.159	-7.441	.000	-.142822	-.083235
renocc * hf	.200522	.053510	1033.016	3.747	.000	.095522	.305523
renocc * hf2	-.261708	.063101	1679.445	-4.147	.000	-.385473	-.137943

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 163: Information criteria for Model 155 adding medren * medval interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6517.769
Akaike's Information Criterion (AIC)	6521.769
Hurvich and Tsai's Criterion (AICC)	6521.774
Bozdogan's Criterion (CAIC)	6535.520
Schwarz's Bayesian Criterion (BIC)	6533.520

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 164: Type III tests of fixed effects for Model 155 adding medren * medval interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	732.362	7.999	.005
inczon	1	376.664	4.576	.033
coccat	2	359.586	5.620	.004
pop	0	.	.	.
bach	1	567.959	35.864	.000
medval	1	1316.579	36.446	.000
renwhi	1	437.600	1.589	.208
renedu	1	803.106	27.142	.000
pov	1	881.767	9.263	.002
vac	1	439.687	10.075	.002
temp	1	2592.698	5.158	.023
hf	1	1485.332	4.496	.034
fund	1	841.050	26.502	.000
pop2	0	.	.	.
hf2	1	2015.985	6.744	.009
yearcoded	1	1777.758	36.493	.000
renocc * hf	1	1048.024	10.559	.001
renocc * hf2	1	1688.765	13.843	.000
medren * medval	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 165: Fixed effects estimates for Model 155 adding medren * medval interaction

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	3.020641	1.195742	682.652	2.526	.012	.672866	5.368415
[inczon=0]	-.367516	.171796	376.664	-2.139	.033	-.705316	-.029717
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.951206	.341271	359.286	2.787	.006	.280066	1.622345
[coccat=2]	.188172	.302490	360.051	.622	.534	-.406697	.783041
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.597886E-7	1.881715E-7	362.737	-2.975	.003	-9.298326E-7	-1.897447E-7
bach	-.077269	.012903	567.959	-5.989	.000	-.102612	-.051927
medval	1.155605E-5	1.914180E-6	1316.579	6.037	.000	7.800875E-6	1.531123E-5
renwhi	.006045	.004795	437.600	1.261	.208	-.003380	.015470
renedu	-.056779	.010899	803.106	-5.210	.000	-.078173	-.035386
pov	.064924	.021332	881.767	3.044	.002	.023057	.106791
vac	.035387	.011148	439.687	3.174	.002	.013476	.057297
temp	.006126	.002697	2592.698	2.271	.023	.000837	.011415
hf	-4.053821	1.911879	1485.332	-2.120	.034	-7.804090	-.303552
fund	.068182	.013244	841.050	5.148	.000	.042186	.094177
pop2	6.22685E-14	2.29726E-14	362.386	2.711	.007	1.70921E-14	1.07445E-13
hf2	5.709165	2.198379	2015.985	2.597	.009	1.397833	10.020497
yearcoded	-.097235	.016096	1777.758	-6.041	.000	-.128803	-.065666
renocc * hf	.174939	.053837	1048.024	3.249	.001	.069298	.280580
renocc * hf2	-.235941	.063414	1688.765	-3.721	.000	-.360319	-.111563
medren*medval	-3.15287E-9	1.090251E-9	1297.199	-2.892	.004	-5.291720E-9	-1.014023E-9

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 166: Information criteria for Model 156 adding medren * renwhi interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6501.315
Akaike's Information Criterion (AIC)	6505.315
Hurvich and Tsai's Criterion (AICC)	6505.320
Bozdogan's Criterion (CAIC)	6519.066
Schwarz's Bayesian Criterion (BIC)	6517.066

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 167: Type III tests of fixed effects for Model 156 adding medren * renwhi interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	736.935	10.417	.001
inczon	1	370.593	3.145	.077
coccat	2	358.975	6.139	.002
pop	0	.	.	.
bach	1	559.338	41.454	.000
medval	0	.	.	.
renwhi	1	562.308	.838	.360
renedu	1	820.274	20.461	.000
pov	1	940.300	9.217	.002
vac	1	443.806	8.386	.004
temp	1	2576.464	5.015	.025
hf	1	1490.419	7.873	.005
fund	1	861.331	24.749	.000
pop2	0	.	.	.
hf2	1	2016.881	10.113	.001
yearcoded	1	1532.268	60.861	.000
renocc * hf	1	1026.904	15.966	.000
renocc * hf2	1	1668.707	18.657	.000
medren * renwhi	1	819.964	6.863	.009

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 168: Fixed effects estimates for Model 156 adding medren * renwhi interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.450487	1.181137	682.776	2.921	.004	1.131390	5.769583
[inczon=0]	-.309757	.174676	370.593	-1.773	.077	-.653237	.033723
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.911919	.342479	359.570	2.663	.008	.238406	1.585432
[coccat=2]	.075174	.304395	358.830	.247	.805	-.523449	.673797
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.010333E-7	1.882444E-7	361.296	-3.193	.002	-9.712256E-7	-2.308410E-7
bach	-.083331	.012943	559.338	-6.439	.000	-.108754	-.057909
medval	5.210784E-6	8.805831E-7	822.753	5.917	.000	3.482330E-6	6.939237E-6
renwhi	-.006564	.007171	562.308	-.915	.360	-.020649	.007521
renedu	-.050372	.011136	820.274	-4.523	.000	-.072231	-.028514
pov	.064988	.021407	940.300	3.036	.002	.022978	.106998
vac	.032505	.011225	443.806	2.896	.004	.010444	.054565
temp	.006045	.002699	2576.464	2.239	.025	.000752	.011338
hf	-5.353025	1.907777	1490.419	-2.806	.005	-9.095239	-1.610812
fund	.065651	.013197	861.331	4.975	.000	.039750	.091553
pop2	6.90614E-14	2.29841E-14	359.972	3.005	.003	2.386148E-14	1.14261E-13
hf2	6.965900	2.190436	2016.881	3.180	.001	2.670147	11.261654
yearcoded	-.135461	.017364	1532.268	-7.801	.000	-.169521	-.101402
renocc * hf	.213476	.053426	1026.904	3.996	.000	.108640	.318312
renocc * hf2	-.271980	.062967	1668.707	-4.319	.000	-.395483	-.148477
medren * renwhi	2.219553E-5	8.472744E-6	819.964	2.620	.009	5.564710E-6	3.882635E-5

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 169: Information criteria for Model 158 adding medren * pov interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6495.428
Akaike's Information Criterion (AIC)	6499.428
Hurvich and Tsai's Criterion (AICC)	6499.432
Bozdogan's Criterion (CAIC)	6513.179
Schwarz's Bayesian Criterion (BIC)	6511.179

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 170: Type III tests of fixed effects for Model 158 adding medren * pov interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	748.769	9.224	.002
inczon	1	373.058	1.988	.159
coccat	2	360.598	6.028	.003
pop	0	.	.	.
bach	1	589.488	35.619	.000
medval	0	.	.	.
renwhi	1	465.202	5.507	.019
renedu	1	826.320	20.678	.000
pov	1	700.687	.559	.455
vac	1	447.275	7.844	.005
temp	1	2583.158	5.035	.025
hf	1	1473.046	5.350	.021
fund	1	855.001	24.680	.000
pop2	0	.	.	.
hf2	1	2000.798	8.453	.004
yearcoded	1	1563.814	64.561	.000
renocc * hf	1	1040.385	11.210	.001
renocc * hf2	1	1665.943	15.790	.000
medren * pov	1	1004.633	9.773	.002

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 171: Fixed effects estimates for Model 158 adding medren * pov interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	3.261887	1.180979	690.817	2.762	.006	.943148	5.580625
[inczon=0]	-.249553	.176988	373.058	-1.410	.159	-.597572	.098465
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.837612	.342598	360.952	2.445	.015	.163874	1.511351
[coccat=2]	-.006589	.305855	362.996	-.022	.983	-.608058	.594881
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.569069E-7	1.884754E-7	362.179	-3.485	.001	-1.027551E-6	-2.862632E-7
bach	-.076883	.012882	589.488	-5.968	.000	-.102184	-.051583
medval	5.347256E-6	8.200185E-7	826.970	6.521	.000	3.737693E-6	6.956818E-6
renwhi	.011591	.004939	465.202	2.347	.019	.001885	.021298
renedu	-.050239	.011048	826.320	-4.547	.000	-.071925	-.028554
pov	-.025187	.033691	700.687	-.748	.455	-.091335	.040961
vac	.031363	.011198	447.275	2.801	.005	.009356	.053370
temp	.006054	.002698	2583.158	2.244	.025	.000763	.011344
hf	-4.387754	1.896939	1473.046	-2.313	.021	-8.108745	-.666764
fund	.065303	.013145	855.001	4.968	.000	.039503	.091103
pop2	7.076270E-14	2.289858E-14	360.112	3.090	.002	2.573096E-14	1.157944E-13
hf2	6.339456	2.180492	2000.798	2.907	.004	2.063184	10.615728
yearcoded	-.141480	.017608	1563.814	-8.035	.000	-.176017	-.106942
renocc * hf	.179054	.053479	1040.385	3.348	.001	.074115	.283992
renocc * hf2	-.249730	.062846	1665.943	-3.974	.000	-.372997	-.126464
medren * pov	.000123	3.927192E-5	1004.633	3.126	.002	4.570660E-5	.000200

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 172: Information criteria for Model 159 adding medren * vac interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6496.511
Akaike's Information Criterion (AIC)	6500.511
Hurvich and Tsai's Criterion (AICC)	6500.516
Bozdogan's Criterion (CAIC)	6514.262
Schwarz's Bayesian Criterion (BIC)	6512.262

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 173: Type III tests of fixed effects for Model 159 adding medren * vac interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	731.017	10.247	.001
inczon	1	370.459	3.340	.068
coccat	2	358.777	6.309	.002
pop	0	.	.	.
bach	1	567.519	38.995	.000
medval	0	.	.	.
renwhi	1	452.256	5.032	.025
renedu	1	804.002	21.964	.000
pov	1	978.303	11.100	.001
vac	1	692.624	2.914	.088
temp	1	2576.312	4.665	.031
hf	1	1467.766	6.315	.012
fund	1	849.387	25.282	.000
pop2	0	.	.	.
hf2	1	1999.958	9.052	.003
yearcoded	1	1666.435	65.213	.000
renocc * hf	1	1016.894	13.133	.000
renocc * hf2	1	1654.524	16.773	.000
medren * vac	1	707.213	9.298	.002

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 174: Fixed effects estimates for Model 159 adding medren * vac interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.416004	1.175257	677.533	2.907	.004	1.108421	5.723587
[inczon=0]	-.315321	.172524	370.459	-1.828	.068	-.654570	.023928
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.903861	.340010	358.375	2.658	.008	.235194	1.572527
[coccat=2]	.056515	.302442	358.997	.187	.852	-.538265	.651296
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.285754E-7	1.872585E-7	360.187	-3.357	.001	-9.968326E-7	-2.603181E-7
bach	-.080024	.012815	567.519	-6.245	.000	-.105194	-.054853
medval	5.724649E-6	7.762778E-7	671.692	7.374	.000	4.200426E-6	7.248872E-6
renwhi	.010954	.004884	452.256	2.243	.025	.001357	.020552
renedu	-.051451	.010978	804.002	-4.687	.000	-.073000	-.029901
pov	.072196	.021670	978.303	3.332	.001	.029672	.114721
vac	-.052941	.031015	692.624	-1.707	.088	-.113835	.007953
temp	.005839	.002703	2576.312	2.160	.031	.000538	.011141
hf	-4.751981	1.890942	1467.766	-2.513	.012	-8.461218	-1.042743
fund	.066042	.013135	849.387	5.028	.000	.040262	.091822
pop2	7.076686E-14	2.284331E-14	359.300	3.098	.002	2.584347E-14	1.156903E-13
hf2	6.556069	2.179028	1999.958	3.009	.003	2.282666	10.829472
yearcoded	-.128228	.015879	1666.435	-8.075	.000	-.159372	-.097083
renocc * hf	.192248	.053048	1016.894	3.624	.000	.088151	.296345
renocc * hf2	-.256817	.062707	1654.524	-4.095	.000	-.379810	-.133823
medren * vac	9.134685E-5	2.995657E-5	707.213	3.049	.002	3.253240E-5	.000150

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 175: Information criteria for Model 164 removing renwhi

Information Criteria[a]

-2 Restricted Log Likelihood	6480.055
Akaike's Information Criterion (AIC)	6484.055
Hurvich and Tsai's Criterion (AICC)	6484.060
Bozdogan's Criterion (CAIC)	6497.808
Schwarz's Bayesian Criterion (BIC)	6495.808

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 176: Type III tests of fixed effects for Model 164 removing renwhi

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	744.116	25.514	.000
inczon	1	378.980	4.777	.029
coccat	2	367.144	5.342	.005
pop	0	.	.	.
bach	1	559.092	42.153	.000
medval	0	.	.	.
renedu	1	782.603	31.688	.000
pov	1	910.644	5.854	.016
vac	1	442.221	10.751	.001
temp	1	2612.282	4.437	.035
hf	1	1531.778	5.138	.024
fund	1	877.764	22.667	.000
pop2	0	.	.	.
hf2	1	2061.418	7.641	.006
yearcoded	1	1832.813	56.569	.000
renocc * hf	1	1055.946	12.080	.001
renocc * hf2	1	1724.433	15.440	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 177: Fixed effects estimates for Model 164 removing renwhi

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	4.661186	.983429	691.081	4.740	.000	2.730318	6.592053
[inczon=0]	-.381389	.174498	378.980	-2.186	.029	-.724495	-.038283
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.841094	.337620	370.695	2.491	.013	.177203	1.504985
[coccat=2]	.048808	.299666	368.667	.163	.871	-.540460	.638077
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.755968E-7	1.835839E-7	367.950	-3.680	.000	-1.036602E-6	-3.145914E-7
bach	-.083441	.012852	559.092	-6.493	.000	-.108684	-.058197
medval	6.286443E-6	7.429514E-7	671.283	8.461	.000	4.827655E-6	7.745231E-6
renedu	-.060117	.010679	782.603	-5.629	.000	-.081081	-.039153
pov	.050990	.021074	910.644	2.420	.016	.009630	.092350
vac	.036987	.011281	442.221	3.279	.001	.014817	.059157
temp	.005614	.002665	2612.282	2.107	.035	.000388	.010841
hf	-4.229334	1.865812	1531.778	-2.267	.024	-7.889151	-.569517
fund	.063296	.013295	877.764	4.761	.000	.037203	.089390
pop2	7.58203E-14	2.25899E-14	363.840	3.356	.001	3.139699E-14	1.202437E-13
hf2	5.979891	2.163359	2061.418	2.764	.006	1.737295	10.222488
yearcoded	-.114235	.015188	1832.813	-7.521	.000	-.144023	-.084447
renocc * hf	.180717	.051995	1055.946	3.476	.001	.078693	.282742
renocc * hf2	-.244017	.062100	1724.433	-3.929	.000	-.365817	-.122218

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 178: Information criteria for Model 167 adding pop * renwhi interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6575.869
Akaike's Information Criterion (AIC)	6579.869
Hurvich and Tsai's Criterion (AICC)	6579.874
Bozdogan's Criterion (CAIC)	6593.620
Schwarz's Bayesian Criterion (BIC)	6591.620

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 179: Type III tests of fixed effects for Model 167 adding pop * renwhi interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	740.140	19.380	.000
inczon	1	376.608	4.926	.027
coccat	2	359.599	8.270	.000
pop	0	.	.	.
bach	1	556.950	41.335	.000
medval	0	.	.	.
renedu	1	779.500	28.362	.000
pov	1	895.101	7.143	.008
vac	1	437.330	11.941	.001
temp	1	2608.978	5.566	.018
hf	1	1500.707	6.613	.010
fund	1	865.453	22.628	.000
pop2	0	.	.	.
hf2	1	2036.674	8.979	.003
yearcoded	1	1810.052	55.774	.000
renocc * hf	1	1032.252	14.634	.000
renocc * hf2	1	1695.862	17.486	.000
pop * renwhi	0	.	.	.
renwhi * pop2	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 180: Fixed effects estimates for Model 167 adding pop * renwhi interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	3.873056	1.034192	677.422	3.745	.000	1.842449	5.903664
[inczon=0]	-.383559	.172810	376.608	-2.220	.027	-.723353	-.043764
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	1.341180	.377252	358.718	3.555	.000	.599277	2.083083
[coccat=2]	.425116	.327059	357.955	1.300	.195	-.218082	1.068314
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-1.435312E-6	3.483569E-7	384.044	-4.120	.000	-2.120237E-6	-7.503865E-7
bach	-.082101	.012770	556.950	-6.429	.000	-.107184	-.057018
medval	6.585060E-6	7.447818E-7	661.379	8.842	.000	5.122639E-6	8.047482E-6
renedu	-.057062	.010715	779.500	-5.326	.000	-.078094	-.036029
pov	.056247	.021045	895.101	2.673	.008	.014943	.097550
vac	.038710	.011202	437.330	3.456	.001	.016693	.060727
temp	.006305	.002672	2608.978	2.359	.018	.001065	.011544
hf	-4.819447	1.874097	1500.707	-2.572	.010	-8.495574	-1.143319
fund	.062886	.013220	865.453	4.757	.000	.036939	.088833
pop2	1.330398E-13	4.92221E-14	371.469	2.703	.007	3.625085E-14	2.298288E-13
hf2	6.497532	2.168398	2036.674	2.996	.003	2.245022	10.750042
yearcoded	-.113087	.015142	1810.052	-7.468	.000	-.142786	-.083389
renocc * hf	.200061	.052298	1032.252	3.825	.000	.097438	.302684
renocc * hf2	-.260307	.062251	1695.862	-4.182	.000	-.382403	-.138211
pop * renwhi	1.390840E-8	6.645377E-9	376.621	2.093	.037	8.417069E-10	2.697509E-8
renwhi * pop2	-9.36675E-16	1.19174E-15	362.941	-.786	.432	-3.28026E-15	1.406910E-15

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 181: Information criteria for Model 168 adding bach * renwhi interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6491.177
Akaike's Information Criterion (AIC)	6495.177
Hurvich and Tsai's Criterion (AICC)	6495.181
Bozdogan's Criterion (CAIC)	6508.928
Schwarz's Bayesian Criterion (BIC)	6506.928

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 182: Type III tests of fixed effects for Model 168 adding bach * renwhi interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	778.209	16.654	.000
inczon	1	375.876	5.136	.024
coccat	2	361.661	6.289	.002
pop	0	.	.	.
bach	1	460.850	44.832	.000
medval	0	.	.	.
renedu	1	824.003	23.953	.000
pov	1	894.239	7.277	.007
vac	1	440.069	10.002	.002
temp	1	2596.311	5.728	.017
hf	1	1499.406	6.927	.009
fund	1	868.166	22.985	.000
pop2	0	.	.	.
hf2	1	2031.052	9.196	.002
yearcoded	1	1810.851	54.846	.000
renocc * hf	1	1037.899	14.942	.000
renocc * hf2	1	1689.527	17.780	.000
bach * renwhi	1	440.346	4.486	.035

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 183: Fixed effects estimates for Model 168 adding bach * renwhi interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.860291	1.049031	718.376	3.680	.000	1.800758	5.919825
[inczon=0]	-.392792	.173328	375.876	-2.266	.024	-.733605	-.051978
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	1.010164	.344858	362.180	2.929	.004	.331989	1.688340
[coccat=2]	.191376	.305050	361.569	.627	.531	-.408520	.791272
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.624230E-7	1.898616E-7	364.223	-2.962	.003	-9.357856E-7	-1.890604E-7
bach	-.099703	.014891	460.850	-6.696	.000	-.128965	-.070441
medval	6.507764E-6	7.463386E-7	659.371	8.720	.000	5.042278E-6	7.973251E-6
renedu	-.053990	.011031	824.003	-4.894	.000	-.075643	-.032337
pov	.057110	.021171	894.239	2.698	.007	.015561	.098660
vac	.035507	.011227	440.069	3.163	.002	.013442	.057573
temp	.006435	.002688	2596.311	2.393	.017	.001163	.011706
hf	-4.991809	1.896663	1499.406	-2.632	.009	-8.712203	-1.271414
fund	.063458	.013236	868.166	4.794	.000	.037480	.089437
pop2	6.380560E-14	2.312494E-14	362.856	2.759	.006	1.832987E-14	1.092813E-13
hf2	6.612463	2.180548	2031.052	3.032	.002	2.336120	10.888807
yearcoded	-.112408	.015178	1810.851	-7.406	.000	-.142177	-.082639
renocc * hf	.205289	.053109	1037.899	3.865	.000	.101077	.309502
renocc * hf2	-.264354	.062693	1689.527	-4.217	.000	-.387318	-.141390
bach * renwhi	.000352	.000166	440.346	2.118	.035	2.536694E-5	.000679

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 184: Information criteria for Model 169 adding medval * renwhi interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6497.534
Akaike's Information Criterion (AIC)	6501.534
Hurvich and Tsai's Criterion (AICC)	6501.538
Bozdogan's Criterion (CAIC)	6515.285
Schwarz's Bayesian Criterion (BIC)	6513.285

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 185: Type III tests of fixed effects for Model 169 adding medval * renwhi interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	761.758	13.777	.000
inczon	1	378.145	5.697	.017
coccat	2	365.798	6.918	.001
pop	0	.	.	.
bach	1	564.210	38.736	.000
medval	1	557.147	3.357	.067
renedu	1	815.466	20.156	.000
pov	1	882.332	8.402	.004
vac	1	444.824	7.848	.005
temp	1	2610.711	6.197	.013
hf	1	1523.128	9.313	.002
fund	1	860.080	24.479	.000
pop2	0	.	.	.
hf2	1	2041.057	11.353	.001
yearcoded	1	1793.999	51.352	.000
renocc * hf	1	1054.511	18.966	.000
renocc * hf2	1	1697.860	21.126	.000
medval * renwhi	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 186: Fixed effects estimates for Model 169 adding medval * renwhi interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	3.348557	1.022108	706.289	3.276	.001	1.341823	5.355291
[inczon=0]	-.408712	.171242	378.145	-2.387	.017	-.745419	-.072006
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	1.103097	.337592	367.395	3.268	.001	.439242	1.766953
[coccat=2]	.302086	.300399	367.150	1.006	.315	-.288631	.892804
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-4.86025E-7	1.858774E-7	369.336	-2.615	.009	-8.515362E-7	-1.205149E-7
bach	-.079021	.012697	564.210	-6.224	.000	-.103960	-.054083
medval	2.260786E-6	1.233925E-6	557.147	1.832	.067	-1.629284E-7	4.684501E-6
renedu	-.048978	.010909	815.466	-4.490	.000	-.070392	-.027564
pov	.060699	.020941	882.332	2.899	.004	.019600	.101799
vac	.031279	.011165	444.824	2.801	.005	.009336	.053221
temp	.006642	.002668	2610.711	2.489	.013	.001410	.011874
hf	-5.770223	1.890818	1523.128	-3.052	.002	-9.479106	-2.061341
fund	.064954	.013128	860.080	4.948	.000	.039187	.090722
pop2	5.97054E-14	2.24911E-14	365.623	2.655	.008	1.547718E-14	1.039338E-13
hf2	7.334592	2.176773	2041.057	3.369	.001	3.065663	11.603520
yearcoded	-.108540	.015146	1793.999	-7.166	.000	-.138246	-.078833
renocc * hf	.230370	.052898	1054.511	4.355	.000	.126573	.334167
renocc * hf2	-.287560	.062563	1697.860	-4.596	.000	-.410268	-.164851
medval * renwhi	8.058153E-8	1.986940E-8	488.249	4.056	.000	4.154146E-8	1.196216E-7

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 187: Information criteria for Model 173 adding renwhi * temp interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6491.668
Akaike's Information Criterion (AIC)	6495.668
Hurvich and Tsai's Criterion (AICC)	6495.672
Bozdogan's Criterion (CAIC)	6509.419
Schwarz's Bayesian Criterion (BIC)	6507.419

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 188: Type III tests of fixed effects for Model 173 adding renwhi * temp interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	778.752	20.291	.000
inczon	1	374.093	5.178	.023
coccat	2	365.619	6.191	.002
pop	0	.	.	.
bach	1	559.498	40.236	.000
medval	0	.	.	.
renedu	1	805.940	27.414	.000
pov	1	898.094	7.304	.007
vac	1	437.495	10.232	.001
temp	1	1081.964	1.463	.227
hf	1	1543.350	6.575	.010
fund	1	862.782	23.049	.000
pop2	0	.	.	.
hf2	1	2061.583	8.938	.003
yearcoded	1	1808.202	55.367	.000
renocc * hf	1	1074.664	14.643	.000
renocc * hf2	1	1724.779	17.561	.000
renwhi * temp	1	1037.217	5.119	.024

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 189: Fixed effects estimates for Model 173 adding renwhi * temp interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	4.130677	1.003996	728.304	4.114	.000	2.159606	6.101748
[inczon=0]	-.393097	.172751	374.093	-2.276	.023	-.732782	-.053411
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.979393	.339942	371.377	2.881	.004	.310941	1.647844
[coccat=2]	.164771	.300938	368.935	.548	.584	-.426998	.756541
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.739947E-7	1.870400E-7	376.997	-3.069	.002	-9.417671E-7	-2.062223E-7
bach	-.081117	.012788	559.498	-6.343	.000	-.106236	-.055999
medval	6.466177E-6	7.415153E-7	663.620	8.720	.000	5.010178E-6	7.922175E-6
renedu	-.056300	.010753	805.940	-5.236	.000	-.077407	-.035193
pov	.057018	.021098	898.094	2.703	.007	.015611	.098426
vac	.035775	.011184	437.495	3.199	.001	.013794	.057757
temp	-.008000	.006615	1081.964	-1.209	.227	-.020979	.004979
hf	-4.815341	1.877889	1543.350	-2.564	.010	-8.498824	-1.131858
fund	.063427	.013211	862.782	4.801	.000	.037497	.089357
pop2	6.52578E-14	2.28246E-14	370.682	2.859	.004	2.037573E-14	1.101400E-13
hf2	6.487344	2.169949	2061.583	2.990	.003	2.231823	10.742865
yearcoded	-.112755	.015153	1808.202	-7.441	.000	-.142475	-.083035
renocc * hf	.200917	.052505	1074.664	3.827	.000	.097894	.303941
renocc * hf2	-.261328	.062360	1724.779	-4.191	.000	-.383638	-.139018
renwhi * temp	.000220	9.703434E-5	1037.217	2.262	.024	2.912719E-5	.000410

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 190: Information criteria for Model 174 adding renwhi * hf interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6487.493
Akaike's Information Criterion (AIC)	6491.493
Hurvich and Tsai's Criterion (AICC)	6491.498
Bozdogan's Criterion (CAIC)	6505.244
Schwarz's Bayesian Criterion (BIC)	6503.244

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 191: Type III tests of fixed effects for Model 174 adding renwhi * hf interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	796.322	20.360	.000
inczon	1	377.781	5.364	.021
coccat	2	364.133	6.016	.003
pop	0	.	.	.
bach	1	577.526	38.660	.000
medval	0	.	.	.
renedu	1	821.264	26.363	.000
pov	1	916.475	6.626	.010
vac	1	442.586	10.668	.001
temp	1	2582.622	5.259	.022
hf	1	1320.991	10.766	.001
fund	1	870.612	22.779	.000
pop2	0	.	.	.
hf2	1	2153.406	12.678	.000
yearcoded	1	1813.895	57.330	.000
renocc * hf	1	1123.306	17.528	.000
renocc * hf2	1	1887.796	21.018	.000
renwhi * hf	1	1183.009	5.651	.018
renwhi * hf2	1	2122.614	5.780	.016

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 192: Fixed effects estimates for Model 174 adding renwhi * hf interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	4.224825	1.023350	739.215	4.128	.000	2.215807	6.233844
[inczon=0]	-.403036	.174018	377.781	-2.316	.021	-.745202	-.060870
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.958725	.344401	367.683	2.784	.006	.281483	1.635968
[coccat=2]	.143168	.305971	364.545	.468	.640	-.458522	.744857
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.176076E-7	1.908799E-7	369.073	-3.236	.001	-9.929562E-7	-2.422590E-7
bach	-.080579	.012960	577.526	-6.218	.000	-.106032	-.055125
medval	6.369170E-6	7.451415E-7	665.602	8.548	.000	4.906059E-6	7.832281E-6
renedu	-.056318	.010969	821.264	-5.134	.000	-.077847	-.034788
pov	.054381	.021126	916.475	2.574	.010	.012920	.095842
vac	.036793	.011265	442.586	3.266	.001	.014653	.058932
temp	.006171	.002691	2582.622	2.293	.022	.000894	.011448
hf	-9.628638	2.934521	1320.991	-3.281	.001	-15.385467	-3.871809
fund	.063304	.013264	870.612	4.773	.000	.037272	.089337
pop2	6.90089E-14	2.32911E-14	365.652	2.963	.003	2.320746E-14	1.148103E-13
hf2	13.144117	3.691461	2153.406	3.561	.000	5.904917	20.383317
yearcoded	-.115411	.015243	1813.895	-7.572	.000	-.145306	-.085516
renocc * hf	.240863	.057531	1123.306	4.187	.000	.127982	.353743
renocc * hf2	-.327298	.071392	1887.796	-4.585	.000	-.467313	-.187283
renwhi * hf	.052455	.022067	1183.009	2.377	.018	.009160	.095749
renwhi * hf2	-.067565	.028104	2122.614	-2.404	.016	-.122678	-.012452

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 193: Information criteria for Model 177 reintroducing gini

Information Criteria[a]

-2 Restricted Log Likelihood	6474.585
Akaike's Information Criterion (AIC)	6478.585
Hurvich and Tsai's Criterion (AICC)	6478.589
Bozdogan's Criterion (CAIC)	6492.336
Schwarz's Bayesian Criterion (BIC)	6490.336

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 194: Type III tests of fixed effects for Model 177 reintroducing gini

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	688.914	9.205	.003
inczon	1	379.012	4.738	.030
coccat	2	368.829	5.105	.007
pop	0	.	.	.
bach	1	692.888	41.892	.000
medval	0	.	.	.
renedu	1	842.042	33.297	.000
pov	1	1083.274	2.769	.096
vac	1	468.033	8.232	.004
temp	1	2600.918	4.062	.044
hf	1	1499.135	4.284	.039
fund	1	889.898	21.538	.000
pop2	0	.	.	.
hf2	1	2033.561	6.784	.009
yearcoded	1	1780.220	58.100	.000
renocc * hf	1	1044.308	10.623	.001
renocc * hf2	1	1707.239	14.150	.000
gini	1	1058.805	1.485	.223

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 195: Fixed effects estimates for Model 177 reintroducing gini

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	3.705489	1.256802	664.269	2.948	.003	1.237705	6.173272
[inczon=0]	-.378997	.174122	379.012	-2.177	.030	-.721363	-.036631
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.783621	.340041	372.629	2.304	.022	.114981	1.452261
[coccat=2]	-.002874	.301966	372.294	-.010	.992	-.596646	.590899
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-7.051038E-7	1.847778E-7	372.231	-3.816	.000	-1.068443E-6	-3.417647E-7
bach	-.089997	.013905	692.888	-6.472	.000	-.117297	-.062696
medval	6.221050E-6	7.437323E-7	670.674	8.365	.000	4.760726E-6	7.681374E-6
renedu	-.063228	.010957	842.042	-5.770	.000	-.084735	-.041721
pov	.038806	.023319	1083.274	1.664	.096	-.006950	.084562
vac	.033389	.011637	468.033	2.869	.004	.010521	.056256
temp	.005387	.002673	2600.918	2.015	.044	.000146	.010628
hf	-3.897778	1.883250	1499.135	-2.070	.039	-7.591862	-.203693
fund	.061896	.013337	889.898	4.641	.000	.035720	.088071
pop2	7.869913E-14	2.266352E-14	366.727	3.473	.001	3.413236E-14	1.232659E-13
hf2	5.669132	2.176627	2033.561	2.605	.009	1.400481	9.937783
yearcoded	-.117878	.015465	1780.220	-7.622	.000	-.148209	-.087547
renocc * hf	.171148	.052511	1044.308	3.259	.001	.068108	.274187
renocc * hf2	-.235041	.062484	1707.239	-3.762	.000	-.357594	-.112487
gini	3.574074	2.932974	1058.805	1.219	.223	-2.181027	9.329176

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 196: Information criteria for Model 180 reintroducing inczon * gini interaction

Information Criteria[a]	
-2 Restricted Log Likelihood	6467.642
Akaike's Information Criterion (AIC)	6471.642
Hurvich and Tsai's Criterion (AICC)	6471.647
Bozdogan's Criterion (CAIC)	6485.393
Schwarz's Bayesian Criterion (BIC)	6483.393

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 197: Type III tests of fixed effects for Model 180 reintroducing inczon * gini interaction

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	666.781	8.232	.004
inczon	1	647.607	1.677	.196
coccat	2	369.378	4.959	.007
pop	0	.	.	.
bach	1	697.624	41.118	.000
medval	0	.	.	.
renedu	1	840.038	34.232	.000
pov	1	1128.254	3.431	.064
vac	1	467.469	7.938	.005
temp	1	2600.262	4.142	.042
hf	1	1496.650	4.138	.042
fund	1	888.532	20.999	.000
pop2	0	.	.	.
hf2	1	2030.576	6.722	.010
yearcoded	1	1777.559	58.462	.000
renocc * hf	1	1044.212	10.156	.001
renocc * hf2	1	1705.620	13.858	.000
gini	1	1017.501	1.767	.184
inczon * gini	1	657.085	2.262	.133

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 198: Fixed effects estimates for Model 180 reintroducing inczon * gini interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.104439	1.645533	573.972	1.279	.201	-1.127561	5.336440
[inczon=0]	2.425475	1.872809	647.607	1.295	.196	-1.252036	6.102987
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	.786946	.339514	372.572	2.318	.021	.119342	1.454550
[coccat=2]	.017198	.301788	373.445	.057	.955	-.576220	.610616
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.80966E-7	1.851799E-7	374.744	-3.677	.000	-1.045088E-6	-3.168443E-7
bach	-.089139	.013901	697.624	-6.412	.000	-.116432	-.061846
medval	6.124457E-6	7.456400E-7	676.299	8.214	.000	4.660409E-6	7.588504E-6
renedu	-.064133	.010961	840.038	-5.851	.000	-.085648	-.042618
pov	.043548	.023510	1128.254	1.852	.064	-.002581	.089676
vac	.032762	.011628	467.469	2.817	.005	.009912	.055611
temp	.005439	.002673	2600.262	2.035	.042	.000199	.010680
hf	-3.829186	1.882391	1496.650	-2.034	.042	-7.521591	-.136781
fund	.061112	.013336	888.532	4.582	.000	.034938	.087286
pop2	7.50873E-14	2.27541E-14	369.403	3.300	.001	3.03435E-14	1.19831E-13
hf2	5.640449	2.175525	2030.576	2.593	.010	1.373955	9.906943
yearcoded	-.118180	.015456	1777.559	-7.646	.000	-.148495	-.087866
renocc * hf	.167377	.052521	1044.212	3.187	.001	.064319	.270436
renocc * hf2	-.232535	.062465	1705.620	-3.723	.000	-.355052	-.110019
gini	7.023717	3.719118	708.979	1.889	.059	-.278086	14.325519
[inczon=0] * gini	-6.236651	4.146816	657.085	-1.504	.133	-14.379259	1.905956
[inczon=1] * gini	0[b]	0	.	.	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 199: Information criteria for Model 181 reintroducing coccat * gini interaction*

Information Criteria[a]	
-2 Restricted Log Likelihood	6452.868
Akaike's Information Criterion (AIC)	6456.868
Hurvich and Tsai's Criterion (AICC)	6456.872
Bozdogan's Criterion (CAIC)	6470.617
Schwarz's Bayesian Criterion (BIC)	6468.617

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 200: Type III tests of fixed effects for Model 181 reintroducing coccat * gini interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	674.262	1.176	.279
inczon	1	653.575	1.100	.295
coccat	2	674.223	.876	.417
pop	0	.	.	.
bach	1	701.735	42.692	.000
medval	0	.	.	.
renedu	1	846.681	35.920	.000
pov	1	1138.646	3.098	.079
vac	1	467.615	7.936	.005
temp	1	2599.230	4.187	.041
hf	1	1498.072	4.185	.041
fund	1	925.987	18.435	.000
pop2	0	.	.	.
hf2	1	2023.631	6.922	.009
yearcoded	1	1761.292	59.161	.000
renocc * hf	1	1043.887	10.328	.001
renocc * hf2	1	1698.141	14.232	.000
gini	1	855.488	2.203	.138
inczon * gini	1	662.515	1.563	.212
coccat * gini	2	675.115	1.219	.296

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 201: Fixed effects estimates for Model 181 reintroducing coccat * gini interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.126017	4.885059	741.876	.435	.664	-7.464168	11.716202
[inczon=0]	1.986411	1.893561	653.575	1.049	.295	-1.731785	5.704608
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-3.543472	5.631671	714.277	-.629	.529	-14.600080	7.513136
[coccat=2]	.784106	4.781196	767.519	.164	.870	-8.601667	10.169879
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.61636E-7	1.851775E-7	373.965	-3.573	.000	-1.025756E-6	-2.975169E-7
bach	-.090970	.013923	701.735	-6.534	.000	-.118305	-.063635
medval	6.153670E-6	7.445956E-7	672.928	8.264	.000	4.691660E-6	7.615680E-6
renedu	-.066035	.011018	846.681	-5.993	.000	-.087661	-.044409
pov	.041495	.023576	1138.646	1.760	.079	-.004761	.087752
vac	.032723	.011616	467.615	2.817	.005	.009897	.055548
temp	.005470	.002673	2599.230	2.046	.041	.000228	.010712
hf	-3.855919	1.884795	1498.072	-2.046	.041	-7.553036	-.158802
fund	.057917	.013489	925.987	4.294	.000	.031444	.084390
pop2	7.05928E-14	2.28871E-14	369.774	3.084	.002	2.55875E-14	1.15598E-13
hf2	5.725803	2.176339	2023.631	2.631	.009	1.457703	9.993903
yearcoded	-.119291	.015509	1761.292	-7.692	.000	-.149709	-.088872
renocc * hf	.168834	.052536	1043.887	3.214	.001	.065745	.271922
renocc * hf2	-.235664	.062467	1698.141	-3.773	.000	-.358186	-.113143
gini	7.351234	11.363781	783.869	.647	.518	-14.955811	29.658279
[inczon=0] * gini	-5.242680	4.193912	662.515	-1.250	.212	-13.477642	2.992281
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	9.126791	12.651132	721.335	.721	.471	-15.710647	33.964228
[coccat=2] * gini	-1.718744	10.979403	768.839	-.157	.876	-23.271909	19.834421
[coccat=3] * gini	0[b]	0	.	.	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 202: Information criteria for Model 182 reintroducing hf * gini interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6437.414
Akaike's Information Criterion (AIC)	6441.414
Hurvich and Tsai's Criterion (AICC)	6441.418
Bozdogan's Criterion (CAIC)	6455.162
Schwarz's Bayesian Criterion (BIC)	6453.162

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 203: Type III tests of fixed effects for Model 182 reintroducing hf * gini interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2229.664	.002	.967
inczon	1	652.970	1.075	.300
coccat	2	677.705	.921	.399
pop	0	.	.	.
bach	1	700.394	42.043	.000
medval	0	.	.	.
renedu	1	841.761	35.209	.000
pov	1	1132.054	2.833	.093
vac	1	467.011	7.926	.005
temp	1	2596.682	4.167	.041
hf	1	2621.042	.042	.837
fund	1	926.510	18.412	.000
pop2	0	.	.	.
hf2	1	2608.204	.016	.901
yearcoded	1	1759.847	58.821	.000
renocc * hf	1	1178.408	8.391	.004
renocc * hf2	1	1954.718	9.860	.002
gini	1	2291.777	1.662	.197
inczon * gini	1	662.007	1.525	.217
coccat * gini	2	678.418	1.270	.282
hf * gini	1	2627.816	.217	.641
hf2 * gini	1	2623.328	.076	.783

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 204: Fixed effects estimates for Model 182 reintroducing hf * gini interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.069637	6.125768	1262.991	-.011	.991	-12.087439	11.948165
[inczon=0]	1.966274	1.896016	652.970	1.037	.300	-1.756750	5.689297
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-3.860185	5.659817	722.410	-.682	.495	-14.971839	7.251468
[coccat=2]	.595674	4.800396	776.289	.124	.901	-8.827621	10.018970
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.57799E-7	1.855347E-7	372.795	-3.545	.000	-1.022625E-6	-2.929740E-7
bach	-.090478	.013954	700.394	-6.484	.000	-.117874	-.063082
medval	6.130822E-6	7.462926E-7	674.628	8.215	.000	4.665487E-6	7.596158E-6
renedu	-.065534	.011044	841.761	-5.934	.000	-.087212	-.043856
pov	.039915	.023716	1132.054	1.683	.093	-.006617	.086446
vac	.032817	.011656	467.011	2.815	.005	.009911	.055722
temp	.005458	.002674	2596.682	2.041	.041	.000215	.010701
hf	2.892496	14.082878	2621.042	.205	.837	-24.722189	30.507181
fund	.057974	.013511	926.510	4.291	.000	.031459	.084490
pop2	6.98884E-14	2.29421E-14	368.696	3.046	.002	2.47745E-14	1.15002E-13
hf2	1.646841	13.201689	2608.204	.125	.901	-24.240007	27.533689
yearcoded	-.119087	.015527	1759.847	-7.669	.000	-.149541	-.088633
renocc * hf	.164272	.056710	1178.408	2.897	.004	.053007	.275536
renocc * hf2	-.222953	.071004	1954.718	-3.140	.002	-.362204	-.083701
gini	12.332136	14.125235	1294.553	.873	.383	-15.378724	40.042996
[inczon=0] * gini	-5.186814	4.199500	662.007	-1.235	.217	-13.432757	3.059130
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	9.795723	12.710788	729.167	.771	.441	-15.158384	34.749830
[coccat=2] * gini	-1.305364	11.021802	777.158	-.118	.906	-22.941393	20.330666
[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	-15.101695	32.410010	2627.816	-.466	.641	-78.653419	48.450028
hf2 * gini	8.483660	30.790369	2623.328	.276	.783	-51.892210	68.859530

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 205: Information criteria for Model 201 adding medval * pov interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6434.321
Akaike's Information Criterion (AIC)	6438.321
Hurvich and Tsai's Criterion (AICC)	6438.326
Bozdogan's Criterion (CAIC)	6452.068
Schwarz's Bayesian Criterion (BIC)	6450.068

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 206: Type III tests of fixed effects for Model 201 adding medval * pov interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2187.093	.340	.560
inczon	1	641.926	.073	.786
coccat	2	654.751	.659	.518
pop	0	.	.	.
bach	1	730.132	26.559	.000
medval	1	755.368	.652	.420
renedu	1	828.789	30.936	.000
pov	1	912.212	4.307	.038
vac	1	460.104	9.174	.003
temp	1	2609.082	4.320	.038
hf	1	2625.225	.000	.995
fund	1	889.576	22.178	.000
pop2	0	.	.	.
hf2	1	2616.628	.053	.818
yearcoded	1	1720.050	62.493	.000
renocc * hf	1	1180.402	2.234	.135
renocc * hf2	1	1925.857	4.834	.028
gini	1	2251.968	.551	.458
inczon * gini	1	651.234	.025	.874
coccat * gini	2	655.251	.927	.396
hf * gini	1	2623.944	.011	.916
hf2 * gini	1	2626.166	.001	.981
medval * pov	0	.	.	.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

Table 207: Fixed effects estimates for Model 201 adding medval * pov interaction

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.613423	6.007234	1226.030	.435	.664	-9.172173	14.399020
[inczon=0]	-.510351	1.882488	641.926	-.271	.786	-4.206930	3.186228
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-1.587286	5.503787	698.475	-.288	.773	-12.393236	9.218663
[coccat=2]	1.892098	4.665346	743.310	.406	.685	-7.266725	11.050921
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-6.01305E-7	1.779338E-7	373.535	-3.379	.001	-9.511833E-7	-2.514285E-7
bach	-.071758	.013924	730.132	-5.154	.000	-.099095	-.044422
medval	-1.16035E-6	1.436570E-6	755.368	-.808	.420	-3.980495E-6	1.659793E-6
renedu	-.060024	.010792	828.789	-5.562	.000	-.081207	-.038842
pov	-.059666	.028752	912.212	-2.075	.038	-.116093	-.003239
vac	.033973	.011217	460.104	3.029	.003	.011931	.056015
temp	.005532	.002662	2609.082	2.078	.038	.000313	.010752
hf	.080928	14.012457	2625.225	.006	.995	-27.395650	27.557506
fund	.061959	.013157	889.576	4.709	.000	.036137	.087780
pop2	5.17442E-14	2.21769E-14	371.254	2.333	.020	8.13608E-15	9.53524E-14
hf2	3.026579	13.138286	2616.628	.230	.818	-22.735905	28.789062
yearcoded	-.120701	.015268	1720.050	-7.905	.000	-.150647	-.090754
renocc * hf	.085116	.056946	1180.402	1.495	.135	-.026611	.196844
renocc * hf2	-.155766	.070843	1925.857	-2.199	.028	-.294703	-.016829
gini	6.779120	13.850624	1257.164	.489	.625	-20.393766	33.952006
[inczon=0] * gini	.661590	4.184780	651.234	.158	.874	-7.555700	8.878881
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	4.561341	12.363352	704.268	.369	.712	-19.712099	28.834781
[coccat=2] * gini	-4.340798	10.712360	744.014	-.405	.685	-25.370849	16.689253
[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	-3.411824	32.256446	2623.944	-.106	.916	-66.662473	59.838825
hf2 * gini	.736026	30.643310	2626.166	.024	.981	-59.351451	60.823503
medval * pov	7.223034E-7	1.229466E-7	770.656	5.875	.000	4.809535E-7	9.636533E-7

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 208: Information criteria for Model 215 adding pov * hf interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6427.524
Akaike's Information Criterion (AIC)	6431.524
Hurvich and Tsai's Criterion (AICC)	6431.528
Bozdogan's Criterion (CAIC)	6445.269
Schwarz's Bayesian Criterion (BIC)	6443.269

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 209: Type III tests of fixed effects for Model 215 adding pov * hf interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2384.775	.196	.658
inczon	1	644.121	.002	.961
coccat	2	654.172	.545	.580
pop	0	.	.	.
bach	1	729.719	26.456	.000
medval	1	767.012	.288	.592
renedu	1	827.625	31.331	.000
pov	1	2359.611	.765	.382
vac	1	464.201	7.874	.005
temp	1	2606.699	4.623	.032
hf	1	2614.834	.015	.902
fund	1	893.979	24.929	.000
pop2	0	.	.	.
hf2	1	2604.372	.287	.592
yearcoded	1	1711.001	57.435	.000
renocc * hf	1	1165.649	3.691	.055
renocc * hf2	1	1889.296	8.169	.004
gini	1	2492.948	.486	.486
inczon * gini	1	653.270	.003	.954
coccat * gini	2	654.640	.793	.453
hf * gini	1	2620.920	.015	.902
hf2 * gini	1	2611.112	.208	.648
medval * pov	0	.	.	.
pov * hf	1	2624.954	.633	.426
pov * hf2	1	2622.138	2.452	.118

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 210: Fixed effects estimates for Model 215 adding pov * hf interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	1.970560	6.288587	1406.097	.313	.754	-10.365463	14.306583
[inczon=0]	-.090920	1.882386	644.121	-.048	.961	-3.787274	3.605435
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-1.389442	5.491205	698.456	-.253	.800	-12.170688	9.391804
[coccat=2]	1.760257	4.655106	741.701	.378	.705	-7.378495	10.899010
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.75348E-7	1.776524E-7	374.037	-3.239	.001	-9.246713E-7	-2.260262E-7
bach	-.071469	.013895	729.719	-5.143	.000	-.098748	-.044190
medval	-7.71360E-7	1.438445E-6	767.012	-.536	.592	-3.595116E-6	2.052395E-6
renedu	-.060284	.010770	827.625	-5.597	.000	-.081423	-.039144
pov	-.058238	.066601	2359.611	-.874	.382	-.188840	.072365
vac	.031512	.011230	464.201	2.806	.005	.009443	.053580
temp	.005714	.002657	2606.699	2.150	.032	.000503	.010925
hf	-1.908128	15.553459	2614.834	-.123	.902	-32.406465	28.590209
fund	.065765	.013172	893.979	4.993	.000	.039914	.091616
pop2	4.87694E-14	2.21396E-14	371.812	2.203	.028	5.23472E-15	9.23040E-14
hf2	7.666855	14.308993	2604.372	.536	.592	-20.391295	35.725005
yearcoded	-.115986	.015304	1711.001	-7.579	.000	-.146004	-.085969
renocc * hf	.110307	.057414	1165.649	1.921	.055	-.002339	.222954
renocc * hf2	-.206536	.072264	1889.296	-2.858	.004	-.348262	-.064810
gini	8.179126	15.236624	1577.244	.537	.591	-21.707043	38.065295
[inczon=0] * gini	-.240543	4.184048	653.270	-.057	.954	-8.456348	7.975261
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	4.156960	12.335249	704.152	.337	.736	-20.061311	28.375231
[coccat=2] * gini	-4.050209	10.689020	742.391	-.379	.705	-25.034514	16.934097
[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	4.840743	39.488575	2620.920	.123	.902	-72.591201	82.272687
hf2 * gini	-16.519346	36.232305	2611.112	-.456	.648	-87.566292	54.527601
medval * pov	7.041679E-7	1.227874E-7	773.460	5.735	.000	4.631318E-7	9.452039E-7
pov * hf	-.182334	.229242	2624.954	-.795	.426	-.631849	.267180
pov * hf2	.328103	.209549	2622.138	1.566	.118	-.082795	.739000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 211: Information criteria for Model 221 adding vac * yearcoded interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6425.769
Akaike's Information Criterion (AIC)	6429.769
Hurvich and Tsai's Criterion (AICC)	6429.774
Bozdogan's Criterion (CAIC)	6443.514
Schwarz's Bayesian Criterion (BIC)	6441.514

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 212: Type III tests of fixed effects for Model 221 adding vac * yearcoded interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2379.592	.114	.735
inczon	1	641.006	.000	.994
coccat	2	650.803	.564	.569
pop	0	.	.	.
bach	1	726.552	26.436	.000
medval	1	762.797	.163	.687
renedu	1	822.563	31.545	.000
pov	1	2354.967	.666	.415
vac	1	779.315	19.666	.000
temp	1	2607.112	5.106	.024
hf	1	2614.625	.011	.918
fund	1	886.398	24.270	.000
pop2	0	.	.	.
hf2	1	2604.475	.232	.630
yearcoded	1	2083.569	1.076	.300
renocc * hf	1	1167.368	5.179	.023
renocc * hf2	1	1890.427	10.703	.001
gini	1	2489.412	.494	.482
inczon * gini	1	650.053	.013	.908
coccat * gini	2	651.274	.802	.449
hf * gini	1	2620.440	.009	.926
hf2 * gini	1	2611.092	.152	.697
medval * pov	0	.	.	.
pov * hf	1	2623.986	.831	.362

pov * hf2	1	2621.343	3.128	.077
vac * yearcoded	1	2210.959	12.422	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 213: Fixed effects estimates for Model 221 adding vac * yearcoded interaction*

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.868503	6.274823	1399.037	.138	.890	-11.440573	13.177578
[inczon=0]	.014288	1.873956	641.006	.008	.994	-3.665547	3.694124
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-.460531	5.473061	694.589	-.084	.933	-11.206258	10.285195
[coccat=2]	2.512242	4.639571	737.435	.541	.588	-6.596100	11.620584
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.808386E-7	1.766663E-7	373.536	-3.288	.001	-9.282239E-7	-2.334534E-7
bach	-.071128	.013834	726.552	-5.142	.000	-.098287	-.043969
medval	-5.782818E-7	1.433348E-6	762.797	-.403	.687	-3.392056E-6	2.235492E-6
renedu	-.060233	.010724	822.563	-5.616	.000	-.081283	-.039183
pov	-.054206	.066436	2354.967	-.816	.415	-.184484	.076072
vac	.065357	.014738	779.315	4.435	.000	.036426	.094287
temp	.005995	.002653	2607.112	2.260	.024	.000793	.011197
hf	-1.594517	15.521384	2614.625	-.103	.918	-32.029959	28.840925
fund	.064648	.013123	886.398	4.926	.000	.038893	.090403
pop2	4.975633E-14	2.201752E-14	371.274	2.260	.024	6.461647E-15	9.305100E-14
hf2	6.874591	14.281530	2604.475	.481	.630	-21.129708	34.878889
yearcoded	-.029885	.028814	2083.569	-1.037	.300	-.086393	.026623
renocc * hf	.130882	.057510	1167.368	2.276	.023	.018048	.243716
renocc * hf2	-.237475	.072589	1890.427	-3.272	.001	-.379838	-.095112
gini	9.607927	15.191920	1570.663	.632	.527	-20.190652	39.406505
[inczon=0] * gini	-.483759	4.165452	650.053	-.116	.908	-8.663124	7.695606
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	2.086779	12.294364	700.259	.170	.865	-22.051452	26.225010
[coccat=2] * gini	-5.763916	10.653184	738.129	-.541	.589	-26.678066	15.150234

[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	3.660029	39.406775	2620.440	.093	.926	-73.611522	80.931580
hf2 * gini	-14.078276	36.164284	2611.092	-.389	.697	-84.991841	56.835290
medval * pov	6.823041E-7	1.224265E-7	767.939	5.573	.000	4.419739E-7	9.226343E-7
pov * hf	-.208697	.228870	2623.986	-.912	.362	-.657481	.240086
pov * hf2	.370452	.209451	2621.343	1.769	.077	-.040253	.781157
vac * yearcoded	-.006905	.001959	2210.959	-3.525	.000	-.010746	-.003063

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 214: Information criteria for Model 224 adding temp * yearcoded interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6421.655
Akaike's Information Criterion (AIC)	6425.655
Hurvich and Tsai's Criterion (AICC)	6425.659
Bozdogan's Criterion (CAIC)	6439.399
Schwarz's Bayesian Criterion (BIC)	6437.399

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 215: Type III tests of fixed effects for Model 224 adding temp * yearcoded interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2377.865	.030	.862
inczon	1	640.378	.007	.934
coccat	2	649.760	.689	.503
pop	0	.	.	.
bach	1	725.781	25.916	.000
medval	1	761.026	.316	.574
renedu	1	818.457	29.275	.000
pov	1	2351.246	1.021	.312
vac	1	785.799	15.399	.000
temp	1	2611.651	21.338	.000
hf	1	2613.567	.001	.974
fund	1	888.094	22.006	.000
pop2	0	.	.	.
hf2	1	2603.142	.135	.714
yearcoded	1	2321.795	4.523	.034
renocc * hf	1	1165.676	5.364	.021
renocc * hf2	1	1892.020	10.191	.001
gini	1	2488.109	.596	.440
inczon * gini	1	649.436	.037	.847
coccat * gini	2	650.222	.961	.383
hf * gini	1	2619.408	.000	.997
hf2 * gini	1	2609.883	.072	.788
medval * pov	0	.	.	.
pov * hf	1	2622.969	.614	.433

pov * hf2	1	2620.157	2.619	.106
vac * yearcoded	1	2218.165	7.496	.006
temp * yearcoded	1	2543.898	16.267	.000

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 216: Fixed effects estimates for Model 224 adding temp * yearcoded interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	.586368	6.256898	1398.599	.094	.925	-11.687548	12.860283
[inczon=0]	.155095	1.868775	640.378	.083	.934	-3.514573	3.824763
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-1.548664	5.463649	692.923	-.283	.777	-12.275958	9.178629
[coccat=2]	1.965403	4.627939	736.322	.425	.671	-7.120126	11.050932
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.78212E-7	1.761453E-7	373.157	-3.283	.001	-9.245744E-7	-2.318506E-7
bach	-.070228	.013795	725.781	-5.091	.000	-.097311	-.043145
medval	-8.03407E-7	1.430230E-6	761.026	-.562	.574	-3.611072E-6	2.004256E-6
renedu	-.057938	.010708	818.457	-5.411	.000	-.078956	-.036919
pov	-.066999	.066318	2351.246	-1.010	.312	-.197048	.063049
vac	.058094	.014805	785.799	3.924	.000	.029033	.087156
temp	.022728	.004920	2611.651	4.619	.000	.013080	.032376
hf	-.512685	15.478773	2613.567	-.033	.974	-30.864579	29.839209
fund	.061489	.013108	888.094	4.691	.000	.035763	.087214
pop2	4.96229E-14	2.19524E-14	370.920	2.260	.024	6.45606E-15	9.27898E-14
hf2	5.230909	14.246023	2603.142	.367	.714	-22.703771	33.165589
yearcoded	.086664	.040749	2321.795	2.127	.034	.006756	.166573
renocc * hf	.132808	.057344	1165.676	2.316	.021	.020299	.245316
renocc * hf2	-.231112	.072395	1892.020	-3.192	.001	-.373094	-.089130
gini	9.320590	15.147782	1569.337	.615	.538	-20.391432	39.032612
[inczon=0] * gini	-.801552	4.153960	649.436	-.193	.847	-8.958365	7.355261
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	4.473250	12.272527	698.578	.364	.716	-19.622208	28.568708
[coccat=2] * gini	-4.486783	10.626633	736.986	-.422	.673	-25.348863	16.375296
[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	.143090	39.302349	2619.408	.004	.997	-76.923709	77.209889
hf2 * gini	-9.708852	36.075868	2609.883	-.269	.788	-80.449061	61.031357
medval * pov	6.819152E-7	1.220673E-7	767.255	5.586	.000	4.422897E-7	9.215407E-7

pov * hf	-.178890	.228327	2622.969	-.783	.433	-.626609	.268829
pov * hf2	.338219	.208997	2620.157	1.618	.106	-.071596	.748035
vac * yearcoded	-.005440	.001987	2218.165	-2.738	.006	-.009336	-.001543
temp * yearcoded	-.003777	.000937	2543.898	-4.033	.000	-.005614	-.001941

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

*Table 217: Information criteria for Model 225 adding hf * fund interaction*

Information Criteria[a]

-2 Restricted Log Likelihood	6420.719
Akaike's Information Criterion (AIC)	6424.719
Hurvich and Tsai's Criterion (AICC)	6424.724
Bozdogan's Criterion (CAIC)	6438.462
Schwarz's Bayesian Criterion (BIC)	6436.462

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 218: Type III tests of fixed effects for Model 225 adding hf * fund interaction*

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2418.720	.027	.870
inczon	1	640.351	.005	.941
coccat	2	649.456	.715	.490
pop	0	.	.	.
bach	1	725.968	26.376	.000
medval	1	766.174	.164	.686
renedu	1	821.725	29.785	.000
pov	1	2405.731	.776	.378
vac	1	783.550	15.926	.000
temp	1	2610.541	21.485	.000
hf	1	2609.294	.006	.940
fund	1	2604.726	2.183	.140
pop2	0	.	.	.
hf2	1	2600.501	.033	.856
yearcoded	1	2325.827	5.028	.025
renocc * hf	1	1281.250	2.649	.104
renocc * hf2	1	2087.905	5.256	.022
gini	1	2528.481	.505	.477
inczon * gini	1	649.461	.035	.852
coccat * gini	2	649.916	.994	.371
hf * gini	1	2611.723	.003	.956
hf2 * gini	1	2601.779	.020	.888
medval * pov	0	.	.	.
pov * hf	1	2619.522	.530	.467
pov * hf2	1	2614.020	2.196	.139

vac * yearcoded	1	2217.889	8.033	.005
temp * yearcoded	1	2543.442	16.210	.000
hf * fund	1	2595.756	.139	.709
fund * hf2	1	2583.599	.009	.924

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

*Table 219: Fixed effects estimates for Model 225 adding hf * fund interaction*

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	.742409	6.345850	1452.748	.117	.907	-11.705600	13.190418
[inczon=0]	.138394	1.871855	640.351	.074	.941	-3.537321	3.814109
[inczon=1]	0[b]	0	.	.	.	.	.
[coccat=1]	-1.878982	5.471649	692.746	-.343	.731	-12.621987	8.864023
[coccat=2]	1.758901	4.633629	737.670	.380	.704	-7.337770	10.855572
[coccat=3]	0[b]	0	.	.	.	.	.
pop	-5.81714E-7	1.765098E-7	372.198	-3.296	.001	-9.287958E-7	-2.346327E-7
bach	-.070947	.013814	725.968	-5.136	.000	-.098068	-.043827
medval	-5.82164E-7	1.439746E-6	766.174	-.404	.686	-3.408480E-6	2.244151E-6
renedu	-.058541	.010727	821.725	-5.458	.000	-.079595	-.037486
pov	-.059866	.067942	2405.731	-.881	.378	-.193097	.073365
vac	.059292	.014857	783.550	3.991	.000	.030127	.088456
temp	.022798	.004918	2610.541	4.635	.000	.013154	.032442
hf	1.206022	16.101985	2609.294	.075	.940	-30.367934	32.779978
fund	.155998	.105583	2604.726	1.477	.140	-.051038	.363034
pop2	4.88791E-14	2.20076E-14	370.382	2.221	.027	5.60342E-15	9.21548E-14
hf2	2.684197	14.837162	2600.501	.181	.856	-26.409648	31.778042
yearcoded	.091465	.040792	2325.827	2.242	.025	.011473	.171458
renocc * hf	.097365	.059825	1281.250	1.627	.104	-.020002	.214732
renocc * hf2	-.175611	.076599	2087.905	-2.293	.022	-.325829	-.025393
gini	8.583556	15.522266	1659.301	.553	.580	-21.861735	39.028847
[inczon=0] * gini	-.778145	4.160574	649.461	-.187	.852	-8.947945	7.391656
[inczon=1] * gini	0[b]	0	.	.	.	.	.
[coccat=1] * gini	5.137486	12.289497	698.534	.418	.676	-18.991293	29.266265
[coccat=2] * gini	-4.069268	10.639258	738.242	-.382	.702	-24.956074	16.817538
[coccat=3] * gini	0[b]	0	.	.	.	.	.
hf * gini	-2.295082	41.348162	2611.723	-.056	.956	-83.373564	78.783400
hf2 * gini	-5.355943	37.912504	2601.779	-.141	.888	-79.697669	68.985783
medval * pov	6.652342E-7	1.232425E-7	777.083	5.398	.000	4.233066E-7	9.071619E-7

pov * hf	-.169765	.233253	2619.522	-.728	.467	-.627143	.287613
pov * hf2	.315860	.213155	2614.020	1.482	.139	-.102110	.733830
vac * yearcoded	-.005637	.001989	2217.889	-2.834	.005	-.009537	-.001737
temp * yearcoded	-.003770	.000936	2543.442	-4.026	.000	-.005606	-.001934
hf * fund	-.125295	.335575	2595.756	-.373	.709	-.783316	.532726
fund * hf2	-.025853	.270699	2583.599	-.096	.924	-.556662	.504956

a. Dependent Variable: People per 1,000 Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Appendix 6: Final Model Results for Subsets of Homelessness

Table 220: Information criterion for sheltered homelessness model

Information Criteria[a]	
-2 Restricted Log Likelihood	2631.088
Akaike's Information Criterion (AIC)	2635.088
Hurvich and Tsai's Criterion (AICC)	2635.093
Bozdogan's Criterion (CAIC)	2648.839
Schwarz's Bayesian Criterion (BIC)	2646.839

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Sheltered Homelessness.

Table 221: Type III tests of fixed effects for sheltered homelessness model

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	703.947	7.790	.005
coccat	2	368.023	12.969	.000
inczon	1	377.736	3.984	.047
pop	0	.	.	.
bach	1	557.223	.014	.907
medval	0	.	.	.
renwhi	1	454.299	10.143	.002
renedu	1	751.529	.630	.428
pov	1	904.207	3.046	.081
vac	1	666.860	10.069	.002
temp	1	2602.589	5.816	.016
hf	1	1437.334	73.844	.000
fund	1	810.006	106.664	.000
pop2	0	.	.	.
hf2	1	1945.737	74.317	.000
yearcoded	1	1618.058	39.833	.000
renocc * hf	1	980.365	71.307	.000
renocc * hf2	1	1594.910	88.135	.000
medren * vac	1	679.627	14.697	.000

a. Dependent Variable: People per 1,000 Experiencing Sheltered Homelessness.

Table 222: Fixed effects estimates for sheltered homelessness model

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	1.315003	.539504	657.748	2.437	.015	.255646	2.374360
[coccat=1]	.571874	.152957	367.958	3.739	.000	.271095	.872653
[coccat=2]	.021806	.136070	369.337	.160	.873	-.245764	.289375
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.155089	.077697	377.736	-1.996	.047	-.307862	-.002316
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-3.069454E-7	8.425347E-8	369.279	-3.643	.000	-4.726222E-7	-1.412686E-7
bach	-.000683	.005852	557.223	-.117	.907	-.012177	.010812
medval	1.314303E-7	3.562310E-7	648.801	.369	.712	-5.680745E-7	8.309350E-7
renwhi	.007052	.002214	454.299	3.185	.002	.002701	.011404
renedu	-.004018	.005062	751.529	-.794	.428	-.013955	.005919
pov	.017530	.010044	904.207	1.745	.081	-.002182	.037242
vac	-.045202	.014245	666.860	-3.173	.002	-.073172	-.017232
temp	-.003139	.001301	2602.589	-2.412	.016	-.005691	-.000587
hf	-7.617765	.886479	1437.334	-8.593	.000	-9.356696	-5.878833
fund	.062659	.006067	810.006	10.328	.000	.050750	.074568
pop2	4.21048E-14	1.02766E-14	367.836	4.097	.000	2.189640E-14	6.231329E-14
hf2	8.880153	1.030096	1945.737	8.621	.000	6.859946	10.900359
yearcoded	-.047133	.007468	1618.058	-6.311	.000	-.061782	-.032485
renocc * hf	.207966	.024628	980.365	8.444	.000	.159637	.256295
renocc * hf2	-.276794	.029484	1594.910	-9.388	.000	-.334625	-.218963
medren * vac	5.277754E-5	1.376685E-5	679.627	3.834	.000	2.574686E-5	7.980821E-5

a. Dependent Variable: People per 1,000 Experiencing Sheltered Homelessness.

b. This parameter is set to zero because it is redundant.

Table 223: Information criterion for unsheltered homelessness model

Information Criteria[a]

-2 Restricted Log Likelihood	5869.934
Akaike's Information Criterion (AIC)	5873.934
Hurvich and Tsai's Criterion (AICC)	5873.939
Bozdogan's Criterion (CAIC)	5887.685
Schwarz's Bayesian Criterion (BIC)	5885.685

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Unsheltered Homelessness.

Table 224: Type III tests of fixed effects for unsheltered homelessness model

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	721.536	4.471	.035
coccat	2	361.591	.937	.393
inczon	1	372.638	1.103	.294
pop	0	.	.	.
bach	1	563.817	50.032	.000
medval	0	.	.	.
renwhi	1	452.670	1.050	.306
renedu	1	785.646	24.186	.000
pov	1	952.653	8.561	.004
vac	1	683.574	.169	.681
temp	1	2585.314	14.134	.000
hf	1	1457.306	2.810	.094
fund	1	835.497	.310	.578
pop2	0	.	.	.
hf2	1	1982.470	1.307	.253
yearcoded	1	1650.497	34.263	.000
renocc * hf	1	1004.302	.062	.803
renocc * hf2	1	1634.960	.064	.800
medren * vac	1	697.482	2.613	.106

a. Dependent Variable: People per 1,000 Experiencing Unsheltered Homelessness.

Table 225: Fixed effects estimates for unsheltered homelessness model

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.032401	1.028680	670.589	1.976	.049	.012578	4.052223
[coccat=1]	.315075	.295610	361.295	1.066	.287	-.266257	.896407
[coccat=2]	.035727	.262954	362.155	.136	.892	-.481381	.552835
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.157607	.150052	372.638	-1.050	.294	-.452663	.137448
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-3.136161E-7	1.628145E-7	362.939	-1.926	.055	-6.337944E-7	6.562282E-9
bach	-.079203	.011197	563.817	-7.073	.000	-.101197	-.057209
medval	5.538393E-6	6.793991E-7	663.532	8.152	.000	4.204362E-6	6.872424E-6
renwhi	.004362	.004257	452.670	1.025	.306	-.004004	.012728
renedu	-.047329	.009624	785.646	-4.918	.000	-.066220	-.028437
pov	.055678	.019029	952.653	2.926	.004	.018335	.093022
vac	-.011166	.027152	683.574	-.411	.681	-.064478	.042145
temp	.009034	.002403	2585.314	3.760	.000	.004322	.013746
hf	2.793430	1.666299	1457.306	1.676	.094	-.475171	6.062032
fund	.006412	.011520	835.497	.557	.578	-.016199	.029024
pop2	2.77769E-14	1.98607E-14	361.872	1.399	.163	-1.12801E-14	6.683402E-14
hf2	-2.200800	1.925391	1982.470	-1.143	.253	-5.976803	1.575203
yearcoded	-.081991	.014007	1650.497	-5.853	.000	-.109465	-.054518
renocc * hf	-.011599	.046602	1004.302	-.249	.803	-.103047	.079849
renocc * hf2	.014021	.055312	1634.960	.253	.800	-.094470	.122511
medren * vac	4.240173E-5	2.623062E-5	697.482	1.616	.106	-9.098714E-6	9.390218E-5

a. Dependent Variable: People per 1,000 Experiencing Unsheltered Homelessness.

b. This parameter is set to zero because it is redundant.

Table 226: Information criteria for family homelessness model

Information Criteria[a]

-2 Restricted Log Likelihood	4219.289
Akaike's Information Criterion (AIC)	4223.289
Hurvich and Tsai's Criterion (AICC)	4223.294
Bozdogan's Criterion (CAIC)	4237.040
Schwarz's Bayesian Criterion (BIC)	4235.040

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 in Families Experiencing Homelessness.

Table 227: Type III tests of fixed effects for family homelessness model

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	598.061	1.491	.223
coccat	2	393.413	.908	.404
inczon	1	393.469	4.529	.034
pop	0	.	.	.
bach	1	503.569	5.667	.018
medval	0	.	.	.
renwhi	1	448.450	3.292	.070
renedu	1	580.060	1.835	.176
pov	1	660.014	3.711	.054
vac	1	565.277	.219	.640
temp	1	2566.127	1.473	.225
hf	1	1271.225	6.409	.011
fund	1	673.193	23.250	.000
pop2	0	.	.	.
hf2	1	1614.917	12.161	.001
yearcoded	1	1356.360	28.501	.000
renocc * hf	1	820.291	10.293	.001
renocc * hf2	1	1271.760	18.856	.000
medren * vac	1	576.250	.649	.421

a. Dependent Variable: People per 1,000 in Families Experiencing Homelessness.

Table 228: Fixed effects estimates for family homelessness model

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.680624	.582971	572.305	1.168	.243	-.464400	1.825649
[coccat=1]	.190378	.153379	395.208	1.241	.215	-.111164	.491919
[coccat=2]	.068397	.136650	400.495	.501	.617	-.200243	.337038
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.166109	.078056	393.469	-2.128	.034	-.319568	-.012651
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-1.481427E-7	8.450224E-8	394.782	-1.753	.080	-3.142733E-7	1.798796E-8
bach	-.014730	.006188	503.569	-2.380	.018	-.026886	-.002573
medval	1.224828E-6	3.839673E-7	562.718	3.190	.002	4.706434E-7	1.979012E-6
renwhi	.004144	.002284	448.450	1.814	.070	-.000344	.008632
renedu	-.007479	.005522	580.060	-1.355	.176	-.018325	.003366
pov	.021572	.011198	660.014	1.926	.054	-.000416	.043561
vac	-.007209	.015391	565.277	-.468	.640	-.037440	.023021
temp	.002132	.001756	2566.127	1.214	.225	-.001312	.005576
hf	-2.692322	1.063451	1271.225	-2.532	.011	-4.778634	-.606010
fund	.032435	.006727	673.193	4.822	.000	.019227	.045643
pop2	2.43348E-14	1.02944E-14	390.929	2.364	.019	4.095516E-15	4.457425E-14
hf2	4.462446	1.279634	1614.917	3.487	.001	1.952529	6.972364
yearcoded	-.048380	.009062	1356.360	-5.339	.000	-.066157	-.030602
renocc * hf	.089977	.028045	820.291	3.208	.001	.034929	.145026
renocc * hf2	-.154652	.035614	1271.760	-4.342	.000	-.224521	-.084782
medren * vac	1.201098E-5	1.491394E-5	576.250	.805	.421	-1.728132E-5	4.130328E-5

a. Dependent Variable: People per 1,000 in Families Experiencing Homelessness.

b. This parameter is set to zero because it is redundant.

Table 229: Information criteria for chronic homelessness model

Information Criteria[a]

-2 Restricted Log Likelihood	593.224
Akaike's Information Criterion (AIC)	597.224
Hurvich and Tsai's Criterion (AICC)	597.229
Bozdogan's Criterion (CAIC)	610.975
Schwarz's Bayesian Criterion (BIC)	608.975

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: People per 1,000 Experiencing Chronic Homelessness.

Table 230: Type III tests of fixed effects for chronic homelessness model

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	649.164	4.895	.027
coccat	2	370.580	7.213	.001
inczon	1	376.828	2.330	.128
pop	0	.	.	.
bach	1	526.736	32.017	.000
medval	0	.	.	.
renwhi	1	443.942	4.077	.044
renedu	1	665.760	21.361	.000
pov	1	786.640	19.817	.000
vac	1	614.560	5.188	.023
temp	1	2629.508	1.004	.316
hf	1	1366.500	.014	.904
fund	1	739.842	12.628	.000
pop2	0	.	.	.
hf2	1	1830.077	.047	.829
yearcoded	1	1514.736	32.841	.000
renocc * hf	1	905.892	.928	.336
renocc * hf2	1	1472.184	1.051	.305
medren * vac	1	625.590	10.213	.001

a. Dependent Variable: People per 1,000 Experiencing Chronic Homelessness.

Table 231: Fixed effects estimates for chronic homelessness model

Estimates of Fixed Effects[a]

						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	.675977	.340103	612.683	1.988	.047	.008068	1.343886
[coccat=1]	.247164	.093641	371.106	2.639	.009	.063031	.431297
[coccat=2]	-.007651	.083330	373.743	-.092	.927	-.171505	.156203
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.072700	.047626	376.828	-1.526	.128	-.166346	.020945
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-1.606095E-7	5.158842E-8	371.743	-3.113	.002	-2.620512E-7	-5.916775E-8
bach	-.020709	.003660	526.736	-5.658	.000	-.027898	-.013519
medval	1.702557E-6	2.243914E-7	602.004	7.587	.000	1.261872E-6	2.143242E-6
renwhi	.002768	.001371	443.942	2.019	.044	7.381208E-5	.005463
renedu	-.014824	.003207	665.760	-4.622	.000	-.021122	-.008526
pov	.028563	.006416	786.640	4.452	.000	.015968	.041158
vac	-.020462	.008984	614.560	-2.278	.023	-.038104	-.002819
temp	.000888	.000886	2629.508	1.002	.316	-.000850	.002626
hf	-.069531	.578772	1366.500	-.120	.904	-1.204910	1.065848
fund	.013719	.003861	739.842	3.554	.000	.006140	.021299
pop2	1.422031E-14	6.290513E-15	369.468	2.261	.024	1.850607E-15	2.659001E-14
hf2	.147401	.681313	1830.077	.216	.829	-1.188833	1.483634
yearcoded	-.028073	.004899	1514.736	-5.731	.000	-.037682	-.018464
renocc * hf	.015230	.015811	905.892	.963	.336	-.015800	.046260
renocc * hf2	-.019814	.019323	1472.184	-1.025	.305	-.057717	.018089
medren * vac	2.777082E-5	8.689786E-6	625.590	3.196	.001	1.070614E-5	4.483550E-5

a. Dependent Variable: People per 1,000 Experiencing Chronic Homelessness.

b. This parameter is set to zero because it is redundant.

Table 232: Information criteria for veteran homelessness model

Information Criteria[a]	
-2 Restricted Log Likelihood	-3954.029
Akaike's Information Criterion (AIC)	-3950.029
Hurvich and Tsai's Criterion (AICC)	-3950.024
Bozdogan's Criterion (CAIC)	-3936.553
Schwarz's Bayesian Criterion (BIC)	-3938.553

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Veterans Experiencing Homelessness per 1,000 People.

Table 233: Type III tests of fixed effects for veteran homelessness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	710.036	.772	.380
coccat	2	373.265	6.961	.001
inczon	1	383.275	.116	.733
pop	0	.	.	.
bach	1	562.390	9.930	.002
medval	0	.	.	.
renwhi	1	457.690	8.734	.003
renedu	1	753.297	9.651	.002
pov	1	884.631	9.020	.003
vac	1	646.749	5.960	.015
temp	1	2239.023	13.475	.000
hf	1	1400.959	.019	.889
fund	1	804.266	12.179	.001
pop2	0	.	.	.
hf2	1	1831.529	.363	.547
yearcoded	1	1794.751	84.559	.000
renocc * hf	1	980.374	6.378	.012
renocc * hf2	1	1552.246	6.337	.012
medren * vac	1	644.954	13.103	.000

a. Dependent Variable: Veterans Experiencing Homelessness per 1,000 People.

Table 234: Fixed effects estimates for veteran homelessness model

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.094683	.143823	664.352	.658	.511	-.187720	.377085
[coccat=1]	.099358	.040965	373.162	2.425	.016	.018808	.179908
[coccat=2]	-.011628	.036406	374.534	-.319	.750	-.083213	.059958
[coccat=3]	0[b]	0	.	.	.	.	.
[inczon=0]	-.007094	.020819	383.275	-.341	.733	-.048028	.033841
[inczon=1]	0[b]	0	.	.	.	.	.
pop	-5.709531E-8	2.250945E-8	374.623	-2.537	.012	-1.013560E-7	-1.283461E-8
bach	-.004932	.001565	562.390	-3.151	.002	-.008007	-.001858
medval	3.571368E-7	9.926381E-8	607.737	3.598	.000	1.621950E-7	5.520785E-7
renwhi	.001755	.000594	457.690	2.955	.003	.000588	.002922
renedu	-.004215	.001357	753.297	-3.107	.002	-.006878	-.001551
pov	.008136	.002709	884.631	3.003	.003	.002819	.013453
vac	-.009498	.003891	646.749	-2.441	.015	-.017138	-.001859
temp	.001224	.000333	2239.023	3.671	.000	.000570	.001878
hf	-.033651	.241785	1400.959	-.139	.889	-.507951	.440649
fund	.005612	.001608	804.266	3.490	.001	.002456	.008769
pop2	5.31243E-15	2.74166E-15	372.676	1.938	.053	-7.86402E-17	1.070352E-14
hf2	.167337	.277686	1831.529	.603	.547	-.377278	.711952
yearcoded	-.018605	.002023	1794.751	-9.196	.000	-.022574	-.014637
renocc * hf	.016632	.006586	980.374	2.526	.012	.003709	.029556
renocc * hf2	-.019731	.007838	1552.246	-2.517	.012	-.035105	-.004357
medren * vac	1.355517E-5	3.744674E-6	644.954	3.620	.000	6.201949E-6	2.090840E-5

a. Dependent Variable: Veterans Experiencing Homelessness per 1,000 People.

b. This parameter is set to zero because it is redundant.

Glossary

Emergency shelter *means any facility, the primary purpose of which is to provide temporary or transitional shelter for the homeless in general or for specific populations of the homeless.*

Housing First *is a homelessness alleviation philosophy rooted in giving people experiencing homelessness immediate access to housing and support services.*

Other permanent housing *means a program that must provide long-term housing that is not otherwise considered permanent supportive housing or rapid re-housing, such as SRO or VA programs that provide permanent housing.*

Permanent housing *means either permanent supportive housing, rapid re-housing, or other permanent housing in which people experiencing homelessness are placed in housing without a limit on how long they may stay, though there may be time limits placed on assistance.*

Permanent supportive housing *means a program that must provide long-term housing to individuals with disabilities experiencing homelessness or families experiencing homelessness in which one member of the household has a disability and supportive services that are designed to meet the needs of the program participants must be available to the household.*

Rapid re-housing *means a program that must provide short-term or medium-term assistance (up to 24 months), the lease for units must be between the landlord and the program participant, the program participant must be able to select the unit they lease, and the provider cannot impose a restriction on how long the person may lease the unit, though the provider can impose a maximum length of time that grant funds will be used to assist the program participant in the unit.*

Transitional housing *means a project that has as its purpose facilitating the movement of homeless individuals and families to permanent housing within a reasonable amount of time (usually 24 months). Transitional housing includes housing primarily designed to serve deinstitutionalized homeless individuals and other homeless individuals with mental or physical disabilities and homeless families with children.*

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