COMMUNITY-LEVEL PREDICTORS OF FAMILY HOMELESSNESS IN THE UNITED STATES

by

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Abstract

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The problem of reducing homelessness in U.S. communities has challenged policymakers and advocates, who have looked to academic research on homelessness to understand its causes and design strategies to prevent and reduce homelessness. Although individual-level research shows important differences between homeless families and homeless individuals, the literature on community-level predictors of homelessness includes little work focused on families. Using newly available data on rates of family homelessness, this study identifies economic and social factors associated with rates of homelessness at the community level, finding that family poverty rates and rental housing costs are strong and consistent predictors of family homelessness, with higher poverty rates and housing costs associated with higher rates of family homelessness. Housing market and economic factors are overall more consistent predictors than public health or demographic factors in these models of family homelessness.

The study also looks closely at the public assistance programs that serve low-income families, asking whether the reach and generosity of these programs, as they vary across states and communities, have any relationship with the rates of homelessness among families. Finding that areas with higher rates of family homelessness tend to have greater enrollment of families in poverty in the TANF program, possible explanations for this result are investigated. The study also finds that the generosity of food stamp benefits is associated with lower family

homelessness rates, while similar measures of TANF and SSI programs do not have a measurable community-level relationship with family homelessness rates.

The study discusses several policy recommendations that could address housing market and economic determinants of homelessness, and the need for further individual-level and cross-national research that would continue this examination of the relationship between public assistance programs and family homelessness rates.

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1. Introduction

The increase in homelessness in the United States that began in the early 1980s was accompanied by a growth of research on homelessness. However, some of the questions and observations that were raised quite early on in this research remain challenging and unanswered.

Geographic variation in homelessness

The fact that homelessness was more prevalent in some places than in others led researchers to investigate the causes of geographic variation in homelessness rates. Although definitions of homelessness, methods to estimate the number of people experiencing homelessness, and the resulting estimations were often contested, the fact that rates differed from place to place was generally accepted. Explaining those differences in rates could help researchers identify causal factors of homelessness. By asking what it was that made one city's homelessness rate lower than another, researchers hoped to be able to isolate influential factors that could inform public policy intended to reduce homelessness.

A number of studies have addressed geographic variation in homelessness rates, many with particular questions motivating them: Could universal causal factors be identified, or were the dynamics of homelessness and causal factors different in every city? Were higher rates of drug abuse in some cities responsible for higher rates of homelessness? Were discharges from state hospitals of adults with mental illnesses responsible for higher rates of homelessness? Did differences in the numbers of homeless people from one city to the next have to do with those cities' responses to homelessness? Did providing emergency shelter beds lead to more homelessness? Were there differences in how cities regulated their housing markets that could explain some differences in homelessness rates?

The current study continues in this vein of research by observing geographic variation in homelessness and identifying community-level factors that vary with homelessness rates, but focuses this research method on a more specific demographic group among the homeless population: families with children.

Family Homelessness

Another important observation made early in the 1980s was that homelessness, which had largely affected single men in earlier decades, had begun, in its expansion, to involve new demographic groups, particularly families with children.

In fact, the effect on a broader array of demographic groups was a primary reason that homelessness began to garner the interest and focus of social science researchers. The phenomenon of homelessness had been a much smaller problem between the end of the Great Depression and the late 1970s, when increased demand on shelter services began to be seen. Since the Depression, the problem had also affected a narrower range of demographic groups, primarily single men, who could be conceptualized as experiencing homelessness due to choices they had made regarding employment, housing, family, and alcohol and drug use. The expansion of the experience of homelessness to greater numbers of people, and to other demographic groups such as families with children, defied this explanation, and therefore made the phenomenon more problematic and difficult to explain, and therefore of interest in social science research.

Family homelessness remains an important and challenging problem. In 2009 persons in families made up approximately 37% of the homeless population, and approximately 22% of homeless families, or 50,800 families, were unsheltered, meaning that they were not staying in temporary residential programs such as emergency shelters, but instead were staying in places

not meant for human habitation, such as in a car, in a train station, or in an abandoned building (HUD, 2010).

Homelessness among families is of particular concern to many advocates and researchers because of the potential effects of homeless living conditions on children whose experiences of stress, health problems, and interruptions in schooling are likely to have significant effects on their future health, social, educational, and economic outcomes. Families with children are also viewed as particularly vulnerable to various dangers of living in shelters or in unsheltered conditions.

Goals and methods of the study

This study combines these threads of homelessness research, by conducting an ecological analysis of family homelessness. The analysis identifies social and economic factors that are associated with family homelessness at the community level. It tests a wide range of economic, housing market, demographic, public assistance, and public health factors, to find factors that vary with the rate of homelessness.

This study will expand the literature on family homelessness, which, up to this point, has included very few national studies of geographic variation. The study also focuses on public assistance program factors, among many other types of factors, to investigate whether public assistance programs that serve poor families have an impact on homelessness at the community level, through the proportion of the population in need that they serve, the levels of their benefits, their rules governing enrollment and eligibility, or their expenditures.

To assess the relationship between these factors and the family homelessness rate, this study uses a multilevel regression model. The study measures the homelessness rate at the community level but includes independent variables at the community level and the state level.

Some variables that are important to this study, including the adequacy of public assistance benefits, are measured at the state level. Because communities are nested within states, and their homelessness rates are likely affected by some of these state level variables, the study uses multilevel methods of analysis, to be sure that the variation among communities is being correctly modeled. An examination of the data shows that there is a significant level of variance between the state mean family homelessness rates – more than would be expected by chance. Approximately 16% of the total variability in homelessness rates is attributable to differences between the states. In order to accurately reflect this variability between states as well as the variability between communities, multilevel modeling methods are used.

Study Findings

The results of the study demonstrate the importance of housing market factors among the determinants of family homelessness rates. Whether all communities are included in the analysis and the total rate of family homelessness is observed, or the focus is on unsheltered family homelessness, or analysis is limited to one type of community such as high-poverty or non-urban communities, housing market dynamics are key predictors of family homelessness. The housing market factors that are the strongest predictors are those that contribute, along with the poverty rate and household incomes, to housing affordability within a community. The models all have two other types of housing market factors in common: those measuring the presence of substandard or low-quality housing in a community, and those that indicate high levels of competition and mobility in a housing market.

The models create a picture summarizing the social and economic dynamics contributing to family homelessness. They describe family homelessness occurring among families in poverty who live in areas with high rental housing costs. In these areas, many units have rental

costs that are greater than 30% of family incomes. In addition, in these communities there is a relatively high proportion of housing that is substandard or in poor enough condition to remain or frequently become vacant. Households move relatively frequently in these communities, and there is strong housing competition, due in part to the presence of many single-person households.

The study results also show that while the adequacy of Temporary Aid to Needy Families (TANF) and Supplemental Security Income (SSI) benefits does not appear to be related to community homelessness rates, the adequacy of the Supplemental Nutrition Assistance Program (SNAP, or food stamps) is negatively associated with the family homelessness rate. Higher adequacy of SNAP benefits is associated with lower rates of family homelessness.

Further, the study found that in some models a larger proportion of poor families enrolled in TANF or General Assistance (GA) is associated with higher family homelessness rates. The study investigated two possible explanations for this relationship and found some evidence in support of both of the explanations. First, contributing to this result is the fact that areas with higher inclusion rates for TANF tend to offer more shelter beds relative to the number of people in poverty. Also contributing to this result is the fact that a primary goal of providers of shelter is to help families enroll in public assistance benefits for which they are eligible, in order to help families exit homelessness by gaining income. Areas with higher rates of homelessness are likely to have higher rates of TANF inclusion because those families are being assisted by social service providers, after entering shelter, to access TANF benefits.

The models also generally demonstrate that public health variables, such as those measuring the prevalence of mental illness and substance abuse in the population, are not strong

or significant predictors in the model. Housing market and economic factors are more important than health factors in predicting family homelessness rates at the community level.

While the models do show these important commonalities, some models also show that there are different dynamics of homelessness occurring in particular types of communities. These differences indicate that while national modeling of homelessness rates is important, this undertaking is not complete without additional analyses of sub-categories of communities, such as low- and high-poverty communities, and urban and non-urban communities.

For example, when the analysis is limited to include only areas that have a poverty rate higher than the national median, the unemployment rate becomes a significant and positive predictor of homelessness. This broadens the understanding of the dynamics of poverty as it contributes to homelessness in these areas. While some families included in the homelessness rate may be experiencing long-term poverty, the rate also reflects families in high-poverty areas who are entering poverty, or for whom poverty is worsening, after the loss of a job.

Second, when the analysis is limited only to non-urban areas, some important factors were seen. The level of spending per capita by the federal government on TANF cash assistance was a negative predictor of homelessness in non-urban areas. The maximum income for TANF eligibility was positively associated with homelessness in these areas, and the rate of admission to alcohol treatment programs was also positively associated with homelessness. Further, among non-urban communities, owner-occupant housing costs were more important in predicting family homelessness rates than rental housing costs.

Policy Implications

The study makes several recommendations for policy change and further research. First, the findings regarding the effect of housing costs on homelessness lead to a recommendation that

an entitlement housing voucher program could be funded through a progressive tax on commercial and residential real estate transactions.

Second, factors identified in the study as covariates of family homelessness should be used to establish a system for allocation of any future federal funding for homelessness prevention and rapid re-housing programs, and of state and local funds for prevention. By using community characteristics to calculate predicted family homelessness rates, homelessness prevention funds can be allocated to areas where there is likely to be the most need.

Third, based on findings that few public assistance programs appear to have an impact on homelessness rates, the study concludes that the US Interagency Council on Homelessness (USICH) should take a lead role in investigating the ineffectiveness of U.S public assistance programs in reducing homelessness. The USICH should advocate for expansion of public assistance programs' inclusion and/or benefit levels. This advocacy should be informed by further longitudinal and cross-national research on public assistance program use and homelessness.

2. Review of the Literature

Researchers have pursued the identification of determinants of homelessness through several methods. One common approach has been to study the homeless population through surveys and cross-sectional studies, and to use housed comparison groups to draw conclusions about key differences between the groups. A second common approach has been to observe rates of homelessness across communities and to identify social and economic factors and population characteristics that are associated with higher or lower rates of homelessness.

Community-level studies generally address the question of why homelessness rates are higher in some areas than in others. These studies have served a variety of purposes. Earlier studies focused on a debate over whether homelessness was primarily the result of structural causal factors such as poverty or unemployment, or individual-level characteristics such as single parent household status, mental illness, or substance abuse. These questions were asked in order to determine broadly what should be the focus of efforts to reduce homelessness. Later community-level studies have focused on more specific questions about interventions, such as whether current federal housing subsidies have the potential to reduce homelessness, or whether increased spending on mental health services are associated with reductions in homelessness.

However, until recently there have been few sources of national data available on numbers of homeless families at the community level, so few national studies of community-level variation in family homelessness rates have been done. However, other types of homelessness research have demonstrated that there are important differences between those who are homeless as part of a family, and those who are homeless as single adults.

Homeless families and homeless individuals are quite different demographically. Most adults in homeless families are women, while most homeless single adults are men. The

proportion of African Americans is much higher among adults in families than single adults. The mean age of adults in homeless families is much lower than the mean age of homeless single adults (HUD, 2010).

Behavioral health characteristics also differ; prevalence of mental illness and substance abuse is much lower among adults in homeless families than among people who are homeless as single adults (Burt, Aron & Lee, 2001; Shinn and Weitzman, 1996). Homeless single adults are much more likely to be chronically homeless, while homeless families are more likely to be transitionally or episodically homeless (Culhane et al., 2007). Because characteristics of these two populations differ so much, including their patterns of homelessness, and prevalence of conditions that have been included in some past studies, community-level studies of family homelessness would likely find results that differ from previous studies that did not distinguish between families and individuals.

Because there have been few community-level studies focusing on homeless families with children, there are several gaps to be filled in regarding community-level predictors of family homelessness. First, studies of the total homelessness rate have established that housing market and economic measures such as poverty and housing costs are more consistent predictors of the total homelessness rate than measures of demographic representation, or health and behavioral health factors. These findings have not been re-assessed regarding the specific outcome of family homelessness, which will be one goal of this study. This study will evaluate the relative importance of five different categories of factors: economic, housing market, public assistance, demographic, and public health.

Second, although public assistance programs such as TANF or Section 8 housing subsidies could be possible interventions that could reduce rates of family homelessness by

increasing incomes of families in poverty, there has not yet been a comprehensive look at the relationship between a range of public assistance programs and family homelessness at the community level.

The questions addressed in this study concerning the relationship between public assistance programs and homelessness rates have often been raised at times of proposed or implemented shifts in public assistance policy. In several instances local or national policies, or expected policy changes, have been scrutinized for their potential impact on the risk of low-income families for homelessness. In some of these instances the focus has been on program benefit adequacy, or the dollar value of public assistance benefits. In other instances, the focus has been on program inclusion, or the proportion of households in need that are enrolled in the program. At other times the focus has been on the program rules that govern individual eligibility for the program, and therefore affect the level of program inclusion among households in need.

Adequacy of public assistance benefits

Debate went on through the late 1980s and 1990s between advocates for the poor, and lawmakers in New York State and City, regarding the adequacy of AFDC benefits in relation to rising area housing costs. Critics argued that the value of AFDC benefits levels had sunk too low to allow families to pay for housing in New York City, and that this was a major factor contributing to the increase in family homelessness.

A 1987 class action lawsuit was filed against New York State on behalf of AFDC recipients who had been evicted because of their inability to pay rent. The lawsuit relied heavily on comparisons between state AFDC benefit levels and the cost of housing in New York City. Data on housing vacancy at the lowest rent levels showed a small and diminishing stock of

housing with rent levels that fit the incomes of public assistance benefits. These comparisons were influential in the court's ruling requiring the state to pay supplemental benefit amounts to affected recipients; the ruling cited the "correlation" between the low level of benefits and levels of family homelessness in New York City. This court decision hinged on the state law that required the state to provide aid to families with children that would allow parents to raise their children in their own home (*Jiggetts v. Grinker*, 1991). With the ruling, the court asserted that the adequacy of existing state benefit levels were, at least in some cases, not sufficient for the state to carry out this responsibility for all families in need.

A 2002 "Care Not Cash" ballot initiative in San Francisco proposed replacing cash General Assistance payments for homeless people with services and housing assistance. The initiative, which passed, was supported by arguments that the relatively high value of General Assistance benefits was a causal factor in San Francisco's high homelessness rate. Supporters of the initiative argued that the relatively generous benefit levels in San Francisco not only attracted homeless individuals from other localities with lower or no benefits, but also contributed to the continuation of homelessness for recipients, by enabling addictions to drugs and alcohol, and failing to engage populations in behavioral health services. Opponents of the initiative held the opposite position on the relationship between cash benefits and homelessness, arguing that lack of access to cash benefits would reduce the ability of people at risk of homelessness to pay for housing and thereby increase homelessness rates (Noy, 2009). While supporters maintained that high General Assistance benefit adequacy contributed to higher homelessness rates through personal addiction and dysfunction, and opponents maintained that low benefit adequacy would prevent participation in the low-income housing market, each group argued that a particular level of benefit adequacy was a direct causal factor contributing to individuals' risk of homelessness.

Inclusion of public assistance programs

The 1996 welfare reform law, Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA), prompted debates over the potential effects of the changes in eligibility and work requirements that resulted in significant reductions in public assistance caseloads in every state. While supporters of the Act generally argued that welfare reform would improve income for poor families and reduce an array of negative outcomes for families, critics warned that, among other outcomes, it could increase risk of homelessness by reducing enrollment in public assistance programs and decreasing income, while failing to connect families with work income to pay for housing costs (Berger & Tremblay, 1999).

Only a small amount of empirical research was conducted that addressed the outcome of homelessness for families affected by the change. A survey of New York State homeless service providers was conducted by the New York City-based Coalition for the Homeless in 1999, eliciting reports on level of demand for food and shelter services and the nature of services requested, before and after the passage of welfare reform. Providers reported a sharp increase between 1995 and 1999 in demand for homeless services, in lengths of stay in shelter, and in the number of clients who were not covered by any public benefits (Coalition for the Homeless, 1999).

In 2006 the New York State Assembly's Committee on Social Services conducted a review of the effects of New York's implementation of PRWORA on families and children living in poverty, by conducting two public hearings, focus group meetings, and a review of relevant literature, including an inquiry into hardship indicators among families who had stopped receiving TANF benefits. While the hearings included a discussion of homelessness as an outcome of loss of public assistance benefits, it was limited by a lack of supporting empirical

research. None of the literature reviewed in the report discussed rates of homelessness. Evidence regarding homelessness discussed in the report included only the verbal testimony of selected social service providers that their clients had, since the beginning of the reform period, often experienced loss of benefits and risk of homelessness simultaneously (NY State Assembly, 2006)

Despite the large quantity of research evaluating various effects of welfare reform policies, these studies have rarely included homelessness as an outcome or indicator of well-being. Among more than sixty empirical studies of welfare reform outcomes synthesized in a 2002 report, only two measured homelessness as an outcome, with contradictory outcomes. In contrast, income outcomes were the subject of over fifty studies (Grogger, Karoly & Klerman, 2002).

In summary, public assistance policy change has spurred debate over the following questions: First, how is the adequacy of a public assistance program's benefits related to the ability of recipient families to remain housed and avoid homelessness? Second, how is the proportion of eligible families in need served by a public assistance program related to the homelessness rate in the population? Third, how are policies that affect inclusion through enrollment and eligibility related to the level of homelessness in the community? This study will investigate each of these questions, focusing on the level of family homelessness and creating a model that predicts variation in rates of family homelessness across communities.

Homelessness Research

The field of homelessness research has expanded from an early focus on examining the behaviors and characteristics of individuals experiencing homelessness (Bassuk, 1986 & 1988). Community-level studies investigating structural causes of homelessness such as housing costs,

loss of housing stock, income and unemployment emerged as a reaction against the previous focus on individual characteristics and behaviors. (Elliot and Krivo, 1991; Burt, 1993; Culhane, Wachter & Lee, 1996).

Since that time, a focus on either individual or structural causes of homelessness has given way to multidimensional models of homelessness that include both structural and individual factors. This type of model includes structural factors that establish the conditions for homelessness to occur, while individual characteristics such as race or behavioral health make risk of homelessness greater for some households than for others (Culhane, Wachter & Lee, 1996; O'Flaherty, 1996; Lee, Price-Spratlen & Kanan, 2003). O'Flaherty (2004) presents an econometric model of homelessness in which both personal characteristics and housing market characteristics contribute to episodes of homelessness, and explains why research identifying individual-level predictors and research identifying community-level predictors are not contradictory.

This study builds on existing multidimensional theoretical models of homelessness and includes predictive factors that have been established in multiple previous studies. The multidimensional model of homelessness includes housing market and economic dynamics that decrease housing affordability and thereby create conditions for homelessness to occur. Public assistance programs have the potential to alter community-level housing affordability by reducing the gap between incomes of poor households and the housing costs of the lowest-cost housing, through cash assistance or in-kind benefits. Demographic characteristics are included in many models, due to their impact on households' vulnerability to homelessness. Chronic behavioral and physical health conditions increase vulnerability to homelessness on an ongoing basis, while medical, economic and family events that act as shocks to households often

immediately precede episodes of homelessness. In these models, structural factors determine the extent of homelessness in an area, while individual factors determine the level of risk for any given household.

This chapter will review previous homelessness research, both individual-level and community-level, that has tested various predictors of the multi-dimensional model of homelessness, including public assistance program measures of inclusion, adequacy and expenditures, housing market, economic, demographic, and public health factors. Findings will be reviewed for each of these subjects. The chapter will go on to review data sources used in previous studies, their shortcomings, and the improvements made in more recent data collection. Finally, the chapter will review literature on public assistance policies that is relevant to the relationship between public assistance policies and homelessness rates at the community level.

Public assistance. This section reviews the findings for three types of studies: cross-sectional individual-level studies of homeless households and comparison groups, community-level studies of variation in homelessness rates across cities or metropolitan areas at one point in time, and studies of variation in homelessness rates within a single city.

Individual-level studies.

While the questions addressed in this study are about community-level homelessness rates, and how state- and community level policies affect those rates, individual-level homeless studies also contribute to the theoretical model of homelessness.

Cash assistance. Findings from cross-sectional studies of people experiencing homelessness show that receipt of cash assistance is high among this group, but that it is somewhat higher among housed comparison groups. Cross-sectional studies have found high rates of receipt of public assistance among people experiencing homelessness, and high

prevalence of homelessness among people who had received public assistance. Bassuk, Rubin and Lauriat (1986) found that 91% of households in a sample of Massachusetts homeless families were receiving AFDC. Toro and Wall (1991) found that 45% of homeless individuals surveyed in Buffalo, NY had received public assistance within the past year.

A national telephone survey found a higher five-year prevalence of homelessness among those with public assistance receipt history than among those who had not received public assistance. Ten percent of those who had received public assistance, compared with less than one percent of those who had never received public assistance, reported having been homeless within the previous five years (Link et al., 1994).

Another group of studies have compared homeless families and poor non-homeless families in their receipt of public assistance benefits. Generally they have found that housed comparison groups were more likely to receive public assistance, for a longer period, and with fewer interruptions in benefits.

Bassuk, Browne, and Buckner (1996) found that 76% of a sample of homeless women had received AFDC in the previous year, compared to 93% of a sample of single mothers in low-income housing. They also found a shorter median period of receipt of AFDC for homeless mothers of 2 years compared to 3.5 years for housed mothers. Bassuk et al. (1997), using a regression model of childhood and adult predictors, found that receipt of AFDC in the past year was a protective factor against homelessness for families, even while controlling for other sociodemographic, housing, income, and social factors. The odds ratio for homelessness was 0.34 among households receiving AFDC at some point in the past year compared with households that did not receive AFDC.

Wood, Valdez, Hayashi and Shen (1990) found that housed families had higher rates of AFDC receipt; almost 100% of a group of poor housed families received their total income from public assistance, while only 61% of homeless families did, and 23% of homeless families reported no income at all. The authors also found that homeless families were more likely to have had interruptions in their public assistance benefits, with 43% of the homeless families reporting that they lost their public assistance at some point during the previous year.

Higher homeless prevalence among public assistance recipients suggests that families eligible for public assistance are at greater risk of homelessness than the general population. The finding that receipt of AFDC benefits was less frequent, shorter, and more frequently interrupted among homeless families than among comparison groups of poor housed families suggests that among poor families who were at risk of homelessness, AFDC benefits acted as a protective factor. However, the existence of homeless families receiving AFDC indicates that in many cases, public assistance benefits were not sufficient to keep households in housing

Housing subsidies. Individual level studies also found that housing subsidies were a protective factor for poor households at risk of homelessness. Shinn et al. (1998) found that families requesting shelter in New York City were much less likely to have a subsidized housing unit (9%) than were families in a comparison group of housed families receiving AFDC at the time of the study (31%).

Bassuk and Rosenberg (1988) found that 96% of homeless families and 100% of housed families were receiving AFDC, and that previous to the homeless episode, homeless families were much less likely (6%) to have had a public housing unit or Section 8 voucher than the housed families, 72% of whom were living in a subsidized unit at the time of the study.

In the regression model used by Bassuk et al. (1997) to predict family homelessness, receipt of a Section 8 voucher was a protective factor against homelessness for families, controlling for other factors including receipt of AFDC. The odds ratio for homelessness was 0.26 among households receiving a housing voucher in the past year compared with households that did not. These findings suggest that housing subsidies could reduce households' risk of homelessness by decreasing the gap between household incomes and housing costs.

Community-level studies. Several types of community-level studies have examined the relationship between public assistance programs and homelessness rates, either by examining variation in homelessness rates across cities or metropolitan areas, or by focusing on individual cities and examining variation in homelessness rates over time, or across census tracts within cities.

Building on findings from individual-level studies, researchers have hypothesized that on a community level, social welfare policies that expand access to income transfer programs would be negatively associated with homelessness rates, because they would increase incomes and housing affordability for a larger proportion of poor households. The level of benefits for poor households has also been expected to be negatively associated with homelessness as higher benefit levels would be more effective at increasing incomes and decreasing the gap between housing cost and income.

Inclusion of cash assistance programs. In a study of welfare reform's effect on city-level homelessness rates, Culhane, Poulin, Hoyt and Metraux (2003) analyzed the effects of the 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) on Philadelphia shelter entries, using both univariate interrupted time series analysis and OLS regression analysis. The authors did not find evidence of an impact of the law or the size of the TANF

caseload on shelter admissions, although they found some changes in the demographic profile of families entering shelter. Discussing these findings, the authors state that in the period studied, which included only one year after implementation of the law began, most exits from public assistance were not the result of sanctions resulting from non-compliance with work requirements; Pennsylvania issued very few sanctions during this period, so reasons other than sanctions appear to have prompted most of the exits during this period. The study results suggest that a decreasing unemployment rate was responsible for most exits. The period of study chosen occurred before the five-year lifetime limit on benefits, introduced by the law, had taken effect. It is therefore difficult to generalize from these results to the effects of the full public assistance eligibility changes that occurred.

Culhane, Wachter and Lee (1996) studied variation in homelessness at the census tract level within New York City and Philadelphia and found that in high-income census tracts in New York City, mean public assistance income of a census tract was positively associated with homelessness, while in low-income tracts it was negatively (but not significantly) associated with homelessness. In their discussion of these findings the authors argued that in high income tracts, the measure of public assistance program inclusion was likely confounded with poverty, a strong risk factor for homelessness.

Studies of inter-city (or inter-metropolitan area) variation in homelessness have measured the proportion of the population that receives program benefits. These studies have had inconsistent findings on the relationship between inclusion of cash assistance programs and homelessness rates. While Burt (1993) found a negative association with GA inclusion, Lee, Price-Spratlen and Kanan (2003) found that the AFDC inclusion rate was a positive predictor of homelessness. Tucker (1987), Quigley (1991), Honig and Filer (1993), Hudson (1998), and

Gould and Williams (2010) found no significant effect for the various measures of public assistance program inclusion used in their models.

Housing Subsidy Program Inclusion. In studies of variation in homelessness rates, measures of housing subsidy spending and inclusion that are standardized by the general population have been either non-significant or positively associated with homelessness. Of several studies that have included measures of housing subsidy program inclusion, three did not find any significant association with homelessness rates (Tucker, 1987; Quigley, 1990; Burt, 1993), while one study found a positive relationship (Troutman, Jackson and Ekelund, 1999).

Two other studies suggest that the relationship between housing subsidies and their effect on the homelessness rate may be limited to housing subsidies targeted to very poor families. Early and Olsen (2001) found that the percent of subsidized housing units going to households with incomes less than $5,000 (in 1995) was a negative predictor of homelessness rates, while the availability of subsidized housing was not significant. This study developed from the findings by Early (1998), who identified a mismatch between the incomes of households at risk for homelessness and the income eligibility criteria of federal housing subsidy programs. The author modeled homelessness as an outcome of individual characteristics and characteristics of city of residence. The income levels that were associated with risk of homelessness in the model were compared to incomes of households eligible for housing subsidies. This comparison showed that a large proportion of households eligible for housing subsidies were not at risk of homelessness. The conclusions of both of these studies was that housing subsidies will only have a stronger impact on homelessness rates if they are targeted to households in the lowest 5% of incomes.

These findings suggest that a measure of housing subsidy inclusion for households with very low incomes may be more significant in modeling homelessness than a standard measure of inclusion. The positive relationship found previously between housing subsidy spending and inclusion may be due to the fact that housing subsidies are allocated according to a federal formula which primarily depends on the level of poverty in a community. Measures of housing subsidy inclusion standardized by the general population may act as a proxy measure for the level of poverty in an area.

Benefit adequacy. Authors of previous studies of variation in homelessness rates have expected the adequacy of benefits for poor households to be negatively associated with homelessness.

In a time series analysis of a period of increase in public shelter use in New York City, Cragg and O'Flaherty (1999) found that the falling value of welfare benefits was one of multiple factors that led to the increase in the New York City family shelter census between 1990 and 1993.

Studies of inter-city variation in rates of homelessness that have included benefit adequacy among the predictors have had mixed results regarding the relationship between benefit levels of various programs and homelessness, with some studies finding a positive association with homelessness (Burt, 1993; Gould & Williams, 2010; Honig & Filer, 1993), some finding a negative relationship (Honig & Filer, 1993), and others failing to find a significant association (Bohanon, 1991; Lee, Price-Spratlen & Kanan, 2003; Hudson, 1998l; Early & Olsen, 2001).

Next, this chapter will review findings from individual-level and community-level research on other elements of the multidimensional model of homelessness, including housing market, economic, demographic, and public health factors.

Housing market factors. Both individual-level and community-level studies have identified housing factors as key predictors of homelessness outcomes. While individual-level studies have focused on households' housing stability, connection to the housing market and receipt of housing subsidies, community-level studies have focused on rent levels, housing stock characteristics, housing tenure, and vacancy.

Individual-level studies. A comparison of housed and homeless families with children (Shinn et al., 1998), found that demographic characteristics and housing factors, including having one's own apartment, crowding, mobility, and serious building problems, were the strongest predictors of whether families were or were not experiencing homelessness. Bassuk et al. (1997) found that three housing history factors were significant predictors in a multivariable model of family homelessness: rent mobility, recent eviction, and being a primary tenant.

Community-level studies. A primary hypothesis tested in community-level studies of homelessness has been the importance of housing affordability, which is determined by an interaction between housing costs and household incomes. Thus measures of housing costs have been included in almost every one of these studies, whether as a simple measure of median rental costs (Lee, Price-Spratlen and Kanan, 2003) or as a contributor to a more complex variable measuring the ratio of low-income renters to low-rent apartments (Burt, 1993).

Among studies of inter-city variation in homelessness rates, the single study that excluded rental costs from its list of predictors was conducted by Tucker (1987), who argued that rent control decreased housing availability and affordability and increased homelessness rates by

decreasing incentives for developers to build or landlords to maintain low-cost rental housing. His statistical methods were criticized by several scholars (Quigley, 1991; Applebaum, Dolny, Dreier and Gilderbloom, 1991) who revisited his analysis and found that the significance of rent control was a spurious result; other housing market characteristics such as rental costs, rental vacancy rate, or percentage of renters were significant.

Other studies of variation across cities and metropolitan areas have consistently found a positive relationship between rent levels and homelessness rates. Quigley (1991), Bohanon (1991), Honig and Filer (1993) Hudson (1998), Troutman, Jackson and Ekelund (1999), Quigley, Raphael and Smolensky (2001), Quigley and Raphael (2001), Early and Olsen (2001), Lee, Price-Spratlen and Kanan (2003) and Fertig and Reingold (2008) all found that median rents, or rental costs in the 10^{th} percentile were positively associated with homelessness. Other studies found similar results for the presence of low-cost rental housing (Elliot and Krivo, 1991), for the difference between median rents and 10^{th} percentile (lowest cost) rents (Grimes and Chressanthis, 1997), and for the ratio of rent to income (Raphael 2010).

Many of these studies have also considered rental vacancy rate as an important housing market factor, expecting that it would be negatively associated with homelessness, as greater numbers of available housing units would increase the ability of households to locate housing. Several previous studies of inter-city variation have found rental vacancy rate to be a significant and negative predictor of homelessness rates (Quigley, 1990; Hudson, 1998; Troutman, Jackson and Ekelund, 1999; Quigley, Raphael and Smolensky, 2001); however, vacancy rates were non-significant in other models (Applebaum, Dolny, Dreier and Gilderbloom, 1991; Honig and Filer, 1993; Early and Olsen, 2001; Lee, Price-Spratlen and Kanan, 2003).

However, studying variation at the census tract level, Culhane, Wachter and Lee (1996) found the opposite result, that the vacancy rate was positively associated with homelessness. The authors also found a positive association between the proportion of boarded-up buildings in a neighborhood and the homelessness rate. They found a positive relationship between overcrowded housing and homelessness. They argued that families were more likely to come from areas where households were crowded, where housing was sitting vacant because of its poor condition.

Several other housing market characteristics indicate conditions that are thought to be precedents of homelessness: rental tenure, residential mobility, and foreclosure. The percent of households that are renter-occupied has at times been found to be a significant and positive predictor (Appelbaum, Dolny, Dreier and Gilderbloom, 1991; Hudson, 1998) although it has not proved to be significant in other models (Troutman, Jackson & Ekelund, 1999; Culhane, Wachter & Lee 1996). Lee, Price-Spratlen & Kanan (2003) found residential mobility to be positively associated with homelessness. Foreclosures create housing instability for renters in foreclosed housing units (Been & Glashausser, 2009) as well as for owners, who may have to re-enter the housing market as renters, making the rental housing market more competitive.

Economic. Along with housing market factors, economic factors are contributors to housing affordability and therefore play an important role in a multi-dimensional model of homelessness. Individual-level research has demonstrated that homeless families and individuals experience homelessness when they have very low incomes and are therefore ill-equipped to compete in housing markets. Burt (1993) reported that in a 1989 survey of people experiencing homelessness, women with children were found to have had a mean income of $121 in the 30 days before the survey, equivalent to a $1452 annual income if that income remained the same

for 12 months. Bassuk et al. (1997) found that a sample of homeless families had a mean annual income that was not only very low ($7900 in 1995), but was also approximately $2,000 less than the mean annual income of a housed comparison groups.

Like housing market factors, the findings on the significance of individual economic factors in community-level models have been mixed. Although some studies have not found poverty to be a significant predictor of homelessness (Appelbaum, Dolny, Dreier & Gilderbloom, 1991; Elliott & Krivo, 1991; Burt, 1993; Honig & Filer, 1993; Grimes & Chressanthis, 1997; Raphael, 2010; Lee, Price-Spratlen & Kanan (2003), when it has been found to be significant, poverty rate has been positively associated with homelessness (Quigley, 1990; Troutman, Jackson & Ekelund, 1999; Quigley, Raphael & Smolensky,2001; Hudson, 1998; Early & Olsen, 2001.)

The unemployment rate had a similarly mixed set of results, with several studies finding unemployment to be a significant and positive predictor of homelessness (Appelbaum, Dolny, Dreier and Gilderbloom, 1991; Bohanon, 1991; Burt, 1993; Hudson, 1998; Troutman, Jackson and Ekelund, 1999; Gould and Williams, 2010), and others finding it to be non-significant (Quigley, 1990; Quigley Raphael and Smolensky, 2001; Lee, Price-Spratlen and Kanan, 2003).

Culhane, Wachter & Lee (1996), in a study of variation in homelessness across census tracts, found that poverty rate was a positive predictor of homelessness, while the unemployment rate was non-significant. However the authors did find labor force non-participation to be positively and significantly associated with homelessness. The authors also found that while poverty was positively associated with homelessness, as predicted, median income was also a positive predictor. The authors concluded that in this study within a single city, of variation

across census tracts, median income was acting as a measure of tightness in the housing market. The rent-to-income ratio was also found to be positively associated with homelessness.

Demographic. In addition to structural factors such as poverty rates and rental housing prices, multi-dimensional models of homelessness assert that some households are at greater risk for homelessness than others. Among household characteristics that have been identified as risk factors, demographic characteristics are the easiest to measure in the population, as these characteristics are regularly identified by surveys and censuses.

Individual-level studies have shown demographic characteristics including race to affect risk of homelessness among individuals. People of Black race and Hispanic ethnicity have been found to be overrepresented among people experiencing homelessness (Burt and Cohen 1989; Rossi, 1989; Burt, Aron & Lee, 2001).

Risk of homelessness associated with demographic characteristics also appeared in a study of variation across census tracts; the proportion of African Americans, Hispanics, and female-headed households with young children were each found to be positively associated with homelessness (Culhane, Lee and Wachter 1996).

In studies of variation across cities and metropolitan areas, results for demographic characteristics have been less consistent. While one study (Elliot and Krivo, 1991) found the percent of the population that is African-American to be a positive predictor of homelessness, several others (Burt, 1993; Early and Olsen, 2001; Lee, Price-Spratlen and Kanan, 2003; Raphael, 2010) have found it to be non-significant. Similarly mixed results were found for female-headed households and age groups under 18 and over 65. Two studies (Burt, 1993; Lee, Price-Spratlen & Kanan, 2003) have found single-person households to be a positive predictor of homelessness. They suggest that people living in single person-households are more likely to

have conditions such as mental illness or substance abuse problems that increase individual risk for homelessness and that single-person households may also make housing markets more competitive by consuming more housing units per person.

While veteran status has not been frequently included in studies of inter-city variation in homelessness rates, there is some evidence that in general, veterans in poverty are at greater risk of homelessness than poor non-veterans (Fargo et al., 2012). However, veteran families constitute only 2.1% of homeless families, the outcome of interest for this study, and being part of a family appears to be a protective factor against homelessness for both female and male veterans (Culhane et al., 2011).

Health. Health conditions play a role in a multidimensional model of homelessness, as household-level characteristics that increase risk for homelessness. In addition to any vulnerability that a health problem may bring due to changes in ability to work or in level of functioning, medical conditions can bring financial shock to households, precipitating an episode of homelessness.

While homeless single adults have been found to be more likely than their housed counterparts to have mental illnesses or substance use disorders (Culhane, Averyt and Hadley, 1997), this comparison for homeless families has not had such clear results. Prevalence of mental illness and substance abuse is much lower among adults in homeless families than among people who are homeless as single adults (Burt, Aron & Lee, 2001; Shinn and Weitzman, 1996). While Bassuk et al. (1997) found groups of homeless and housed families to be significantly different in their rates of mental illness and substance use, Shinn et al. (1998) found in a comparison of families in poverty that did and did not enter shelter, that neither mental illness, substance use disorder, nor medical condition were significant predictors of shelter entry.

Health factors have not appeared to be strong predictors of variation in community-level studies of homelessness rates. Although several studies tested variables that measured hospitalization rates for substance abuse or mental illness, only one found a significant result: the size of the institutionalized mental health population (Bohanon, 1991).

Thus, while health factors have been identified as risk factors for homelessness in general, their importance in modeling homelessness among families is not as clear, and will be tested by inclusion in this study's model of family homelessness.

Data sources for studies of inter-city variation

National studies of homelessness rates at city, metropolitan or state levels require estimates of homelessness obtained through standardized methods across a large number of areas. Estimating numbers and rates of people experiencing homelessness has been a challenging task, with several obstacles involved. First, enumerators, advocates and government officials have disagreed about meaningful definitions of homelessness; second, reliable methods of locating and enumerating people who lack fixed addresses have been difficult to design; and third, geographic units in which people experiencing homelessness have been enumerated have sometimes been incomparable to more commonly used units, such as Census geographies, which could be used to give contextual information for an enumeration, such as the total population to be used in calculating homelessness rates.

The first estimates and enumerations of homelessness were conducted within metropolitan areas or cities of a minimum population, which limited their representativeness by excluding non-metropolitan areas, or smaller cities and rural areas. The most recent estimates have been created by the Department of Housing and Urban Development (HUD), using enumerations reported by coalitions of homeless service providers across the country. These

coalitions of service providers are called Continuums of Care (CoCs), and they were formed in response to requirements of HUD, which provides federal funding for local homeless services.

Since 1987 the federal government, under the McKinney Homeless Assistance Act has been providing financial assistance, awarded by HUD through competitive grants, to providers of homeless services such as emergency shelters. In 1994, HUD changed the grant application requirements; applications from individual providers were no longer accepted. Providers could only apply for grants by organizing with other service providers in their community into CoCs. This change was intended to encourage providers of services to different homeless subpopulations to make community-wide plans and coordinate their efforts. CoCs are made up of public, non-profit and private organizations that serve people experiencing homelessness, such as shelters funded and managed by a city government, religious organizations that provide shelter or other services, and non-profit organizations that provide shelter, transitional housing, or permanent supportive housing.

CoCs, because they are organized by service providers that have linked together to make services in a community more coherent, may be small in denser areas, or quite large in less densely populated areas. Approximately 9% of CoCs comprise the area within a city's boundaries (e.g. New York City or Philadelphia). Approximately 52% of CoCs comprise a county (e.g. El Paso County, Colorado). Most of these cases are urban counties. Thirty-seven percent of CoCs comprise multiple counties. These may be rural counties, or a mixture of suburban, rural and urban counties. In only 6 cases, the CoC comprises an entire state. These states have relatively small populations, such as North Dakota (HUD 2009)

HUD guidelines for the formation of CoCs recommend that CoCs should aim to provide each of the following types of service: homelessness prevention, outreach, emergency shelter,

transitional housing, permanent supportive housing, and permanent affordable housing. While not all CoCs currently provide all of those services, many of them are made up of a variety of types of service providers. For example, the Philadelphia CoC is led by the City of Philadelphia's Office of Supportive Housing, a city government agency that oversees the daily operations of the CoC, submits the application for funding, and administers funds to other agencies within the CoC. In 2009, the Philadelphia Continuum of Care was awarded grants for 94 different agencies to provide shelter, permanent housing, and/or supportive services to people experiencing homelessness. (HUD 2012)

Because CoCs are expected to plan for year-round service needs, a primary function of the CoC is to collect data on people using homeless services, in CoC-wide databases called Homeless Management Information Systems (HMIS). HMIS record individuals and families using homeless services, and allow unduplicated enumeration to be made of these individuals and families. In addition to enumeration of people using services through HMIS, CoCs are required by HUD to conduct an enumeration of people who are homeless in places not meant for human habitation, such as parks, streets, or train stations. HUD uses these enumerations to create a nation-wide estimate of sheltered and unsheltered homelessness.

Before 2005, very few large-scale estimates had been made of homelessness and the existing estimates had serious methodological flaws. Data sources for homelessness estimates have used problematic methods of sampling and estimation. Most previous studies of variation in homelessness rates across cities relied on one of three estimates of homelessness: the 1984 HUD estimate of homelessness, the 1990 Census S-Night Enumeration, or the 1989 Burt survey of shelter beds. Each had flaws that make them problematic for use in studies of geographic variation.

The 1984 HUD Estimate of homelessness was based on a survey of local experts in homelessness in 60 metropolitan areas, reporting on the size of the homeless population in their area (Ranally Metropolitan Areas, which differ from the Census Metropolitan Statistical Areas). This estimate is problematic for use in comparing rates across metropolitan areas because it did not rely on any standardized method of enumeration. The estimate was further criticized because it was conducted in only a limited number of metropolitan areas, excluding approximately 275. Critics also argued that while experts were asked to provide estimates of homelessness in the central city areas they were familiar with, these estimates were applied to entire metropolitan areas, thus underestimating rates of homelessness in the population (Appelbaum, Dolny, Dreier and Gilderbloom, 1991)

A second source of homelessness estimates was a 1989 survey of shelter beds, covering 182 cities with populations greater than 100,000. The survey was conducted by contacting providers of shelter and requesting information on the current shelter capacity. The fact that this survey enumerated shelter beds instead of persons experiencing homelessness makes it problematic for use in studying variation in homelessness, because it does not provide information on unsheltered homelessness, and does not reflect turnover in shelter beds, or unused beds (Burt, 1993)

The third data source, the 1990 Census S-Night count, was not intended by the Census Bureau to be an estimate of total homelessness, but was an effort to include more homeless people in the decennial census. However, it has been used in approximately six studies of variation in homelessness rates. The S-Night enumeration was conducted in emergency shelters and in outdoor locations where homeless people were expected to be seen, within municipalities with populations over 50,000. Communities under 50,000 were not required to participate in

enumeration, although some smaller communities did so voluntarily (Taeuber and Siegel, 1991). Critics of this estimate argued that because the focus of enumeration was in communities of populations over 50,000, homelessness in smaller areas was undercounted. Evaluations of the effort found that enumeration of unsheltered homelessness was not conducted consistently across sites, with enumerators in some sites failing to interview people or to adequately canvass assigned areas (Quigley, Raphael & Smolensky 2001, Lee, Price-Spratlen and Kanan, 2003).

Since 2005 the data available on homelessness has improved considerably, as HUD has begun producing annual estimates based on enumerations that occur in a large number of communities of diverse size and urbanization. These estimates, obtained through mandated reporting, use more reliable and standardized methods of reporting and estimating than those of previous estimates. Point-in-Time counts, enumeration of sheltered and unsheltered homeless individuals in a given area are conducted annually. For the estimate used in this study, the count was conducted on a single night in January 2009 by 425 CoCs in the U.S. Very few national studies to date have made use of the new HUD annual Point in Time estimates: Raphael (2010) used state-level estimates to study the impact of housing construction regulations on homelessness rates and Moulton (unpublished) used estimates from 2005-2007 to model variation in rates of chronic homelessness. These estimates have not previously been used to model rates of family homelessness at the CoC level.

In addition to CoC-level data, this study also makes use of state-level data on public assistance programs and other topics. Both CoCs and states are used as geographic units of interest in this study. CoCs are used because they are the smallest geographic unit at which homelessness is nationally measured, and states are used because of their importance as units at

which some public assistance policies are made. The next section reviews public policy literature on state-level public policy variation.

Public Policy Literature

Public policy literature has established states as an important geographic level at which to study public policy in the United States, due to important variations that occur in some areas of public policy at the state level, such as education and public assistance programs (Sharkansky and Hofferbert, 1969).

The literature has produced a wide range of explanatory factors for this variation. Political factors have been most frequently discussed, including state political culture (Elazar, 1984), ideology of the state's citizens, ideology of the state's government officials (Berry, 1998), and political participation (Hill, Leighly & Hinton-Anderson, 1995). Other types of factors have also been examined including racial and ethnic composition and the degree of diversity in the state (Hero and Tolbert, 1996) and economic factors such as level of wealth (Hwang, 1991).

Because of the degree of state-level variation in policies governing public assistance programs, this area has been the policy area of focus for a number of scholars studying state level policy variation. Although programs such as AFDC and TANF have been regulated by the federal government, a substantial amount of autonomy has been held by states in determining eligibility policies and benefits levels. Hanson (1983) argued that to ignore the state-level variation in public assistance policy choices governing eligibility and benefit levels was to ignore the content of policies that had important implications for citizens who receive public assistance benefits – which citizens receive benefits, and what value those benefits have – and that knowledge of this varied content was also essential to understanding the political processes that created the policies.

While this study does not focus on causes of variation in state level public assistance policies, in the process of testing explanations for why some public assistance factors appear to be significant predictors of homelessness, the study does investigate factors that may be covariates of public assistance policies, and may help to explain the role of the public assistance factors in the model.

Clustered social policy approaches. Studies of variation in state-level public assistance policy have assumed that there are patterns and similarities in state-level policy choices among different public assistance programs. Several of these studies have taken one or two measures of public assistance programs, such as benefit levels of AFDC, and allowed these variables to stand in for a broader assessment of the qualities of the state's public assistance policies (Hill, Leighley & Hinton-Anderson, 1995).

Meyers, Gornick and Peck (2001) observed multiple qualities of social policy characteristics simultaneously, and described more complex patterns across public assistance programs. They compared social policy packages across states and found that there was a large amount of variation across the states for all the dimensions of social policies that they measured, especially in inclusion rates. They found that correlations for inclusion measures across different programs were inconsistent: strong for one pair of programs, and moderate or weak for other pairs (470). They found that in some cases, association between measures of inclusion across programs was positive, and in other cases, correlations were negative.

The authors organized states by clusters according to multiple characteristics of their social policy packages. The clusters are not a simple linear arrangement from less generous to more generous, however they found a general trend from the first to the last cluster of less to more spending.

Cross-program enrollment effects. Research on public assistance programs and their effects on one another have found that rates of enrollment in one program affect rates of enrollment in other programs, because enrollment increases the likelihood that recipients gain information about their eligibility for other programs, and assistance in applying for benefits from other programs.

This phenomenon has been observed among different public assistance programs for some time. Yelowitz (1996) found that expansion of Medicaid eligibility for children in the late 1980s that led to increased Medicaid enrollment from 1988 to 1993, led to an expansion in food stamp benefits, as families who enrolled their children in Medicaid became aware of their eligibility for food stamps, although food stamp eligibility policies had not changed.

A 1999 report on the impacts of welfare reform on outcomes for single mothers found substantial evidence that fewer eligible families were enrolling in SNAP programs, as a result of decreasing enrollment in AFDC/ TANF because families who stopped receiving or did not apply for TANF benefits were not aware of their eligibility for the SNAP program (Beebout, 1998; Primus, et al., 1999). The report cited Congressional testimony that approximately half of the decline in enrollment in food stamps from 1994 to 1998 was associated with the reduction in enrollment in the AFDC/TANF program. A Congressional Budget Office report (1998) stated that reductions in food stamp enrollment could not be fully accounted for by changes in food stamp eligibility rules, or by changes in the unemployment rate. An evaluation of a welfare reform demonstration project found that many families that stopped receiving AFDC benefits also stopped receiving food stamp benefits, despite the continued eligibility of the majority of them for food stamp benefits.

Application to the current study. This study extends the concept of social policy to include the provision of public shelter to people experiencing homelessness, and suggests that just as correlations have been found between inclusion of various public assistance programs, there may be a moderate correlation between a public assistance policy such as TANF inclusion rates and the rate of shelter bed provision (number of shelter beds per person in poverty.)

This study will explore the possibility of such a correlation between public assistance measures and shelter bed provision. If such a correlation existed, it would complicate the conception of the relationship between public assistance factors and homelessness rates. If communities within states that have more generous public assistance program policies tend to respond to the need for emergency shelter by operating more shelter beds, this would be expected to affect the measured level of homelessness in a community, because the number of sheltered homeless families is limited by the number of family beds provided within a public shelter system. Families that are unable to stay in shelter because of a shortage of shelter beds may experience homelessness in other settings in which they would be much less likely to be included in an enumeration.

This study also extends the findings on spillover effects from one public assistance program to another. Public shelter could operate in much the same way as a public assistance program, in which enrollment and interactions with program staff may serve to educate households about their eligibility for public assistance programs, and may provide a venue for assistance in application for benefits.

There are reasons to expect that in many communities, enrollment in shelter services may lead to an increased rate of enrollment in public assistance programs. One service provided in many family shelters is assistance with access to public assistance. Therefore, the provision of

emergency shelter or transitional housing services could increase the proportion of families applying for public assistance, which would contribute to a positive relationship between the homelessness rate and rate of receipt of public assistance benefits.

This may occur as local governments or organizations of homeless service providers try to seek more long-term housing solutions for households that apply for emergency shelter. Strategies to assist families in accessing housing are likely to include application for public assistance programs such as TANF and SNAP. Local governments may be motivated to encourage and assist households to apply for state public assistance programs as a means to enable them to increase their income, obtain housing, and exit shelter. One example of this phenomenon was well-publicized in the *New York Times*. In 1991 a lawsuit against the New York State agency managing the AFDC program resulted in a judge's order that AFDC recipients threatened with loss of housing due to inability to pay rent could apply for a shelter grant increase from the state. The city agency managing emergency shelter began an official program to refer applicants for shelter to legal aid services to help them apply for the shelter grant increase.

Currently, many communities are using "Ten Year Plans to End Homelessness" to plan and coordinate homeless services, most of which highlight the need to assist homeless households to apply for public assistance. Of the 90 plans that were studied in a 2006 report, 30% articulate a plan to assist homeless families to apply for TANF benefits, and 43% state that they will assist households to apply for SSI benefits (National Alliance to End Homelessness, 2006). It is clear that the use of shelter within a community could be associated with higher inclusion rates for TANF or for SSI due to households being informed of their eligibility for one program due to their enrollment in the other.

Summary

In summary, hypotheses about the effects of public assistance inclusion and adequacy on rates of homelessness have been raised in debates over policy change in public assistance programs, but the social welfare policy and homeless policy literatures have not provided sufficient empirical evidence to inform those debates.

Individual-level research has demonstrated that homeless families have very low incomes, and that public assistance programs can be a protective factor against homelessness, although the benefits provided by these programs are not always sufficient to help families avoid homelessness. In addition, this body of literature has shown housing subsidies to be a protective factor against homelessness for families. Demographic and health characteristics have been shown by individual-level studies to be factors that can increase the risk of homelessness for a household.

The multi-dimensional model of homelessness that has emerged from a number of sources in the field of homelessness research highlights the importance of economic and housing market factors that determine housing affordability in an area, in altering rates of homelessness. When these factors have been significant in modeling homelessness rates, housing costs and poverty measures have both been positively associated with homelessness rates. Public assistance programs have the potential to alter housing affordability by increasing incomes or lowering housing costs. Community-level studies have had mixed results for public assistance inclusion and adequacy measures, sometimes showing positive associations with homelessness, which contradicts individual-level findings.

The literature on public assistance policies lends support to two possible explanations for the positive correlation between inclusion rates and homelessness rates in previous studies. First,

public assistance policies may have some correlation with policies governing shelter effort. Communities that make greater effort to provide public shelter to families in need may also be communities that maintain higher inclusion and adequacy for their public assistance programs. The resources committed by communities for public shelter may be correlated with the community's inclusion rates for public assistance programs. In areas in which inclusion of eligible families in TANF is low, for example, public investment in shelter for poor families may also be low. If this were the case, it would also lead us to expect a positive association between homelessness rates and public assistance inclusion rates, since homelessness rates are determined in part by how many public shelter beds operate in an area.

Two schematic diagrams depict possible relationships between public assistance policies and shelter effort. Figure 1 displays a relatively simple relationship between public assistance policies and homelessness rates, with public assistance policies affecting household income and the ability of households to afford housing, which then in turn affects the family homelessness rate.

In contrast, Figure 2 displays a more complicated relationship, with public assistance policies correlated with community effort to provide shelter for families in need. The shelter bed rate, by limiting the number of families that can access shelter, in turn affects the number of families in shelter, and therefore the number of families enumerated in a point-in-time count. (In this model, families who are not able to obtain shelter will continue to be homeless, but will be less likely to be enumerated, as they may move from one living situation to another, so the total family homeless rate will be less). Initially models will be tested that will assume the relationships between public assistance policies and family homelessness rates are simple, as

displayed in Figure 1. Later models will go on to test the more complicated hypothesized relationship displayed in Figure 2.

As Meyers, Gornick and Peck described clusters of state policy packages as arrays of indicators, each with a distinctive approach, a consistent relationship is not expected between shelter effort and inclusion or between shelter effort and adequacy. Rather it is expected that shelter effort would have associations with different programs that varied in direction and strength.

Second, public assistance enrollment could be increased by higher levels of shelter use, as families using shelter are informed of their eligibility for public assistance benefits. Engagement with a governmental social service such as a homeless shelter could increase the proportion of families that apply for benefits for which they are eligible. The provision of emergency shelter or transitional housing services could increase the proportion of families applying for public assistance, which would contribute to a positive relationship between the homelessness rate and rate of receipt of public assistance benefits.

Figure 1: Theoretical Schematic, Model 1

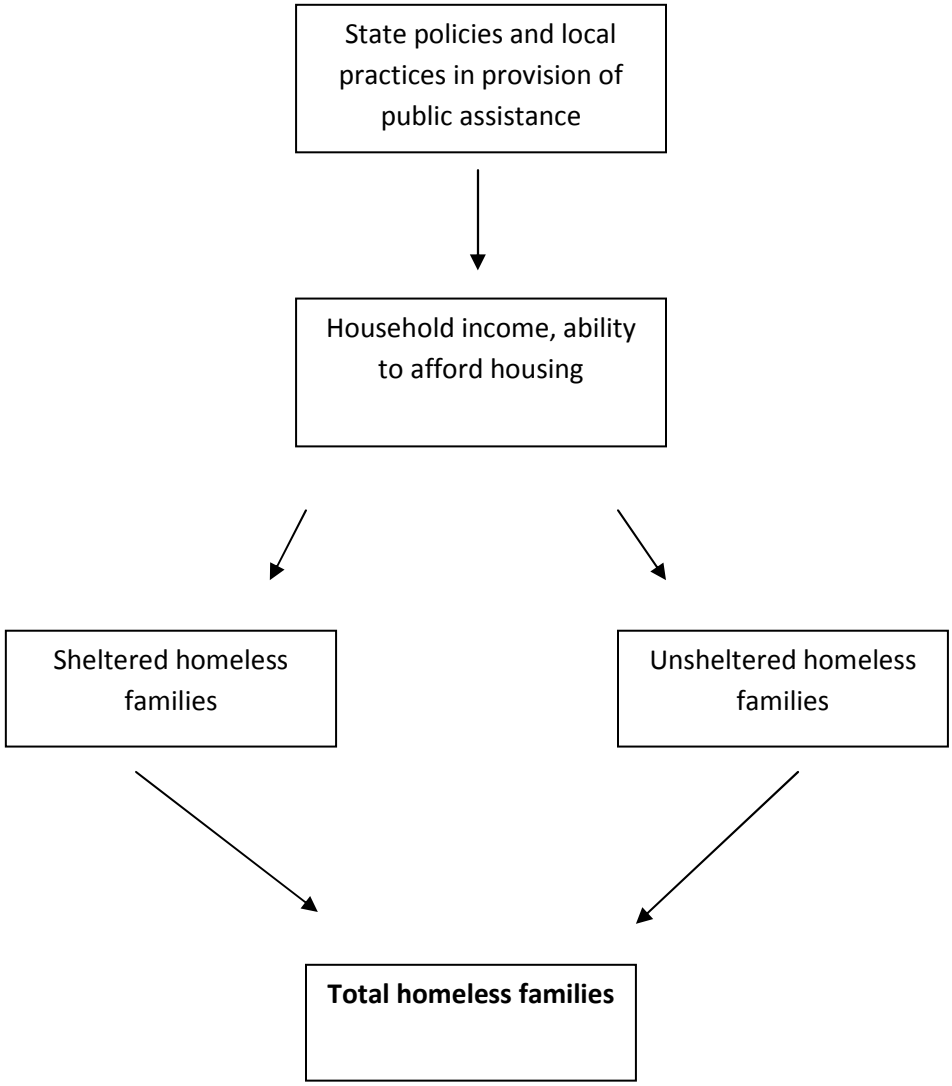
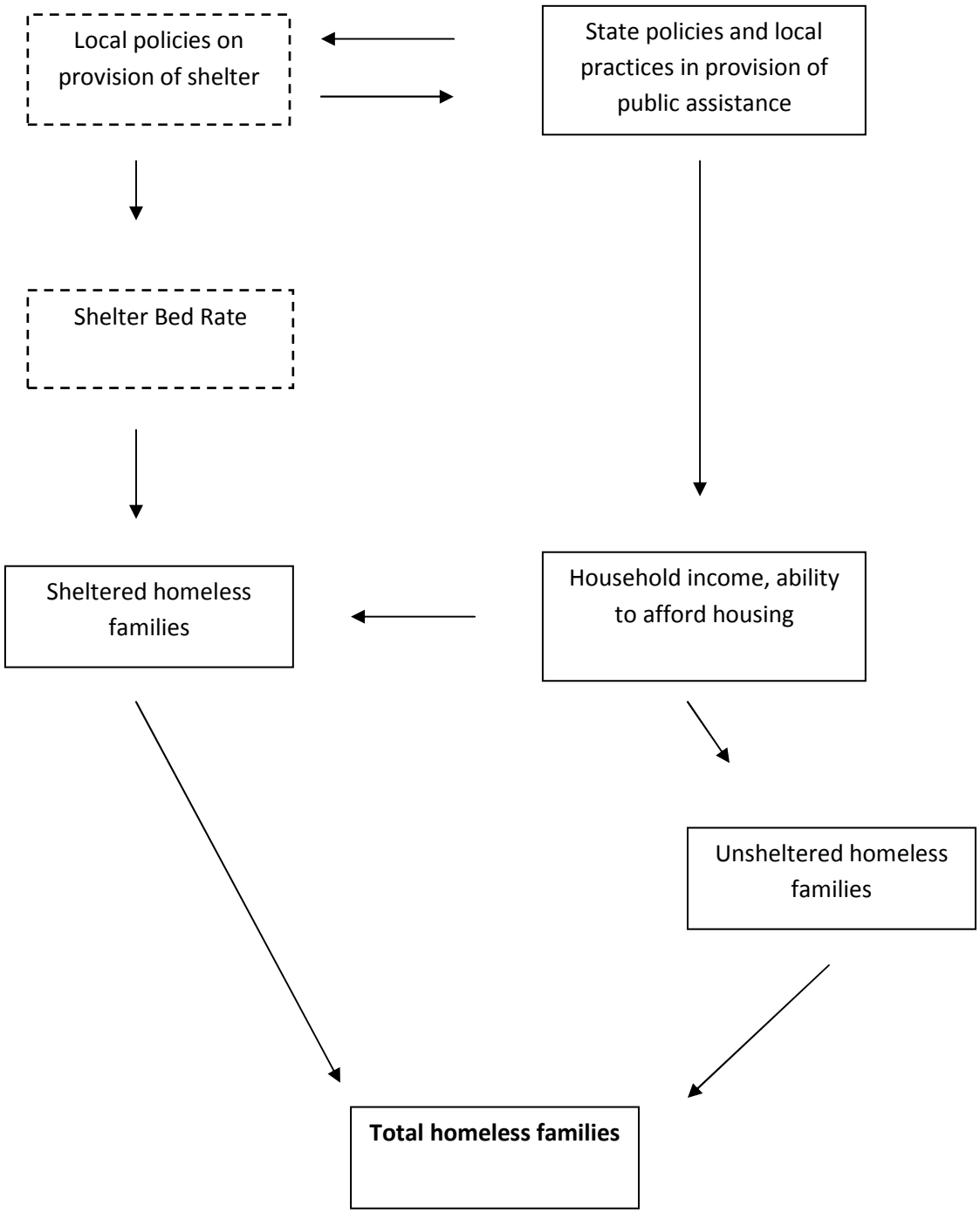


Figure 2: Theoretical Schematic, Model 2



3. Research Design and Methodology

This chapter begins by describing the goals of the study, providing definitions of key terms, and listing the research questions and hypotheses that motivate the study. The chapter goes on to summarize the research design of the study and describe the dependent and independent variables. It then describes the different geographic units of analysis of each set of variables, as well as the methods used to match these geographic units to create a single dataset. The chapter summarizes the multilevel modeling methods that are used in analysis. The chapter then discusses the research questions that are the focus of the study, and outlines the initial hypotheses that will help to structure the analysis and discussion.

The study contributes to the literature on homelessness by identifying factors associated with family homelessness, while most previous research of this type has not distinguished between different types of homeless households, due to the lack of data on homeless subpopulations. The study also provides a unique contribution by exploring the importance of public assistance programs, which have shown inconsistent results in previous studies. Investigating the connections or lack of connection between various measures of public assistance programs and family homelessness will address the question of whether this existing set of public policies has the potential to affect family homelessness rates.

To fill in some of the gaps in the literature on community-level predictors of family homelessness, the study observes relationships between communities' homelessness rates and a variety of factors such as poverty rate, percent of the population that is African American, and rate of admission into substance-abuse treatment. By including a wide range of possible community-level social and economic factors, the study attempts to determine whether there are factors that tend to vary along with family homelessness rates.

Factors are identified that are most important in explaining the variation in family homelessness rates across communities and compare these factors with those identified in previous studies of homelessness in the general population. The study specifically focuses on several measures of public assistance programs at state and community levels, to assess whether these programs, intended to mitigate poverty, can make family homelessness more or less prevalent at the community level, through the number of households that they serve or the level of benefits that they provide.

Definitions

Because the data used for this study are reported by HUD, the definitions used for homelessness, homeless families, and sheltered and unsheltered homelessness are those used by HUD in 2009 for collection of data on homelessness.

The 2009 HUD definition of homelessness includes people who are homeless in emergency shelters and transitional housing, and people who are homeless in places not meant for human habitation (HUD, 2007). HUD's definition and estimates do not include people who are living temporarily with family or friends, people living in other temporary housing situations, such as a motel, or people who are unstably housed. The discussion in this dissertation of homelessness rates also excludes those groups.[1]

[1] HUD's official definition of homelessness changed in early 2012 to include people who will lose their housing within 14 days, and families with children who are unstably housed on an ongoing basis. This new definition has been used in legislation to set guidelines on eligibility for assistance through federally funded homeless programs. This means that persons who are precariously housed, such as those who are threatened with eviction, can be assisted by homelessness prevention programs funded by HUD. This change in definition occurred after the period of study for this research, and has not changed the HUD's methods of estimation of homelessness (National Alliance to End Homelessness, 2012).

An unsheltered homeless person is someone who is living in a place not meant for human habitation such as the street, a train station, a car, or an abandoned building. A sheltered homeless person is defined as someone who is living in an emergency shelter or a transitional housing program for homeless persons.

HUD defines a homeless family as a household experiencing homelessness with at least one adult and one child. Other households are defined as homeless individuals: single adults, multi-adult households, and unaccompanied youth.

Emergency shelter and transitional housing are two types of residential services provided to homeless families. Emergency shelters are generally facilities which families can enter immediately, with fewer services. Transitional housing programs generally provide longer-term and more supportive residential services to families. Both are temporary living situations in which families are considered homeless.

Research Questions

Several research questions are investigated in this study. First, a model of family homelessness is constructed and comparisons are made to previous studies that have modeled total family and non-family homelessness. How does the model of family homelessness rates support or contradict findings from these previous studies?

Question 1. How do individual factors identified as significant predictors of homelessness in the general population perform in a model of family homelessness? Are new predictors identified that were not previously significant?

Hypothesis 1. It is expected that cost of rental housing would be positively associated with homelessness and that housing vacancy rates will be negatively associated with homelessness rates, as has been found in some previous studies.

It is also expected that poverty rate will be positively associated with homelessness rates and that unemployment will show a significant and positive association with family homelessness. However, it is expected to show a weaker association with homelessness than the poverty rate as not every household that experiences unemployment becomes a household in poverty.

The proportion of the population that is African American, and the proportion of female-headed households are expected to be significant positive predictors of family homelessness as these groups have been identified in community-level and individual-level research as being at elevated risk of homelessness.

The prevalence of medical conditions and substance abuse will likely be highly correlated with poverty and will not provide much explanatory power in addition to poverty rates.

Question 2. What is the direction and significance of measures of public assistance programs in this model of family homelessness?

Hypothesis 2. In general, homelessness is expected to be positively associated with measures of inclusion of public assistance programs, as has been found in some previous studies of variation in homelessness rates.

The adequacy of states' average benefit level for TANF, SSI and SNAP benefits are expected to have negative associations with the rate of homelessness. Households that obtain a more generous benefit level should have a greater ability to afford housing costs and should be more frequently able to weather financial crises that could threaten their ability to pay rent.

In general, TANF rules that affect inclusion or adequacy rates are expected to reflect the same positive relationship as inclusion rates with homelessness. However, because these rules

should impact inclusion or benefit adequacy, they are likely to drop out when added to a full model that already includes measures of TANF inclusion and adequacy.

Question 3. Shelter effort is added as a control variable to the model of homelessness to assess its impact on the public assistance variables of interest. Does correlation with shelter effort fully account for a positive relationship between inclusion of public assistance programs and homelessness rates?

Hypothesis 3. When the shelter-bed measures are added, any positive and significant relationship between public assistance inclusion and family homelessness rate is expected to become smaller or non-significant, and any negative relationship between public assistance adequacy and the family homelessness rate are not expected to change.

Question 4. Does testing the rate of unsheltered family homelessness instead of the rate of total family homelessness result in a non-significant or negative relationship between public assistance inclusion and family homelessness?

Hypothesis 4. When the unsheltered rate of family homelessness is modeled, the relationship between public assistance inclusion and homelessness is expected to decrease or become non-significant, while the relationship between benefit adequacy and family homelessness is expected to remain significant and negative.

Question 5. When the sample of communities is divided into areas of higher poverty and areas of lower poverty and into urban and non-urban areas, how do predictive factors change when the observations are limited to these stratified samples?

Hypothesis 5: In areas of higher poverty, measures of adequacy of public assistance programs are expected to become stronger predictors of homelessness because these programs will affect a larger proportion of the population in high-poverty areas.

In areas of lower poverty, housing market factors are expected to become stronger predictors of homelessness because homelessness will be driven less by the income and poverty and more by the limitations of the housing market, such as availability, quality, and cost of housing.

The models are expected to be similar for urban areas as for the total sample, but in non-urban areas, housing market factors are expected to become less important, while poverty and public assistance variables will become more important in the model.

Research Design

The study uses a multi-level (hierarchical) regression analysis of inter-community variation in point-prevalence rates of family homelessness, examining a variety of social and economic factors to identify those that are significant in predicting variation in family homelessness rates. The study of economic, political, and social factors that predict variation in homelessness rates across geographic units has been reported in a number of previous studies. This design is developed further by the use of multilevel methods to accurately model rates of family homelessness, measured at the CoC level and affected by factors at the CoC and state levels. The study uses two levels of analysis. The first level, at which homelessness rates are measured, is the CoC. The second level, at which some public assistance policies are made, is the state level.

Dependent variable

The dependent variable for the study is a measure of the point prevalence of family homelessness: the total number of family households experiencing homelessness in both sheltered and unsheltered locations on one night in January 2009, as a proportion of all family

households. A homeless family is defined within HUD data collection as a household experiencing homelessness that includes at least one adult and one child.

The Continuum of Care (CoC) is used as the basic geographic unit of this study because it is the unit at which data on homelessness is collected. CoCs are local networks of homeless service providers. The CoC is the unit at which homeless service use and enumerations are reported and estimates of point and annual prevalence are made.

The geographic boundaries of CoCs range widely in size: Some are comprised of a single city, some are single counties, some are multiple counties, and a few cover an entire state. There are fifty-seven rural counties that are not part of a CoC, but areas within CoC boundaries include approximately 99% of the population. (See Appendix A for a map of all CoCs in the U.S.)

Every other year, the Department of Housing and Urban Development (HUD) requires CoCs, as part of their application for McKinney-Vento federal funding for homeless programs, to submit a Point-in-Time (PIT) enumeration of individuals and families experiencing homelessness. Although there is some variation across CoCs in the methodologies used for these enumerations, methods must meet HUD's standards of statistical rigor.

Demographic information is also collected as part of the PIT enumerations; thus the estimates can be broken down by household type to provide an estimate of those who are homeless as part of a family. For this study, the PIT estimates were used to calculate a rate of family homelessness as a proportion of all family households.

Annual prevalence estimates of sheltered homelessness are also created by HUD, but a much smaller number of communities report usable data for this estimate. Excluded communities

include a number of large cities with significant homeless populations. Therefore the more nationally representative point prevalence estimates are used in this study.

Independent variables

The study makes use of state and county-level data within five subject domains to model rates of family homelessness. Factors within each of these subject domains have been identified in existing theoretical and empirical studies as related to homelessness rates or risk of homelessness among individuals.

Housing market factors. Factors were included in the model that measure housing costs and housing cost burden, property value, housing tenure, vacancy, residential mobility, housing conditions, and foreclosure.

Economic factors. Economic factors are included that reflect the ability of households to afford housing: measures of income levels and poverty. Unemployment rate is included as the rate affects the ability of households in an area to afford housing.

Demographic factors. Because various demographic characteristics have been shown to put some households at greater risk of homelessness than others, measures of the representation of racial groups, age groups, household types, veteran status, and nativity are included.

Public assistance programs. The impact of public assistance programs can be assessed in multiple ways. This study focuses on four ways of assessing the degree to which public assistance programs serve poor households. Two of these measures, inclusion and adequacy, are terms used by Meyers, Gornick, and Peck (2001) to describe characteristics of social welfare policies, and the terms are defined in similar ways in this study. Meyers, Gornick, and Peck (2001) write that inclusion "concerns the penetration of benefits into the potentially eligible population" and that inclusion depends on government policies and practices governing

eligibility and enrollment, the size of the population in need of benefits, and the decisions of the eligible population whether or not to enroll. The adequacy of a program benefit measures the value of the benefit. The authors measure adequacy by dividing the total amount spent on benefits within a geographic area by the average or total caseload.

In this study inclusion is defined as the proportion of total households with income below the poverty threshold who receive program benefits. The TANF/GA, SSI and SNAP inclusion rates were constructed by dividing the number of households receiving TANF/GA, SSI or SNAP, in the past year by the number of households in poverty. The Section 8 and Public Housing inclusion rates were constructed by dividing the number of Section 8 units or Public Housing units by the number of households in poverty. The Veterans Pension inclusion rate was constructed by dividing the number of veterans receiving pension benefits in the last year by the number of veterans because the number of veterans in poverty was not available at the county level.

In this study, adequacy is defined as the dollar value of public assistance benefits relative to the median cost of housing in the state. The adequacy of a program measures the extent to which the benefits provided by the program assist households in paying for housing and avoiding homelessness. The adequacy of the TANF benefit was constructed by dividing the amount of the maximum monthly TANF benefit amount for a family of three by the state median monthly rent. The adequacy of the SSI and SNAP benefits were each constructed by dividing the average monthly benefit amounts by the state median monthly rent...

This definition was chosen for benefit adequacy for the study because of the importance of standardizing the benefits in terms of how they enabled families within a given state to pay for housing costs. Although there was a moderate correlation between this state-level variable and

the CoC-level variable measuring median monthly rent for a three-bedroom apartment, this correlation was low enough (.63) that they could both be included in the model. Checks for multicollinearity that were conducted are detailed further at the end of this chapter, under "Evaluation of Model Assumptions."

Third, expenditures assess the total funds spent on a program or category of programs per capita by the state government and measure the dollar amount relative to other categories of public expenditures. Fourth, state-level policies governing the TANF program are included that would affect the level of inclusion of this program.

Because people generally experience homelessness when their incomes are below the poverty line, in choosing predictive factors the study focuses on social welfare programs that serve households in poverty, including Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), the Supplemental Nutrition Assistance Program (SNAP, or food stamps), Medicaid, Veterans' Pension payments, Housing Choice Vouchers, and Public Housing. State General Assistance (GA) programs were not a focus of the study because they generally serve single adults without minor children, while homeless families are defined in this study as a homeless household including at least one adult and at least one minor child. However, information on GA programs is included in two variables used. The available data on inclusion of public assistance included both TANF and GA programs without distinguishing between the two types of aid. The data available on spending by state governments on SSI also included spending on GA.

Variables were used that measure the inclusion of TANF, SSI, SNAP, Veterans' Pension payments, Housing Choice Vouchers, and Public Housing. Some of these programs exhibit more variability across states in their rules governing eligibility than others. For example, states

have the authority to set benefit levels and income limits for eligibility for TANF as well as to impose restrictions on recipients through program rules. Eligibility rules for SSI, in contrast, are set at the federal level (Center on Budget and Policy Priorities, 2011). However, while eligibility rules for some programs are standardized nationally, variation in state and local implementation, such as accessibility of program offices and how readily applicants are granted benefits, could result in variation across counties and states in the proportion of the eligible population that receive benefits. Therefore this study included county-level measures of inclusion for each of these programs.

The study also included state-level measures of adequacy of benefits for the TANF, SSI, GA, and SNAP programs. While TANF benefits are set by each state, the SSI program provides nationally standardized payments based on income and household size. However, states are free to add supplemental payments to this basic federal amount. The amounts of state supplements were included in the study. While the rules governing calculation of SNAP benefits are for the most part nationally standardized, there are some state-level variations. States have some authority to waive rules regarding assets as they are counted against households' benefits (Center on Budget and Policy Priorities, 2011a & 2011b). Adequacy measures of the Housing Choice Voucher and Public Housing programs were not included because they do not vary by state (Center on Budget and Policy Priorities, 2008 & 2009). The percentage of Veterans receiving pension payments was also included. Pension payments are made to wartime veterans who have limited or no income, and who are 65 and older, or permanently disabled (Veterans Benefits Administration, 2011).

The variables tested also include indicators of rules governing eligibility and benefits for the TANF program. These rules vary at the state level. Several policies were included in the

dataset. First, the presence of a formal diversion payment system is used as an alternative to enrollment in TANF in some states, providing a one-time payment of cash assistance instead of ongoing enrollment in the TANF program. Second, the requirement for a job search at the time of application to TANF would tend to decrease the eligible population, as some households may not be willing or able to participate in the job search. Third, the maximum income for initial eligibility for TANF for a family of three would tend to increase the pool of eligible households as the maximum increased. Fourth, the severity of the sanction policy for noncompliance with work requirements for single parents is measured in the percent of the benefit that is cut as the sanction. The greater the severity of the sanction, the less overall will be paid to the eligible population. Finally, work exemption is measured in the maximum age of a child that permits a parent an exemption from work requirements. As the child's age limit for the parent's work exemption increased, the number of households that would experience loss of benefits from sanctions would decrease.

Also included in the dataset were measures of state expenditures on several programs providing cash assistance or in-kind assistance to households in poverty: state spending on TANF cash assistance, combined GA and SSI state supplement cash assistance, and the Medicaid program.

Shelter effort. A shelter-bed rate is included in this dataset, which assesses the number of family shelter beds provided by the CoC, standardized by the CoC's population in poverty. Both emergency shelter and transitional housing beds are included.

Public health factors. A series of variables measuring the prevalence of various conditions that affect health and mental health were included. County-level variables measuring the availability of medical facilities and services, general public health and wellness, prenatal

and neonatal health indicators, and the prevalence of diseases and chronic conditions were included. Rates of drug and alcohol abuse and treatment for these conditions were measured at the state level as well as rates of use of mental health treatment. Also included were variables measuring rates of incarceration and release from jail and prison. Appendix B, Tables 1 and 2 describe the individual variables and sources of the data.

Geographic level of independent variables. Data in the six subject domains above were selected either at the county or state level. County-level data was used because in the majority of cases, the county is the most comparable geographic unit to the CoC. The county is also the smallest geographic level for which many types of data were available. In some cases, state-level data was used because it was the most appropriate level at which to measure the variable (e.g. policies that are made at the state level and are uniform within a state). In other cases, data was included at the state level because it could not be obtained at the county level (e.g. imprisonment rates). The geographic level of measurement for each type of variable is indicated in Appendix B, Table A.

Matching CoC and County Geographies

The Continuum of Care is used as the first level of analysis in this study because it is the level at which data on homelessness is collected nationally. The data collection mandated by HUD is the most comprehensive, reliable, and regular data collection process on homelessness, but the geographic unit presents obstacles for analyzing other types of data in concert with homelessness data. In order to create a dataset that used the CoC as its basic geographic unit and that also made use of county- and state-level data on predictive factors, CoCs and counties were matched using geospatial matching procedures. The county-level data was then statistically adjusted to create CoC-level data.

While many CoCs' boundaries are coterminous with those of the county in which they are located, others are smaller than the county that encompasses them, while others encompass multiple counties. Three basic types of geographic matches were conducted in the data preparation for this study. In the first case, a CoC has the same boundaries as a county. This is treated as a "one-to-one" match. In the second type, a CoC is made up of more than one county. This is treated as a "one-to-many" match. In the third type, multiple CoCs are located within a single county, which is treated as a "many-to-one" match (see Appendix A for examples of each type of match.)

In one-to-one and one-to-many matches, the geographic center of each county was identified and overlaid on CoC boundaries. By identifying the CoC in which the county center fell, Geographic Information System (GIS) software was used to match one CoC and one county in one-to-one matches, and to match one CoC with multiple counties in one-to-many matches. One-to-one matches were conducted for 227 CoCs, or 51% of the total number. [2] One-to-many matches were conducted for 171 or 38% of all CoCs.

For the remaining 49 CoCs (11%), there were multiple CoCs within a single county. In each of these cases multiple CoCs had to be combined into a single "super-CoC," making the boundaries of the super-CoC coterminous with the county.[3] In this step, the total number of CoCs used as observations in the study was reduced from 447 to 414.

Next, the county-level and CoC-level data had to be adjusted to account for the changes. For one-to-one matches, the data did not have to be adjusted as the CoC and the county shared

[2] In four cases CoCs crossed county boundaries but could logically be matched with a single county because the majority of the area lay within a single county. These were included in the one-to-one matches.

[3] In two cases, the CoCs within multiple counties were combined into a single super-CoC, because the CoC boundaries were too irregular to make a logical match with a single county.

the same boundaries. For one-to-many matches, in which the data from multiple counties applied to a single CoC, county-level data was aggregated to the CoC level by summing the value of raw numbers and applying a weighted average (by county population) to rates. For example, in Appendix A, Map 3, the number of households in poverty in the Metropolitan Denver CoC was constructed by summing the number of households in poverty in six counties.

For many-to-one matches, in which multiple CoCs were combined to match the boundaries of a county, county-level data was not adjusted, but CoC-level homelessness data for the CoCs that were combined was summed. In the example shown in Appendix B, Map 3, the numbers of homeless families in 2 CoCs were summed to obtain the total number of homeless families for a combined super-CoC, which matched the boundaries of Polk County. The Polk County independent variable data was used unchanged.[4]

For state-level data, the second level of analysis in the multilevel model, there were no statistical adjustments to be made. CoC boundaries fell within state boundaries, and therefore adding each state-level variable to the CoC-level dataset was done by assigning the same value of the state-level variable to all CoCs within a state.

Database Development

The database used for this study was developed and maintained by the Research and Methodology Core of the National Center on Homelessness among Veterans, under the direction of Dennis Culhane, PhD, Director of Research, and Vincent Kane, MSW, Center Director. The database was developed for the purpose of identifying community-level determinants of homelessness among veterans and among other homeless subpopulations such as chronically

[4] In these cases, the PIT counts of all the included CoCs were summed and the county-level measures were used to construct new super-CoC-level measures using the sum and weighted average procedures described above.

homeless individuals and homeless families. Several Research and Methodology Core members contributed to the development of the database, a task which was supported by the Center. Dennis Culhane conceptualized the database design and facilitated access to HUD's data on homelessness. Data was acquired from multiple publically available sources by Ann Elizabeth Montgomery, PhD, Jamison Fargo, PhD, Thomas Byrne, MSW, and Ellen Munley (author). Jamison Fargo led the development of the database. Thomas Byrne and Jamison Fargo conducted geographic matching of data at CoC, county and state level. Ellen Munley and Thomas Byrne verified accuracy of the dataset and identified unmatched geographic areas.

Multilevel Modeling

A multilevel model is needed to analyze this data because, while homelessness is measured at the CoC level, these CoCs are nested within states. States are an important geographic level of analysis to include in the analysis because policies affecting program inclusion and the adequacy of benefits for some public assistance programs are made at the state level. These policies will be included as explanatory factors to be evaluated for their relationship with homelessness rates. Because these state-level independent variables are used together with predictors that are measured at the CoC level, a multilevel modeling approach is used, using CoCs as the Level 1 unit of analysis and the state as the Level 2 unit of analysis.

Most previous studies of variation in homelessness rates have used Ordinary Least Squares (OLS) regression. However, for datasets that are grouped into two levels of data, with one level nested within the other, using OLS regression can result in errors in estimation of standard errors of regression coefficients. These errors result from the OLS regression assumption that error terms are randomly distributed because observations are assumed to be independent from one another. However, since in multilevel data, observations are clustered into

groups, observations in one group are more like each other than they are to observations in other groups. (Cohen, Cohen, West & Aiken, 2003; Raudenbush and Bryk 1986, 2002)

For example, OLS regression applied to this dataset would assume that any two CoCs picked at random would be independent, while this study hypothesizes the opposite: that state-level predictors may make CoCs within one state more similar to each other than they are to CoCs in other states.

In addition to solving problems of estimation of error, multilevel modeling also allows us to test hypotheses that factors at one level affect outcomes measured at a lower level. In this case, multilevel modeling allows us to test the hypothesis that state level benefit levels for public assistance programs, as well as other state-level factors, affect rates of family homelessness measured at the CoC level.

Analytical Strategy and Models

The study uses a large dataset of independent variables from five subject domains and multilevel modeling methods to test the significance of these variables and to construct a full model including both CoC-level and state-level predictors of homelessness.

The first step was to create a basic multilevel model with no predictors, with CoCs grouped by state. The second step was to test CoC-level predictors one at a time in a bivariate, multilevel model, to identify strong predictors of the family homelessness rate. The third step was to build a model with CoC-level predictors by choosing variables that were strong predictors, eliminating variables that exhibited collinearity with other important predictors, and evaluating and comparing models with model fit statistics. The fourth step was to test each CoC-level predictor in the model for random effects, to determine whether the slope of the predictor varied across states. The fifth step was to add state-level predictors to the model using similar

methods as for the CoC-level predictors. (Appendix C includes equations for each type of model.)

Once a multilevel model had been created, individual predictors were examined to assess the direction and strength of their relationship with the outcome. Regression coefficients were used to interpret the relationship of each predictor with the outcome, and standardized regression coefficients were used to identify the relative importance of predictors within the model.

Intercepts-only model. A model without predictors, or an "intercepts-only" model, was created, including the outcome, the family homelessness rate, and the grouping variable, states. The intercepts-only model provides several pieces of information about the data. First, the variance in homelessness rate intercepts across and within states can be used to calculate the intraclass correlation. A likelihood statistic provides a baseline of explanatory power that can be compared with more complicated models to determine if they improve the explanatory power. (Hox, 2002).

Intra-class correlation. The variance in family homeless-rate intercepts across states is .0251, which is more than would be expected by chance. However there is also a significant residual variance (0.1359), which indicates that there are significant differences among CoCs after taking differences across states into account.

The intraclass correlation was found to be 0.156. Approximately 16% of the total variability in homelessness rates is attributable to differences between states. This suggests that it will be informative to include states as groups in which CoCs are clustered and to use multilevel modeling techniques for analysis.

Fit statistics, intercepts-only model. The Null Model Likelihood Ratio Test compares fit statistics for the intercepts-only model, in which intercepts vary across states, with a model

that has a single fixed intercept. The test indicates, with a p-value of <.0001, that this intercepts-only model differs significantly from a model with a single fixed intercept.

The -2 Log Likelihood fit statistic of this intercepts-only model is 385.9, which will be compared to the more complex models to compare model fit.

Developing a model with Level 1 predictors.

CoC-level predictors were then added to the model to determine which individual predictors were significant in modeling homelessness rates. The variable selection procedures detail how these variables were chosen to be included in the model.

Variable selection. Variables were included in the dataset on the basis of theoretical importance and significant results in previous studies of variation in homelessness. One limitation of previous studies has been the lack of comparability between the variables tested across studies. In order to address this problem, variables from six subject domains were included in the original dataset. A large number of variables measuring factors within these domains were included to ensure that relevant factors would not be missed or inappropriately measured. For example, because rent levels have been identified frequently in previous theoretical and empirical work, multiple measures of rental costs, as well as the relationship of rental costs to income, were included in the model.

Variable selection was conducted through multiple steps. First, bivariate multi-level regression models were created that included one predictor variable at a time, to assess each variable's relationship with the rate of homelessness. Variables that were significant at the .05 level were retained.

Next, from this subset of variables, many were eliminated because of collinearity. Independent variables that had correlations of 0.70 or higher or Variance Inflation Factors (VIFs)

larger than 10 were identified. From pairs with high correlation or VIF values, one variable was deleted and a single variable was retained from each pair. In this process of variable selection, those variables that demonstrated a stronger association with the outcome variable were generally selected. For example, of the multiple measures of rental costs in an area, all highly correlated, only median rent for a three bedroom apartment was included in the model, because it demonstrated the strongest association with the rate of family homelessness.

In other cases, however, variables that had a stronger theoretical relationship with homelessness were selected. For example, the proportions of the general and the poverty populations who were foreign born were highly correlated. The proportion of the population in poverty was retained, and the general population proportion discarded, as the population in poverty is at much higher risk for homelessness than the general population, and therefore this variable is of greater interest in a model of homelessness than the other.

Model development. Once a subset of variables had been identified that were significant in a bivariate model but did not exhibit collinearity, a model with CoC-level predictors was developed by comparing model-fit statistics as variables were removed from the model. The -2 Log Likelihood Ratio and Akaike Information Criteria (AIC) were both used to compare the fit of various models. The AIC was used because it took into account the number of parameters included in the model and penalized models that included additional parameters without a significant increase in explanatory power (Tabachnik and Fidell, 2006).

Up to this point, each of the included predictors had been tested in the model with its slope as a fixed effect, meaning that the slope was considered to be the same across all states. At this point, each CoC-level predictor included in the model was then tested as a predictor with random slope, to identify any predictor with a slope that varied significantly across states.

Model with Level 1 predictors. Adding Level 1 predictors to the model provided the average (national) slope of each predictor variable. Allowing the slopes of predictors to vary among states provided estimates of two random effects: variance of states' slopes from the average (national) slope, and the co-variance between state means and state slopes.

Model with Level 2 predictors: Once a model had been developed that included all the relevant fixed and random CoC-level predictors, state-level variables were included in the model. This provided the estimates of the slopes of the state-level predictors, taking into account all Level 1 predictors.

Stratified analysis. When a full model was developed for the full set of CoCs, the observations were then divided into two groups, according to their status as high-poverty or low-poverty areas. The median family poverty rate was used as the dividing point for the two samples. All CoCs with family poverty rates of 0.09 or higher were included in the high-poverty sample, which consisted of 207 CoCs. All CoCs with family poverty rates of 0.89 or lower were included in the low-poverty sample, which included 205 CoCs. Models were developed separately for each subset. Differences in significant predictors required to model homelessness for the two samples were identified.

Stratified models were also created for urban and non-urban CoCs. The US Department of Agriculture scores every U.S. county according to its urban or rural status. CoCs were given scores according to a weighted mean of the scores of the counties that they encompass. Those in metropolitan areas of 250,000 people or more were considered urban in this analysis, while all others were considered non-urban. The resulting urban sample was made up of 244 CoCs and the non-urban sample included 168 CoCs. Models were created separately for the two samples,

but the urban sample is not reported in the study findings as it closely resembled models of the total sample.

Evaluation of Model Assumptions

Multilevel modeling depends on many of the same assumptions that are important in OLS regression. Sample size, outliers, multi-collinearity, heteroscedasticity and normality of residuals must be evaluated (Maas and Hox, 2005.) Changes to the dataset to address these assumptions and limitations are summarized here.

There were originally 413 CoCs in the dataset, grouped within 50 states. This analysis fits into the recommended sample size discussed by Maas and Hox (2005), who recommend that the number of groups in Level 2 of the analysis (the state level, in this case) be at least 50. With as few as 50 groups, the authors warn that the standard errors for the Level 2 estimates may be estimated approximately 9% too small, which they assess as "probably practically acceptable."

Because the distribution of the dependent variable, the family homelessness rate, was positively skewed, the dependent value was logarithmically transformed. Further, logarithmically transformed versions of several skewed predictors were evaluated; however, using these logged values did not substantively change the results of the analysis so they were not used in the final models. One outlier was deleted from the dataset, CoC-517 in Florida, which had a residual value larger than 2. This deletion also improved the normality of the residuals. This Continuum of Care is located in southern Florida and is made up of six counties. The total population of the Continuum of Care is 250,000 people. This Continuum of Care had 1619 homeless families, who made up 2% of the entire sample of homeless families.

For the model of unsheltered family homelessness, three CoCs were excluded from the analysis because their unsheltered PIT counts were considered unreliable by HUD. The

unsheltered counts for the CoCs that encompass the cities of Los Angeles, Detroit, and New Orleans were excluded. These are large cities with significant numbers of homeless families, and their exclusion is certainly not ideal. The problems with their unsheltered enumerations were specific to 2009, and in future studies using data collected in other years, these cities should be included. These cities were excluded from only a single model in this study, that of unsheltered family homelessness, and were included in all other models. These cities' sheltered homelessness data was not judged to be problematic, and the utility of their sheltered homelessness data outweighed potential error introduced by the unsheltered data.

Multicollinearity was avoided in the selection selecting the variables for the model. Because some of the variables that showed significant associations with the outcome variable had high intercorrelation, some of these variables were eliminated. Correlation tables for the multidimensional models of homelessness are shown below. For the most part, correlations between model variables were low. This model contains two variables which were moderately correlated, SNAP benefit adequacy and median rental cost for a three bedroom apartment. The effect of the two variables on one another was evaluated to ensure that they could both be included in the model. First, the correlation was not as high as .70, a rule of thumb for exclusion. More importantly, including the SNAP benefit adequacy in the model did not change the coefficient of the rental variable by more than 25%, another rule of thumb that would require exclusion from the model. Because including SNAP benefit adequacy in the model reduced the coefficient of median monthly rent by 12%, the two variables were considered sufficiently independent to both be included in the model.

Table 1
Correlation Matrix, Multidimensional Model 1 (N=412)

Variable	**Name**	**1**	**2**	**3**	**4**	**5**
1	Family poverty rate					
2	Residential mobility rate	0.32				
3	Median rent, 3 BR apt.	-0.47	-0.12			
4	TANF and GA coverage rate	-0.25	-0.21	0.24		
5	Percent of population 0-18 years	0.16	0.03	0.00	0.22	
6	SNAP benefit adequacy	0.37	0.16	-0.63	-0.25	0.05

Table 2
Correlation Matrix, Multidimensional Model 2 (N=412)

Variable	**Name**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Family poverty rate							
2	Residential mobility rate	0.32						
3	Median rent, 3 BR apt.	-0.47	-0.12					
4	Percent of population 0-18 years	0.16	0.03	0.00				
5	Emergency shelter bed rate	-0.27	-0.07	0.28	-0.11			
6	Transitional housing bed rate	-0.31	0.08	0.29	-0.04	0.41		
7	TANF and GA coverage rate	-0.25	-0.21	0.24	0.22	0.15	0.18	
8	SNAP benefit adequacy	0.37	0.16	-0.63	0.05	-0.25	-0.17	-0.25

Table 3
Correlation Matrix, Multidimensional Model 3 (N=410)

Variable	**Name**	**1**	**2**	**3**	**4**	**5**	**6**
1	Poverty Rate						
2	Median Rent, 2BR apt.	-0.53					
3	% renters	0.45	0.18				
4	% age 35-54 who are veterans	0.11	-0.30	-0.02			
5	% African American	0.32	-0.01	0.32	0.25		
6	Mean January Temperature	0.26	0.09	0.15	0.15	0.29	
7	SNAP Benefit Adequacy	0.38	-0.63	-0.09	0.08	0.09	-0.20

4. Models of Family Homelessness for all Communities

This chapter begins with a description of family homelessness in 2009, including characteristics of homeless families, a discussion of patterns of family homelessness, and the effects of the recession on family homelessness during this period. The chapter goes on to review results of three domain-specific models of homelessness, models in which the predictor variables have been limited to one or two types of variables. These separate models allow us to observe the results for individual variables that have been tested in previous models, and also allow us to compare the model fit for each of the three models. Research Questions 1 and 2 are investigated in this section.

Next, the chapter presents the results of a multidimensional model of homelessness, including variables from all four domains in a single model. The significance and direction of individual variables is discussed, further addressing Research Questions 1 and 2.

Variables measuring shelter effort are then added to the model as control variables, and changes to the model are discussed, addressing Research Question 3. Then a model of unsheltered family homelessness is presented, and differences between this model and the model of total family homelessness are discussed, addressing Research Question 4.

In Chapter 5 separate models of family homelessness are created for communities with high poverty, communities with low poverty, and non-urban communities. The significance and direction of the individual variables, relative importance of variables from each domain, and differences in comparison to models of the total sample are discussed, to address Research Question 5.

Characteristics of Homeless Families in 2009.

Homeless families make up a significant portion of the homeless population – 35% of people experiencing homelessness in 2009. Homeless families make up a much larger proportion of the sheltered homeless population (48%) than of the unsheltered population (18%). Most homeless families are headed by single women. The typical adult in a homeless family in 2009 was female, African American and under the age of 30. In contrast, homeless single adults are much more likely to be male, more likely to be white than African American, and more likely to be older than 30 (HUD, 2010).

Patterns of Shelter Use among Homeless Families

Homeless families most frequently enter shelter after staying in a housed setting, such as the home of friends or family, or their own housing unit. Another frequent living situation immediately preceding shelter entry is another shelter or transitional housing program. Much less frequently do homeless families enter shelter after staying in an institutional setting or a place not meant for human habitation. In contrast, single adults are more likely than families to come from another shelter or a place not meant for human habitation (41% compared to 26%), and less likely to come from a housed living situation (37% compared to 63%). Single adults are more likely than families to enter shelter from an institutional setting (15% compared to 3%)

The median stay for homeless families in emergency shelter is approximately 1 month, and the median stay in transitional housing programs is approximately 6 months. These stays are generally longer than those of single adults, who average 17 and 107 nights in emergency shelter and transitional housing (HUD, 2010).

Effects of the Recession and Homelessness in 2009.

In 2009, the year in which this study's data was collected, the United States was in the midst of a severe economic recession. The impact of the recession affected the demographic composition of homeless families. In 2009, families were more likely than in 2007 to include two parents, or to be headed by a single father, than they were in 2007.

In addition, the situations that homeless families lived in before becoming homeless changed over this period. Homeless families more frequently entered shelter after staying with family, or coming directly from rented housing. The recession also may have altered the way that families use shelter, with median stays for both emergency shelters and transitional housing programs becoming longer between 2007 and 2009.

Finally, the geography of family homelessness changed over the period from 2007 to 2009. While only 27% of homeless families in 2007 were located in suburban and rural locations, that percentage had increased to 39% by 2009. This resulted from an increase in family homelessness in suburban and rural areas (HUD, 2010).

Table 4
Family homelessness and total homelessness

	Total homeless persons		Homeless Persons in Families (% of total homeless persons)	
Sheltered Status	2007	2009	2007	2009
Sheltered	391,401	403,308	178,328 (46%)	187,313 (48%)
Unsheltered	280,487	239,759	70,183 (25%)	50,797 (18%)
Total	671,888	643,067	248,511 (37%)	238,110 (35%)

Table 5

Demographic breakdown of adults in sheltered homeless families

Characteristics	**2007 (%)**	**2009 (%)**
Gender	100	100
Male	18	20
Female	82	80
Race	100	100
White	31	38
Black	55	48
Other Single Race	6	6
Several races	8	8
Age	100	100
18-30	55	55
31-50	42	42
51-61	2	2
62 and older	1	1

Table 6

Living situation prior to shelter entry for homeless families

Living Situation	2007	2009
Place not meant for human habitation	3.6	4.0
Another emergency shelter or transitional housing program	26.7	22.0
Rented housing	13.0	17.1
Owned housing	3.8	2.6
With family	24.2	29.4
With friends	13.4	13.5
Hospital setting	1.9	2.1
Jail or prison	0.4	0.4
Motel or other	13.0	8.7

Table 7

Median length of stay in shelter for homeless families

Shelter Type	2007	2009
Emergency shelter	30	36
Transitional housing	151	174

Table 8
Family homelessness by geographic type (urban vs. rural and suburban)

Geographic Type	2007	2009
Urban	73.1%	61.2%
Suburban and Rural	26.9%	38.8%

Descriptive Statistics

The following table presents descriptive statistics for the variables that appear as significant in any of the models discussed in this chapter. The total and unsheltered homelessness rates are highly skewed, making log transformations necessary for these two variables.

Table 9
Descriptive Statistics, Significant Variables

Variable Name	**Level**	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
% 0-18 years	CoC	0.24	0.24	0.03	0.14	0.34
% African American	CoC	0.11	0.07	0.12	0.00	0.64
% 35-54 who are veterans	CoC	0.08	0.08	0.03	0.02	0.26
Low birth weight prevalence	CoC	0.08	0.08	0.01	0.05	0.14
% Medicaid recipients	CoC	0.18	0.17	0.07	0.03	0.42
% Obese	CoC	0.26	0.27	0.03	0.16	0.34
Family poverty rate	CoC	0.09	0.09	0.04	0.01	0.23
Poverty rate	CoC	0.13	0.13	0.04	0.03	0.33
Residential mobility rate	CoC	0.16	0.16	0.04	0.07	0.29
Median rent, 3 BR ($100s)	CoC	11.86	10.93	3.50	7.01	24.94
Substandard housing (lacks complete plumbing facilities)	CoC	0.0035	0.0004	0.0057	0.0000	0.0776
Housing vacancy rate	CoC	0.12	0.11	0.06	0.03	0.54
Percent of renters with housing cost burden	CoC	0.45	0.45	0.06	0.29	0.61
Median rent, 2 BR ($100s)	CoC	8.95	8.15	2.58	5.43	17.48
% Renter households	CoC	0.31	0.30	0.08	0.13	0.66
TANF and GA inclusion rate	CoC	0.20	0.20	0.09	0.03	0.88
SNAP benefit adequacy	State	0.15	0.15	0.03	0.12	0.23

Variable Name	Level	Mean	Median	Std Dev	Minimum	Maximum
Federal housing subsidy inclusion rate, (per families in extreme poverty)	CoC	0.01	0.01	0.01	0.00	0.10
State TANF expenditures ($ per capita)	State	15.02	7.98	17.83	0.0	78.26
SSI inclusion rate	CoC	0.31	0.30	0.08	0.08	0.61
Emergency shelter bed rate (per family in poverty)	CoC	0.0035	0.0024	0.0034	0.0000	0.0251
Transitional housing bed rate (per family in poverty)	CoC	0.0052	0.0036	0.0057	0.0000	0.0528
Mean January Temperature	State	32.56	31.47	12.35	0.00	58.09
Family homelessness rate (per 1,000 family households)	CoC	1.13	0.75	1.27	0.00	11.81
Unsheltered family homelessness rate (per 1,000 family households)	CoC	0.28	0.04	0.92	0.00	10.64

Domain-specific models

Three separate multivariable models of the total family homelessness rate were constructed, using variables from the housing and economic domains, the demographic and public health domains, and the public assistance domain, respectively.

Housing and Economic Model. When a model of family homelessness rates is built using variables measuring housing and economic factors, the best-fitting model is made up of five factors: housing cost burden for renters, median rent levels, substandard housing, residential mobility, and housing vacancy are each positively associated with the family homelessness rate. For every 1% increase in the percent of renters who pay more than 30% of their income for housing costs, the family homelessness rate increases by 1.3%. An increase of $100 in the median rent is associated with a 0.02% increase in homelessness, when other factors are held

constant. For every 1% increase in the proportion of substandard housing units, the family homelessness rate increases by 11.3%. For every 1% increase in the mobility rate, or the percentage of the population that has moved in the past year, the model predicts a 2.2% increase in homelessness, with other factors held constant. Finally, for every 1% increase in the vacancy rate the model predicts a 0.65% increase in the family homelessness rate, with all other model variables held constant.

The random effects in the model show us the degree to which the variance is attributable to differences between the states, and differences within each state. In this model, there was significant variance both between the states and within the states, which indicates that the multi-level model, which accounts for both types of variance, is the appropriate method to use. Comparing the between- and within-state variance, the within-state variance is greater, so from one CoC to another within a state, there is in general greater variance than from one state to another.

Table 10
Housing and Economic Model

			95% CI		
Variable	**B**	***B***	**lower**	**upper**	**P**
Median rent, 3BR apt	0.02	0.20	0.01	0.04	0.0011
Substandard housing (lacks complete plumbing facilities)	11.38	0.16	5.07	17.69	0.0005
Residential mobility rate	2.24	0.22	1.19	3.29	<.0001
Housing vacancy rate	0.65	0.10	0.05	1.26	0.0356
Percent of renters with housing cost burden	1.29	0.18	0.47	2.11	0.0022
Random effects					
Between-state variance	0.01				0.0275
Within-state variance	0.12				<.0001
Model Fit Statistics					
R^2	0.18				
-2 Log Likelihood	320.90				
AIC	336.90				

Discussion. Of the three domain-specific models, the model using housing and economic variables is the best-fitting model, explaining 18% of the variance. For the most part, the significance and direction of the coefficients in the model are consistent with the hypotheses. The importance of housing affordability is clear. All measures of poverty tested were significantly and positively related to the homelessness rate, as were all measures of housing cost. The proportion of renter households paying more than 30% of their income for rent and median rental housing costs are two of the strongest predictors in the model. When the proportion of households with a rental cost burden is held constant, area rental costs are still associated with higher rates of homelessness, and vice versa.

The residential mobility rate appears in the model as a positive and significant predictor. Although this predictor has not been included in most previous studies of homelessness rates, this finding is consistent with that of Lee, Price-Spratlen and Kanan (2003), who suggest that residential mobility may be related to homelessness in two ways: it may create more competition in a housing market; in addition, shorter tenure in housing units may also be an indication of residents who are more vulnerable to homelessness.

The proportion of housing units that lack complete plumbing facilities has a positive association with homelessness. As a measure of the proportion of substandard housing units, this measure is highly correlated with, but is a stronger predictor than the lack of complete kitchen facilities. Previous studies of city and metropolitan-area homelessness rates have not included measures of substandard housing or housing quality; however, in a study conducted at the census tract level within individual cities, Culhane, Wachter and Lee (1996) found that the percent of boarded up housing units was a positive predictor of homelessness. This study's results are consistent with this general finding that the presence of substandard housing is positively associated with homelessness.

Also consistent with Culhane, Wachter and Lee (1996) is the finding on the vacancy rate. Previous studies of city- or metropolitan area-level variation found that vacancy rates were negatively associated with homelessness, supporting the hypothesis that higher housing vacancy rates would improve households' chances of accessing housing, and lead to a lower homelessness rate. In contrast, Culhane, Wachter & Lee (1996) hypothesized that within a city, homeless families' last addresses before entering shelter would more often be in census tracts with poor housing quality and high housing vacancy rates. Thus they predicted, and found, a positive association between homelessness rates and vacancy rates. Our result for the vacancy

rate supports this hypothesis that housing vacancy may be indicating more than availability of housing units. Vacancies may occur in tandem with substandard units and may not occur because units are usable and empty, but because they are substandard.

Although this is the best fitting model, an alternative model is also shown to further investigate the relationship between housing cost, income, and housing cost burden. In the alternative model, the family poverty rate is retained in place of the rental cost burden. The two variables are moderately correlated and if both are included in the model, the family poverty rate becomes non-significant. In the alternative model, the poverty rate and rental housing costs are both positively associated with homelessness, with a 1% increase in family poverty predicting a 1.6% increase in homelessness, and a $100 increase in median rent predicting a 0.04% increase in homelessness. In this model, rental-housing costs are the strongest predictor of family homelessness. As expected, removing rental cost burden from the model has increased the strength of both housing cost and poverty predictors. The between- and within-state variances are both significant, with greater variance within states.

Table 11
Alternative Housing and Economic Model

			95% CI		
Variable	**B**	***B***	**lower**	**upper**	**p**
Family poverty rate	1.61	0.15	0.35	2.87	0.0126
Median rent, 3BR apt	0.04	0.35	0.03	0.05	<.0001
Substandard housing (lacking complete plumbing facilities)	8.02	0.11	1.53	14.52	0.016
Residential mobility rate	2.46	0.24	1.39	3.52	<.0001
Housing vacancy rate	0.64	0.10	0.03	1.25	0.0391
Random effects					
Between-state variance	0.02				0.0079
Within-state variance	0.12				<.0001
Model Fit Statistics					
R^2	0.15				
-2 Log Likelihood	324.10				
AIC	340.10				

Public Assistance Model. Turning to variables that measure public assistance programs, the best-fitting model of the family homelessness rate includes measures of inclusion, adequacy and expenditures. SSI program inclusion is negatively associated with homelessness. With all other variables held constant, an increase of 1% in the rate of households in poverty receiving SSI is associated with a 0.59% decrease in the family homelessness rate. The SNAP benefit adequacy is negatively associated with the family homelessness rate, with a 1% increase in this ratio predicting a 3.04% decrease in family homelessness. Finally, a measure of state expenditures on TANF cash assistance per capita is positively associated with homelessness in this model. For every 1% increase in spending per capita, the model predicts a 0.01% increase in

the homelessness rate, with other variables held constant. Both types of variance are significant in this model; again, within-state variance is greater.

Table 12
Public Assistance Model

Fixed Effects			**95% CI**		
Variable	**B**	***B***	**Lower**	**upper**	**p**
SNAP benefit adequacy	-3.04	-0.20	-5.02	-1.05	0.005
State TANF expenditures	0.01	0.26	0.00	0.01	0.001
SSI inclusion rate	-0.59	-0.12	-1.16	-0.02	0.044
Random effects					
Between-state variance	0.01				0.0325
Within-state variance	0.13				<.0001
Model Fit Statistics					
R^2	0.11				
-2 Log Likelihood	352.50				
AIC	366.50				

Discussion. Previous studies have found both positive and negative relationships between inclusion and homelessness rates. There is only one inclusion measure that emerges as significant in this model; inclusion of the SSI program is negatively associated with homelessness.

The finding that there is a positive relationship between state TANF expenditures and the family homelessness rate supports Hypothesis 2. Because the measure is not standardized by the population in poverty, but by the total population, higher levels of spending may simply indicate higher levels of poverty.

One measure of benefit adequacy, of the SNAP program, is significant in this model. The finding that the adequacy of SNAP benefits is negatively associated with homelessness is

consistent with the hypothesis that higher levels of public assistance benefits will assist families paying for and maintaining housing. However, the fact that adequacy of the SNAP benefit is significant while the adequacy of the TANF benefit is not is surprising. Comparing the importance of TANF and SNAP benefits in reducing household risk for homelessness, TANF benefits would be expected to have a greater significance because the benefits provided by the TANF program are generally higher in value than those provided by the SNAP program. The average maximum TANF benefit is 53% of the state median rent, while the average SNAP benefit is only 15% of the state median rent. Further, TANF provides cash benefits that can be used to pay for any type of household need, including housing costs. In contrast, SNAP provides "near-cash" benefits that can be used only to buy food. These dollars would not be as effective in helping families to pay for housing costs and avoid homelessness because they could not be used directly to pay rental costs to a landlord.

However, there are ways that SNAP benefits could improve a household's ability to maintain housing and avoid homelessness. First, by paying for food costs, SNAP benefits could free up a part of the household income to pay for housing costs. Second, families that are "doubled up," or sharing a housing unit with another family, could contribute their SNAP benefits to the total household income, thereby making their stay with another household less burdensome and their continued stay more desirable.

Observing the mean inclusion rates of the two figures also suggests that the reach of the SNAP program, at 65% of households in poverty averaged over all CoCs, means that it is reaching and affecting the incomes of more families than the TANF and GA programs, which have a mean inclusion rate of 20% of households in poverty, averaged over all CoCs. This higher inclusion rate could give it more influence at the CoC level to reduce homelessness risk.

Demographic and Public Health Model. In a model of family homelessness that includes only demographic and public health variables, the best-fitting model has six variables. The representation of children in the population is negatively associated with homelessness, with a 1% increase in the percent of the population under 18 predicting a decrease in the family homelessness rate of 2.9%. The representation of African Americans is positively associated with homelessness. With other factors held constant, for an increase of 1% in African American representation, the model predicts an increase in the family homelessness rate of 1.1%. Veteran status among the 35-54 age group is also positively associated with homelessness. A 1% increase in this group is associated with a 2.0% increase in the family homelessness rate. The model shows a negative association between low weight births and homelessness. A 1% increase in the percent of births that are low weight is associated with a 0.09% decrease in family homelessness. A 1% increase in Medicaid recipients is associated with a predicted 2.0% increase in homelessness. Obesity is negatively associated with homelessness, with a 1% increase in obesity rates associated with a 0.03% decrease in homelessness. In this model, the variances are both significant. Within-state variance remains greater than between-state variance.

Table 13
Demographic and Public Health Model

Fixed Effects			**95% CI**		
Variable	**B**	***B***	**lower**	**upper**	**p**
% 0-18	-2.91	-0.20	-4.31	-1.51	<.0001
% African American	1.13	0.33	0.55	1.71	0.0001
% 35-54 who are veterans	2.02	0.15	0.63	3.40	0.0045
Low birth weight prevalence	-0.10	-0.35	-0.15	-0.04	0.0004
% Medicaid recipients	2.01	0.36	1.34	2.68	<.0001
% Obesity	-0.04	-0.32	-0.05	-0.02	<.0001
Random effects					
Between-state variance	0.01				0.0157
Within-state variance	0.12				<.0001
Model Fit Statistics					
R^2	0.17				
-2 Log Likelihood	317.70				
AIC	335.70				

Discussion. The model confirms two hypotheses about demographic groups that have been found to be at increased risk of homelessness. Higher percentages of African Americans and of veterans among the 35-54 age group are found to be associated with higher rates of family homelessness. The model has a surprising finding regarding age groups: it shows that the representation of children in the population is negatively associated with homelessness. Because the focus is an outcome of family homelessness, the presence of children in the population would, if anything, be expected to be associated with higher family homelessness rates, just as areas with higher proportions of adult age groups might have higher rates of single adult homelessness. However, it is possible that the age composition of the area could be associated with other community factors, such as levels of poverty or housing costs, which may be more

direct predictors of family homelessness. When all domains are included in a single model, the result for representation of children in the population is expected to become non-significant.

The results for public health variables are mixed. None of the variables measuring the prevalence of mental illness or substance abuse, or the frequency of mental health treatment or substance abuse treatment, are significant in the model. Three public health measures that are positively correlated with poverty have mixed results: two are negatively associated with family homelessness, and one is positively associated. These effects are expected to disappear when combined in a model with measures that more directly impact levels of homelessness, such as poverty.

Multidimensional Model of Homelessness

When the variables from all domains are tested in a single multivariable model, some predictors that were significant in the individual models become non-significant, while one variable that did not appear in the domain-specific models becomes significant. Six variables remain significantly associated with the rate of family homelessness per 1,000 family households in the population. The model fits better than any of the domain-specific models, with an R-squared value of 0.215.

The family poverty rate is one of the strongest predictors in the model; for every 1% increase in the family poverty rate, the homelessness rate increases by 2.83% when other predictors are held constant.

The rate of residential mobility, or the percent of the population that has moved in the past year, is also a strong positive predictor of homelessness. For every one percent increase in the mobility rate, the model predicts an increase in the family homelessness rate of 2.21%. Rental cost is a positive, significant determinant of family homelessness; the model shows that

for every $100 increase in median rent level, the family homelessness rate increases by .04% when other predictors are held constant.

The model includes two significant public assistance predictors. The inclusion rate of the TANF and GA programs, out of families in poverty, is significantly and positively associated with homelessness. For every 1% increase in the proportion of families in poverty receiving TANF benefits, the model shows a 0.92% increase in family homelessness rate, when other predictors are held constant.

The adequacy of the food stamp benefit is one of only two variables in the model that have a significant and negative relationship with the family homelessness rate. For every 1% increase in the ratio of the food stamp benefit to the median monthly rent, the homelessness rate is predicted to decrease by 1.9%.

One demographic variable, the percent of the population that is 18 years or younger, is significant in the model. The representation of children in the population is negatively associated with homelessness. The model shows that for every 1% increase in the percent of the population that is 18 or younger, the rate of family homelessness is predicted to decrease by 3.6%.

The model shows similar variance to the previous models, with significant between-and within-state variance, but greater variance within states.

Table 14
Multidimensional Model 1: Family Homelessness Rate, All Predictors

Fixed Effects			**95% CI**		
Variable	**B**	***B***	**Lower**	**upper**	**P**
Family poverty rate	2.83	0.26	1.63	4.03	<.0001
Residential mobility rate	2.21	0.21	1.19	3.24	<.0001
Median rent, 3 BR apt ($100s)	0.04	0.31	0.00	0.00	<.0001
TANF and GA coverage rate	0.92	0.20	0.43	1.41	0.0003
SNAP benefit adequacy	-1.91	-0.12	-4.02	0.20	0.0801
% 0-18 years	-3.60	-0.25	-4.97	-2.22	<.0001
Random effects					
Between-state variance	0.01				0.0237
Within-state variance	0.11				<.0001
Model Fit Statistics					
R^2	0.22				
-2 Log Likelihood	300.70				
AIC	318.70				

Discussion. Four domains (demographic, public assistance, housing and economic) contribute significant predictors to the model. The strongest predictors in the model are from the housing market and economic factors. Public assistance factors are also significant predictors in the model, and public health variables were not significant.

These results confirm the overall findings in the previous literature about the importance of structural factors in the housing and economic domains, and demonstrate that these factors remain important when the outcome is family homelessness. These results are consistent with theoretical studies of the causes of homelessness that have identified housing affordability as a

product of both housing costs and household incomes, and as the primary driver of the extent of homelessness in an area. The results demonstrate that this theoretical model applies to family homelessness as well as homelessness in the general population.

The results indicate that rental housing costs and the proportion of family households in poverty are both influential, supporting Hypothesis 1. Although in the domain-specific housing and economic model the rental cost burden emerged as the best housing affordability predictor of the family homelessness rate, when all domains are combined into a multivariate model, the family poverty rate is a better predictor than rental cost burden.

However, other findings contradicted expectations for Hypothesis 1. First, neither unemployment nor vacancy rates were significant in this model. Second, representation of African Americans and female-headed households were not significantly related to homelessness in this model. In contrast, the representation of minors remained significant in the multivariate model, with a negative relationship with homelessness. The continued presence of the 0-18 age group as a significant and negative predictor in the model was contrary to the expectation that this would drop out of the model when other factors were included.

Predictors assessing public assistance programs have varying results depending on the type of measure (inclusion, adequacy, expenditures and rules) and depending on the program. Hypothesis 2 was confirmed by the finding that the measure of benefit adequacy that appears in the domain-specific model, SNAP benefit adequacy, remains significant and negatively related to homelessness. While adequacy of state SSI supplement and maximum TANF benefit were both positively related to the homelessness rate, neither are significant, which was not predicted by Hypothesis 2.

The prediction that expenditure measures would have positive and significant association with homelessness rates was not correct. None of the variables measuring state-level expenditures were found to be significant in this multidimensional model. It appears that when TANF expenditures and poverty rates are included in a single model, the coefficient of TANF expenditures was reduced, as poverty explained this variation.

Measures of program inclusion (for TANF and GA, SSI and SNAP) are all positively related to the homelessness rate in this multidimensional model, although only TANF and GA inclusion is a significant predictor. The inconsistent findings on the direction of the relationship with inclusion rates between the public assistance model and this model are not surprising, given that previous studies have had similarly inconsistent results, with a mix of positive and negative associations between inclusion of various programs and homelessness rates. These results suggest that the relationship between public assistance inclusion rates may be more complex than what is reflected by this model.

The results also showed that state-level rules for the TANF program were likely to have similar relationships as the inclusion measure. When they are added in to the model along with inclusion measures, however, they drop out as they primarily act through increasing or decreasing inclusion.

Adding Shelter Bed Rate as a Control Variable

The possible link is examined between public assistance inclusion and sheltered homeless families by observing whether there is a correlation between "shelter effort" and inclusion of public assistance programs. If there is, it could help to explain why some public assistance inclusion variables are positively correlated with homelessness rates. If the effort that a community makes to shelter homeless families has a relationship to county-level and state-level

policies and practices influencing the inclusion and adequacy of public assistance programs, then in order to clearly view the impact of variability in public assistance programs on the homelessness rate, it is necessary to include shelter effort in the model of the family homelessness rate in order to control for this variable. Thus the effect of inclusion and adequacy of public assistance programs when shelter effort is held constant can be observed.

First, bivariate correlations between the rate of shelter bed provision and inclusion and adequacy rates of public assistance programs are examined. Emergency shelter beds and transitional housing beds are included. Shelter beds are examined as a rate of the population in poverty to standardize the measure across communities of different sizes and levels of need.

Table 15
Correlation of Shelter Effort and Public Assistance Variables

	Emergency shelter bed rate	Transitional housing bed rate	Total shelter bed rate
TANF adequacy*	0.13432	0.18859	0.19771
P	0.0064	0.0001	<.0001
SNAP adequacy*	-0.24582	-0.17306	-0.23527
P	<.0001	0.0004	<.0001
SSI adequacy	-0.01366	0.07968	0.05261
P	0.7825	0.1067	0.2873
TANF and GA inclusion*	0.15039	0.17526	0.19497
P	0.0022	0.0004	<.0001
SNAP inclusion*	-0.1088	-0.09197	-0.11543
P	0.0274	0.0625	0.0192
SSI inclusion*	0.17447	0.01392	0.08688
P	0.0004	0.7784	0.0785

*correlation significant at the .05 level

A bivariate correlation shows that across programs, measures of inclusion have different relationships with shelter bed rates. The TANF and GA inclusion rate has a significant positive

correlation with the emergency shelter bed rate, the transitional housing bed rate, and the total rate. SSI inclusion has a significant positive correlation with the emergency shelter bed rate and with the total number of beds, but its correlation with transitional housing beds is not significant. In contrast, the inclusion rate for SNAP is negatively and significantly correlated with the emergency shelter, transitional housing and total bed rates.

In general, programs' adequacy rates have similar relationships with shelter effort as their inclusion rates. Consistent with the positive relationship for its inclusion rate, the TANF adequacy measure also has a positive and significant correlation with all shelter bed rates. Consistent with the negative relationship for its inclusion rate, the SNAP adequacy measure has a negative relationship with emergency shelter, transitional housing and total bed rates. The SSI adequacy measure is not significantly correlated with shelter bed rates.

These results show that there is a relationship between CoC-level shelter bed rates and CoC-level inclusion rates, as well as between CoC-level shelter bed rates and state-level adequacy measures. The relationship between shelter effort, adequacy and inclusion should be further examined to determine whether this relationship is affecting the model results for public assistance adequacy and inclusion. For example, CoCs in which eligibility policies and easier access to the program make TANF inclusion relatively high may also be more likely to respond to demand for public shelter by increasing the number of shelter beds in the community. In these communities, homeless families would be easier to identify, and more likely to be included in an annual PIT count.

Two variables were added to the existing model to control for shelter effort: the number of transitional housing beds and the number of emergency shelter beds, both as a proportion of the population in poverty. These are added to the model to act as control variables, and to view

whether and how they affect the significance and direction of the relationship between the public assistance variables. After these variables were added to Model 1, measures of inclusion and adequacy that had not been significant in Model 1 were re-tested to assess whether their significance in the model had changed as a result of adding the shelter bed rate control variables.

Table 16

Multidimensional Model 2: Family Homelessness Rate, Including Shelter Beds

Fixed Effects			**95% CI**		
Variable	**B**	***B***	**lower**	**upper**	**p**
Family poverty rate	4.11	0.37	3.15	5.07	<.0001
Residential mobility rate	1.55	0.15	0.74	2.36	0.0002
Median rent, 3 BR apt ($100s)	0.02	0.05	0.01	0.03	0.0010
Percent of population 0-18 years	-2.91	-0.20	-3.99	-1.83	<.0001
TANF and GA coverage rate	0.59	0.13	0.21	0.97	0.0029
SNAP benefit adequacy	-1.66	-0.11	-3.26	-0.06	0.0449
Emergency shelter bed rate	45.79	0.39	36.72	54.87	<.0001
Transitional housing bed rate	22.76	0.32	17.19	28.33	<.0001
Random effects					
Between-state variance	0.01				0.036
Within-state variance	0.07				<.0001
Model Fit Statistics					
R^2	0.52				
-2 Log Likelihood	99.80				
AIC	121.80				

When shelter bed rates are added as control variables to Model 1, overall, the variables from Model 1 retain similar relationships to the family homelessness rate. The family poverty rate becomes a stronger predictor; its coefficient increases from 2.8 to 4.1, the second strongest predictor in the model. Residential mobility rate becomes a weaker predictor, with the coefficient decreasing from 2.2 to 1.55. The median rent predictor also becomes weaker, with the coefficient decreasing from 0.04 to 0.02. As expected, the emergency shelter and transitional housing bed rates are both strong positive predictors of the family homelessness rate.

Adding the shelter bed rates alters the coefficient for the TANF and GA inclusion, which decreases from 0.92 to 0.59. This confirms Hypothesis 3, which stated that adding shelter beds as control variables to the model would decrease the coefficient of the public assistance inclusion measure. However, TANF and GA inclusion does remain a significant predictor.

Adding these control variables to the model also changes the coefficient for SNAP benefit adequacy. SNAP adequacy, which was a negative and significant predictor in Model 1, remains so in this model, but decreases slightly in its absolute value, from -1.91 to -1.66. When shelter beds are added to the model, the within-state variance is decreased somewhat, although both types of variance remain significant.

Discussion. Model 2 results show that when shelter effort is added as a control variable to the model of family homelessness, the positive association between TANF and GA inclusion rates and family homelessness rates becomes weaker, but still remains significant. This result supports the hypothesis that a correlation between shelter effort and public assistance policies is contributing to positive relationship between inclusion and homelessness rates. However, it does not entirely explain the positive relationship because it is diminished but still significant in Model 2. This chapter will continue to examine explanations for this relationship.

The model also shows that when shelter effort is added as a control variable to the model of family homelessness, the negative association between SNAP benefit adequacy and homelessness rates is diminished slightly but remains significant. This chapter will go on to examine how this variable behaves in Model 3, although this variable is not expected to change when unsheltered homelessness is isolated as the outcome. While public assistance inclusion is expected to be affected by enrollment in shelter, benefit adequacy is not, as it is determined solely by the state-level policy to set the benefit level, and is not altered by recipient behavior or the behavior of implementers.

Model of Unsheltered Family Homelessness Rate

As discussed in the literature review, use of shelter services may make families much more likely to enroll in the public assistance benefits that they are already eligible for. This relationship could be contributing to the positive relationship between TANF and GA inclusion. In the third multidimensional model of family homelessness rates unsheltered homelessness is modeled as an outcome, to examine whether the coefficient of TANF and GA inclusion changes when the homelessness rates examined do not involve enrollment in public shelter.

The hypothesis is that when the outcome of unsheltered family homelessness is modeled, other predictors in Model 1 will remain significant, and will retain the same sign of association, but TANF/GA inclusion will lose its significance as a predictor in the model. Other public assistance variables that were not significant in Model 1 are also re-tested, including county-level measures of program inclusion, state level measures of benefit adequacy, state-level measures of expenditures on public assistance programs, and state-level measures of rules governing eligibility for the TANF program, to assess whether they are significant predictors in a model of unsheltered family homelessness.

Table 17
Multidimensional Model 3: Unsheltered Family Homelessness Rate

Fixed Effects			**95% CI**		
Variable	**B**	***B***	**lower**	**upper**	**p**
Poverty rate	8.03	0.39	4.89	11.17	<.0001
Median rent, 2BR apt ($100's)	0.07	0.19	0.00	0.00	0.016
% renters	-2.44	-0.21	-3.87	-1.01	0.001
% age 35-54 who are veterans	5.75	0.19	2.76	8.74	0.000
% African American	-1.45	-0.18	-2.51	-0.38	0.011
Mean January Temperature	0.01	0.15	0.00	0.02	0.018
SNAP benefit adequacy	-3.77	-0.11	-7.91	0.37	0.075
Random effects					
Between-state variance	0.58				<.0001
Within-state variance	0.19				0.003
Co-variance, mean and slope of % Af. Am.	-0.93				0.013
Variance of slope of % Af. Am. between states	4.44				0.0239
Model Fit Statistics					
R^2	0.18				
-2 Log Likelihood	976.40				
AIC	1000.40				

A model of unsheltered family homelessness retains some of the predictors of Model 1 and 2, while losing some and gaining other new predictors that were not previously significant. Poverty rate and median rent both remain positive and significant variables in Model 3. Poverty rate is, by far, the strongest predictor in this model, with a Beta coefficient of .39.

Two variables that were significant in Model 2 have dropped out. The mobility rate is not a significant predictor for unsheltered family homelessness rate, nor is the representation of children in the population.

One housing market factor has emerged as significant: the proportion of renters in an area is negatively associated with the rate of family homelessness. Two demographic variables have become significant predictors in this model. The proportion of those in the 34-54 age group who are veterans is significantly and positively associated with the unsheltered family homelessness rate. The model provides a fixed slope for the proportion of African Americans in the population that is negative. The model also shows that its slope varies significantly by state. The variance between states of the slope of this variable is 0.5805.

January mean temperature has also become significant in this model of unsheltered family homelessness. The TANF/GA inclusion rate is no longer significant in Model 3; however, the adequacy of the SNAP benefit remains a negative and significant predictor of family homelessness in this model.

Other adequacy and inclusion measures are not significant predictors. The state level measures of expenditures were not significant predictors of unsheltered homelessness, nor were the state-level rules governing eligibility for the TANF program.

Discussion. The model of unsheltered family homelessness that emerges in Model 3 shares some important elements of earlier models. Poverty and rental costs have both become stronger predictors in this model. The total poverty rate is a stronger predictor in this model than the family poverty rate was in Model 2; a 1% increase in the family poverty rate in Model 2 was associated with a 4% increase in family homelessness, while the total poverty rate is associated

in Model 3 with an 8% increase in family homelessness. Rental cost is a stronger positive predictor in this model, the coefficient having increased from 0.035 to 0.05.

The addition of January mean temperature to this model is consistent with the way that unsheltered homelessness is enumerated in the annual PIT count. Communities survey public spaces including streets, parks, bus stations and subway cars, to identify those who are sleeping in places not meant for human habitation. It is more likely that homeless families will remain in places not meant for human habitation in areas with higher temperatures, and less likely that local shelter operators will temporarily expand seasonally operational shelter beds in areas with higher temperatures. The model shows that a one-degree increase in January median temperature is associated with a .01% increase in the unsheltered family homelessness rate.

Although veteran status was not expected to be significant in a model of family homelessness, given the small proportion of heads of homeless families who are veterans, veterans have been identified in previous studies as a group that is at elevated risk of homelessness. The model shows that veteran representation in this age group is associated with a 5.7% increase in the family homelessness rate.

Two variables have results in the model that contradict findings in previous literature: first, the proportion of renters is a negative predictor of homelessness, while it has been identified as significant and positive in previous models. However, it has not been previously evaluated as a predictor of unsheltered family homelessness.

Further, the proportion of African Americans in the population has been identified in some previous studies as a positive predictor of homelessness, but the fixed effect is found here to be negative. This relationship varies across states. It remains a negative slope across all states, ranging between approximately -2.51 and -0.38 in 95% of the states. The co-variance of the

mean and slope of this variable is negative, meaning that the slope decreases as the mean increases. In areas with greater proportions of African Americans, the negative slope is stronger.

Model 3 provides interesting results for the questions about public assistance variables. Model 3 supports Hypothesis 4 by showing that TANF/GA inclusion is not be a significant predictor when the outcome modeled is unsheltered family homelessness. As predicted, SNAP benefit adequacy remains a significant and negative predictor of unsheltered family homelessness.

The fact that the TANF and GA inclusion measure becomes non-significant when unsheltered family homelessness is modeled supports the hypothesis that the positive relationship between TANF/GA inclusion and total family homelessness in Model 1 and 2 was a result of increased enrollment in TANF benefits for families using public shelters.

Summary

The domain-specific models of family homelessness confirmed some of the hypotheses regarding the importance of housing market and economic factors, specifically measures determining housing affordability such as rental costs, poverty and housing cost burden. Some predictors in domain-specific models did not remain significant when domains were combined into one multidimensional model. Public assistance variables had generally inconsistent results. Only the adequacy of the SNAP benefit remained a significant negative predictor in both single-domain and multidimensional models. The inclusion rate of the TANF and GA programs was also significant as a positive predictor in the multidimensional model.

When shelter effort was added to the model as a control variable, the two public assistance variables became weaker predictors but remained significant, suggesting that there was some correlation between shelter effort and public assistance measures, which accounted for

some but not all of the predictive power of the public assistance measures. When unsheltered homelessness was evaluated as the outcome, the significant association between TANF/GA inclusion and family homelessness rate disappeared, but SNAP adequacy remained a significant predictor. This finding supports the hypothesis that use by families of public shelter may increase enrollment rates in TANF by increasing their information about eligibility for TANF and providing assistance in application.

Across the multidimensional models, poverty rate remained a strong predictor of homelessness, particularly when shelter effort was controlled for, and in the model of unsheltered family homelessness.

5. Stratified Models of Family Homelessness

An important contribution of this study is that it explains some variation in family homelessness across different types of areas. However, it is also useful to create more precise models of homelessness by observing a more limited set of areas in which it is likely that the dynamics of homelessness or the causal factors leading to homelessness are different. Because poverty has been shown in the previous national models to be such an important factor in determining homelessness rates, the sample of CoCs is divided into those with higher and lower rates of poverty. Further, because less is known about homelessness in nonurban areas, the sample is divided into urban and nonurban CoCs. The following section discusses the results of models of family homelessness for low-poverty and high poverty areas, and non-urban areas. The model of homelessness for urban areas closely resembles the national model and therefore is not discussed here.

Stratification by poverty rate

Stratifying the total sample into areas with high and low family poverty rates shows that some results are inconsistent across communities of differing poverty rates. Some predictors, such as rent and poverty rates, are stronger predictors when used to model the full sample, across the range of low- to high-poverty areas. These predictors become weaker in general when the sample is stratified. Other predictors that played a role in the original model, such as the representation of children in the population, are only significant among either the high-poverty or the low-poverty sample. Still others, such as the unemployment rate, which are not significant when modeling the full sample, emerge as significant in one or both samples when they are stratified. The descriptive statistics for both samples of CoCs is displayed, followed by the results of each model.

Table 18
Descriptive Statistics, Low Poverty Sample (N=207)

Variable	Mean	Median	Std Dev	Minimum	Maximum
Level 1 Variables (CoC)					
Family Homelessness Rate (Per 1,000 Homeless Families)	1.1532174	0.7984429	1.3919277	0	11.805422
Median Rent, 3 BR ($100s)	13.4465736	12.3793871	3.7719894	7.1489004	24.94
Rental housing cost burden	0.4543248	0.45	0.0543102	0.2894937	0.57
% Renters	0.2893731	0.2885092	0.0752622	0.13	0.62
Substandard housing	0.0028783	0	0.0066844	0	0.0776451
Housing vacancy rate	0.1102757	0.0848428	0.0753443	0.03	0.54
% African American	0.0785867	0.0547706	0.0842851	0.0034662	0.6383592
% Veterans in 35-54 age group	0.0742305	0.0711106	0.0320171	0.0204458	0.2085671

Table 19
Descriptive Statistics, High Poverty Sample (N=205)

Variable	Mean	Median	Std Dev	Minimum	Maximum
Level 1 Variables (CoC)					
Family Homelessness Rate (Per 1,000 Families)	1.1092242	0.7207344	1.1379153	0	7.4055248
Median rent, 3 BR ($100s)	10.2647135	9.7681187	2.2725182	7.0053364	20.25
% Renters	0.3344332	0.32	0.0765344	0.1467857	0.66
Unemployment rate	0.0830243	0.0792182	0.0173126	0.0474641	0.1533816
Substandard housing	0.0041187	0.0029191	0.0044378	0	0.0252415
% Age 0-18	0.2425565	0.240021	0.0265614	0.1817491	0.3280946

Low-poverty areas

Among communities below the median family poverty rate, the median rent for a 3-bedroom apartment is positively (though not significantly) associated with homelessness. Although neither median rent nor family poverty rate are significant predictors in this model, rental housing cost burden is a significant predictor. For every 1% increase in the proportion of renter households whose housing costs exceed 30% of income, the model predicts there will be a 1.5% increase in the family homelessness rate.

The proportion of renter households is also a positive predictor in these communities, with a 1% increase in renters associated with a 1.17% increase in homelessness. Substandard housing is also positively associated with homelessness. This model predicts that a 1% increase in the percent of housing units with incomplete plumbing will be associated with a 7% increase in the homelessness rate. The vacancy rate is positively associated with homelessness, with a 1% increase in the vacancy rate predicting a 0.8% increase in the family homelessness rate.

The representation of veterans among the 35-54 age group has a positive association with the family homelessness rate. A 1% increase in this rate is associated with a 2.4% increase in the homelessness rate. The representation of African Americans in the population is the only negative predictor in the model. Among low-poverty communities, a 1% increase in the proportion of African Americans in the population is associated with a 1% decrease in the family homelessness rate.

Table 20
Model of Total Family Homelessness Rate for Low-Poverty CoCs

Variable	**B**	***B***	**Lower**	**Upper**	**p**
Level 1 Variables (CoC)					
Median Rent, 3 BR ($100s)	0.01	0.13	0.00	0.03	0.12
Rental housing cost burden	1.54	0.21	0.41	2.67	0.01
% Renters	1.17	0.22	0.47	1.87	0.00
Substandard housing	7.60	0.13	-0.11	15.30	0.05
Housing vacancy rate	0.83	0.16	0.13	1.54	0.02
% African American	-1.01	-0.22	-1.65	-0.37	0.00
% Veterans in 35-54 age group	2.40	0.19	0.68	4.12	0.01
Random Effects					
Between-state variance	0.00				0.43
Within-state variance	0.12				<.0001
Model Fit Statistics					
R^2	0.24				
-2 Log Likelihood	144.4				
AIC	164.4				

High-poverty areas

In the high-poverty sample, as in the low-poverty sample, median rent is a positive but non-significant predictor. The proportion of renter households is a positive and significant predictor of homelessness, with a 1% increase in renter households predicting a 1.88% increase in the family homelessness rate. In this sample, the inclusion rate for TANF and GA programs is positively associated with homelessness. A 1% increase in the coverage rate predicts a 0.76% increase in the family homelessness rate. The unemployment rate is also a positive predictor among high-poverty communities. A 1% increase in the unemployment rate is expected to coincide with a 3.7% increase in the homelessness rate.

The only negative predictor of the family homelessness rate in this model is the proportion of the population that is under 18. An increase of 1% in this proportion is associated with a decrease in the family homelessness rate of 4%.

Table 21
Model of Total Family Homelessness Rate for High-Poverty CoCs

Variable	**B**	***B***	**Lower**	**Upper**	**p**
Level 1 Variables (CoC)					
Median rent, 3 BR ($100s)	0.03	0.16	0.00	0.06	0.068
% Renters	1.82	0.35	0.98	2.66	<.0001
Unemployment rate	4.20	0.18	1.04	7.35	0.009
Substandard housing	11.46	0.13	0.78	22.14	0.035
% Age 0-18	-3.85	-0.25	-5.93	-1.76	0.000
Random Effects					
Between-state variance	0.02				0.043
Within-state variance	0.10				<.0001
Model Fit Statistics					
R^2	0.30				
-2 Log Likelihood	127.9				
AIC	143.9				

Differences in stratified and non-stratified models

Treating the high-poverty and low-poverty communities as separate samples, important differences in the modeling results emerge. First, while family poverty rate was a positive predictor in the non-stratified model, it is not a significant predictor for either stratified sample. When the family poverty rate is used to stratify the sample, this variable loses its significance as a predictor.

Second, median rent, which was a positive predictor of homelessness in the non-stratified model, is no longer a significant predictor in either of the reduced models, but it continues to be positively associated with the family homelessness rate in both models, and close to significant. It improves the fit of both low- and high-poverty models.

The residential mobility rate, which was a positive predictor in the non-stratified sample, acts as a negative predictor of the family homelessness rate in low-poverty areas and as a positive predictor in high-poverty areas, but is significant in neither model.

While the unemployment rate was not a significant predictor in models using the entire sample of CoCs, it emerged as a positive predictor of homelessness within high-poverty areas. The importance of unemployment in the dynamics of homelessness in 2009 is supported by knowledge of how family homelessness has been affected by the economic recession. From 2007 to 2009, the number of families using shelter over the course of a year increased by 40,000. In addition to an increase in families using shelter, there was an increase in the number of sheltered families with adult men, suggesting that loss of jobs and income had an impact on the structure of families using shelter (HUD, 2010). A strong risk factor for homelessness, living doubled up with family or friends out of economic need, increased as the effects of the economic recession were felt. From 2008 to 2009, the number of people doubled up in the U.S. increased by 12% (NAEH, 2011).

Testing hypotheses. Hypothesis 5 predicted that in areas of lower poverty, housing market factors would become stronger predictors of homelessness relative to the strength of economic factors. In fact, median rent loses its significance as a predictor, but is replaced by a measure that assesses both housing costs and income at the individual level, aggregated at the CoC level. The percent of renter households for whom housing costs are more than 30% of income is significant in lower poverty areas.

Three housing market factors that were not significant in the non-stratified model did become significant in the low-poverty sample: the proportion of renters is the strongest predictor in the low-poverty model; the proportion of substandard housing and vacancy rate both emerge as significant positive predictors. However, a fourth housing market variable, the residential mobility rate, loses its significance in the low-poverty model.

As hypothesized, housing market factors do play an important role in this model, making up a majority of the significant predictors. Other than these four housing market variables (one of which takes income, an economic measure, into account) the only other significant variables in this low-poverty model are two demographic variables.

The representation of African Americans here is a negative predictor, associated with a decrease in homelessness. This variable has shown very different results when included in various models of family homelessness in this study. In the domain-specific model using demographic and public health variables, it was a positive predictor of homelessness, in keeping with previous studies of homelessness rates. However, in the model of unsheltered homelessness, this predictor appeared as negative and significant.

While individual-level studies have consistently found higher risk for homelessness among African Americans, community-level studies have not confirmed that higher risk for African Americans translates into higher rates of homelessness at the community level. Culhane, Lee, and Wachter (1996) did find that neighborhoods with a higher representation of African Americans within a single city were more likely to be the neighborhoods from which families entered shelter, but the overall homelessness rate of cities or metropolitan areas have not consistently been shown to be affected by the representation of this group at the community level. A single study showed representation of African Americans to be positively associated with the total homelessness rate at the community level (Elliot and Krivo, 1991) while several others showed no significant relationship (Burt, 1993; Early and Olsen, 2001; Lee, Price-Spratlen and Kanan, 2003; Raphael, 2010).

The representation of veterans in the 35-54 age group is a positive predictor within low-poverty areas, as it was in the Demographic/Public Health model and the model of unsheltered family homelessness.

Hypothesis 5 also predicted that in high-poverty areas, public assistance adequacy rates would become stronger predictors of homelessness because these programs would affect a larger proportion of the population. The results of the high-poverty model did not support this hypothesis. In fact, when the sample was stratified into low- and high-poverty areas, the significance of the SNAP adequacy variable, which had been significant in the non-stratified model, disappeared.

Differences: Low- and high-poverty models

The models for low-poverty and high-poverty models are quite different from one another. There are a few variables shared by both models; rental costs are positive and close to significant, but not significant at the 0.05 level. The proportion of renters and the proportion of substandard housing units are both positive predictors.

The vacancy rate and the rental cost burden, each of which were positive predictors of the family homelessness rate in the domain specific model using housing and economic factors, but were not significant in the multidimensional model, emerge again in the low-poverty model as positive and significant but not in the high-poverty model.

While the public assistance inclusion rate remains a positive predictor in the stratified sample, this predictor is significant only among the high-poverty communities. The representation of children in the population remains a negative predictor in the stratified models, but is significant only in the sample of high-poverty communities.

The unemployment rate, which was not significant in the non-stratified model, is significant only in the high-poverty model. Each model has significant and unique demographic predictors: in the low-poverty model the representation of African Americans is negative and the representation of veterans in the 35-54 age group is positive. In the high-poverty model, the representation of minors is a negative predictor.

Non-urban Areas

Five Level 1 or CoC-level variables were significant predictors of family homelessness in non-urban locations. The strongest predictor of family homelessness was the owner-occupant housing cost burden. An increase of 1% in the percent of owner-occupants whose housing costs were over 30% of their income was associated with a 2.8% increase in the rate of family homelessness. The second strongest predictor was the residential mobility rate, with a 1% increase associated with a 3.97% increase in the family homelessness rate. The remaining CoC-level variables were roughly similar in their importance in the model: an increase in the housing vacancy rate was associated with a 0.8% increase in the family homelessness rate, an increase in the proportion of households that consisted of a single person was associated with a 2.59% increase, and an increase in the SNAP inclusion rate of 1% was expected to accompany a 0.34% increase in the family homelessness rate.

Three state level (Level 2) variables were significant. The maximum income for eligibility for TANF for a family of three was positively associated with the family homelessness rate, with a $100 increase in the maximum income level associated with a 0.03% increase in homelessness. The amount of federal spending on the TANF program in the state had a negative relationship with the family homelessness rate. For every $10 increase in the amount spent per capita by the federal government on TANF, the family homelessness rate was expected to

decrease by 0.03%. Last, the frequency of alcohol abuse treatment in the state was positively associated with family homelessness. A 1% increase in the number of treatment admissions per 1,000 people in the population was associated with a 0.03% increase in the family homelessness rate.

Table 22
Descriptive Statistics, Non-Urban Sample (N=168)

Variable	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
Level 1 Variables (CoC)					
Family Homelessness Rate (Per 1,000 Families)	1.040505	0.6596743	1.2901566	0	11.280212
Owner-Occupant Housing Cost Burden	0.3283575	0.3105059	0.0784314	0.2192308	0.62
Housing vacancy rate	0.1473628	0.1298034	0.0705892	0.05	0.54
Residential mobility rate	0.1632278	0.16	0.0328229	0.09	0.29
SNAP inclusion rate	0.6831858	0.6900751	0.1854727	0.2173634	1.475604
Single-person households	0.2677713	0.2724152	0.0290029	0.1314118	0.3409964
Level 2 Variables (State)					
Income Max., TANF Eligibility ($100s)	7.56	7.17	3.11	2.68	18.02
Federal spending on TANF cash assistance per capita ($10 per person)	3.30	1.82	4.05	0	13.29
Alcohol treatment admissions per 1,000 people	2.16	1.46	2.04	0.30	13.10

Table 23
Model of Total Family Homelessness rate for Non-urban CoCs

Variable	**B**	***B***	**Lower**	**Upper**	**P**
Level 1 Variables (CoC)					
Owner-occupant housing cost burden	2.77	0.53	1.92	3.62	<.0001
Housing vacancy rate	0.78	0.13	-0.10	1.66	0.082
Residential mobility rate	3.97	0.32	2.02	5.91	<.0001
SNAP inclusion rate	0.34	0.15	0.00	0.67	0.050
Single-person households	2.59	0.18	0.59	4.59	0.011
Level 2 Variables (State)					
Income Max., TANF Eligibility ($100s)	0.03	0.21	0.01	0.05	0.012
Federal spending on TANF cash assistance per capita	-0.02	-0.20	-0.034	-0.006	0.006
Alcohol treatment admissions per 1,000 people	0.03	0.14	0.0004	0.06	0.046
Random Effects					
Between-state variance	0				.
Within-state variance	0.12				<.0001
Model Fit Statistics					
R^2	0.35				
-2 Log Likelihood	110				
AIC	130				

Differences between total sample models and nonurban model

When the sample of CoCs is stratified into urban and nonurban areas, the model for non-urban areas stands out as unique from other models. While models of the total sample of CoCs have included very few state-level predictors, in this model three state-level predictors appear. The most important difference, within the context of this study's focus on public assistance programs, is the presence in the non-urban model of a negative association between a measure of the TANF program and the family homelessness rate. In other models, TANF inclusion rates were either positive or non-significant, and TANF adequacy rates were non-significant. In non-

urban areas, however, greater federal spending on TANF cash assistance was associated with a decrease in the family homelessness rate.

The importance of federal expenditures among all expenditures on TANF cash assistance was particularly strong during this time period. Beginning in 2009, federal funding has been of greater importance to public assistance programs, as state spending on these programs remained flat from federal fiscal year 2008 to 2009, and decreased from 2009 to 2010. Increases in federal funding of 10.6% from 2008 to 2009 and of 14% from 2009 to 2010 are responsible for the slight overall increase in spending on public assistance programs over this period. This increase in federal funding was delivered through the American Recovery and Reinvestment Act of 2009 (NASBO, 2010).

A second state-level variable related to the TANF program appears in this model: one of the state-level rules governing TANF eligibility. The maximum income allowed for eligibility for TANF is positively associated with homelessness. This finding confirms Hypothesis 2, which predicted that rules affecting inclusion rates for TANF would have the same positive relationship as inclusion rates.

The third state-level variable in the model of family homelessness in non-urban areas is the rate of admissions to alcohol abuse treatment, which has a positive association with the family homelessness rate. This is the only public health variable to appear as significant in any of the multidimensional models. This result contradicts the expectation that public health variables would not appear as significant in the multidimensional models. However, this result does fit with existing knowledge about the conditions under which households often enter homelessness. Periods of residential instability such as an exit from an institutionalized setting are times of increased risk for homelessness. In 2009, two percent of adults in homeless families

entered shelter directly from an institutional setting such as a hospital or rehabilitation facility (HUD, 2010), and it is likely that a larger number exited an institutional setting, stayed temporarily with family or friends, and later entered shelter.

Another contrast between the non-urban model and models of all CoCs is a different measure of housing cost. While all previous models included a measure of rental costs or rental cost burden, in the non-urban sample the owner-occupant housing cost burden is a better predictor of family homelessness. There is a difference between the proportion of owner-occupied housing in non-urban areas (mean 70%) and in urban areas (mean 67%), which could partially explain this, but the difference is not very large.

Another explanation for this difference is indicated by the data on the last living situation for families entering shelter. In 2009 a greater proportion of homeless adults in non-urban locations (33%) than in urban locations (26%) entered shelter either from owned housing or from the homes of families or friends (HUD, 2010). Although the data does not allow the comparison to be made specifically for homeless families, and the degree to which the homes of families and friends were owner-occupied housing units is not known, it appears likely that families in suburban and rural locations entered homelessness more often from owner-occupied housing, or that their housing stability was affected more often by owner-occupant housing costs than families in urban locations.

Finally, in the non-urban model of family homelessness, in place of the TANF inclusion rate, which in models of the total sample was a positive predictor of family homelessness, the SNAP inclusion rate is a better predictor of homelessness. This result suggests that while in urban areas the proportion of families in poverty that fit the eligibility requirements for TANF is a good proxy for families at risk of homelessness, in non-urban areas, the proportion of

households in poverty who are eligible for SNAP may be a better proxy for family homelessness risk.

Summary

The relationship between poverty and homelessness diminishes when samples are selected that represent a more limited range of poverty rates, but housing market factors, including rental costs, remain important predictors. In areas in which the poverty rate is above the national median, unemployment rate is a positive predictor of homelessness. Lack of housing affordability is a significant predictor of homelessness even in areas in which the poverty rate is below the national median. Communities with more renters, higher vacancy rates and more substandard housing appear to produce more homelessness. No demographic group was found to be a consistent predictor of homelessness in both low- and high-poverty areas.

Models of family homelessness in non-urban areas stand out from those of all CoCs with two significant state-level TANF program predictors, the only significant public health variable in any of the models, and by showing owner-occupied housing costs to be more important than rental housing costs.

6. Summary of Results

Consistent Results

Overall, the multidimensional models of family homelessness share a number of common characteristics, whether they model the total family homelessness rate, focus only on unsheltered family homelessness, or are limited to a subset of areas such as high poverty areas or non-urban areas. Every model includes three types of variables:

Housing affordability. The models developed in this study indicate that family homelessness occurs with greater frequency in housing markets in which housing costs are higher, where households competing for housing have incomes that are below the poverty level, and where there is a mismatch between housing costs and income, such that a large proportion of households are paying more than 30% of their income for housing costs.

Quality of the housing stock. The models also indicate that homelessness occurs most frequently in housing markets in which there is a relatively high proportion of substandard housing units, and a relatively high level of housing vacancy. The repeated presence of both housing quality and vacancy variables as predictors suggests that in these housing markets, vacancy is not occurring due to less competition for housing, and is not providing more opportunity for families to access housing units, but instead is due to low quality of the units preventing the units from being rented, such as presence of pests, lack of timely repairs, presence of mildew, or even substandard conditions in units that are being incorrectly reported as habitable by the landlord.

Housing mobility and housing market competition. In general, the models show that family homelessness is occurring at higher rates in housing markets in which households are less stably and permanently housed, where there is a high level of mobility, and where the housing

market is more competitive, meaning that each household is competing in its housing search with a large number of other households for the same apartments.

Poverty

This study tested a number of measures of poverty and household income, including family poverty rate, adult poverty rate, individual poverty rate, household poverty rate, and the rate of extreme poverty, or the percent of the population with an income below 50% of the poverty threshold. While extreme poverty was expected to be the best predictor among poverty measures of family homelessness, given the very low incomes that homeless families have been found to have in individual-level research, the models demonstrate that in general, the best predictor of the family homelessness rate is the family poverty rate. Although the extreme poverty rate is always a significant predictor of family homelessness, the models created using the family poverty rate fit the data more accurately than models using the extreme poverty rate. This result suggests that the poverty threshold is a more important income measure to use in predicting family homelessness than 50% of that threshold. However, it is also important to consider that the extreme poverty rate is calculated as a proportion of the total population, while the family poverty rate is a proportion of only family households. Using family households in the denominator may make this poverty measure more precise a predictor of family homelessness than any general population poverty measure.

Housing Cost

This study tested several measures of housing costs, including median rental costs, fair market rental costs, property values, and housing cost burdens for renters and owners. In general, rental housing indicators were the key predictors in the models, although owner occupied housing costs were significant. The study found that in general, the median cost of

rental housing units is the best predictor of family homelessness rates. However, in some cases, housing cost burden, which measures the mismatch between housing costs and income at the household level, took the place of both housing costs and poverty measures in the models.

Table 24
Results common across models

Variables	**Result**	**Models**
Housing affordability: Median rental costs Family poverty rate Rental housing cost burden Owner housing cost burden	Lack of housing affordability is a strong positive predictor of family homelessness.	All
Poverty rate Family poverty rate Extreme poverty rate	Family poverty rate is a better predictor of family homelessness than the extreme poverty rate	All except poverty-stratified models
Housing stock quality Substandard units (incomplete plumbing) Vacancy rate	Presence of low-quality housing units is a consistent positive predictor of family homelessness	All
Housing mobility and competition Residential mobility rate Renters Single person households	Residential transition and competition in the housing market created by mobility and a high rate of consumption of housing per person are linked with higher rates of family homelessness.	All

Unique Results

Although there were strong consistencies across the models of family homelessness, models of unsheltered family homelessness, and models of homelessness in high and low-poverty areas and in non-urban areas exhibited a number of important differences from models of total homelessness in all CoCs.

Unsheltered homelessness and lower-poverty areas. Both the model of unsheltered family homelessness and the model of family homelessness in areas with lower poverty rates included the representation of African-Americans as negative predictors of family homelessness. This finding is difficult to reconcile with what is known about the risk of homelessness for African-Americans, that individually, people of African-American race are at higher risk of homelessness than the general population.

Both of these models also showed that the representation of veterans among 35-54 year olds was a positive predictor of homelessness. While families are only a small proportion of homeless veteran households, they are a growing segment of this population, and this result suggests that as this population grows, rates of unsheltered family homelessness, and rates of total homelessness could grow in some areas.

Higher poverty areas. The results show that in areas with poverty rates that are above the median, higher unemployment rates are linked with higher rates of family homelessness. This result demonstrates the importance of stratifying samples when analyzing homelessness nationally. This important economic dynamic contributing to family homelessness is not clear when the full sample of CoCs is analyzed together. Only by directing the focus to areas of high poverty is the importance of the unemployment rate seen. This predictor adds important complexity to the model of homelessness rates. Up to this point, the understanding of the economic situation of families entering homelessness was limited to the fact that these families were in poverty, with no context for the poverty, or indication of timing. This finding for the higher poverty areas suggests that in some cases, poverty that is leading to homelessness may not be a long-term condition, but could be a temporary condition that some families are entering after a household member loses a job.

Non-urban areas. Non-urban areas have several unique predictors of family homelessness. First, this is the only model in which a measure of the TANF program was found to have a negative association with family homelessness. Greater federal spending per capita on TANF cash assistance is associated with lower rates of family homelessness. This was also the only model in which a public-health factor was found to be a significant predictor: in non-urban areas, the rate of admissions to alcohol-treatment programs is a positive predictor of homelessness. Third, in contrast to other models developed in the study, owner-occupant housing costs were found to be a more precise predictor than rental housing costs. Fourth, this model showed that the rate of SNAP (food stamp) receipt was a good predictor of homelessness – a better predictor than the TANF receipt rate. This differs from the other models and suggests that in non-urban areas the broader population eligible for SNAP may be a better match of the population at risk for homelessness, while in urban areas, the narrower population eligible for TANF may be a better match of the population at risk for homelessness.

The unique results for the non-urban sample of CoCs suggest that the dynamics and determinants of homelessness differ significantly in non-urban and urban areas. In order to obtain accurate pictures of causal factors of homelessness, national modeling should always include a focused look at non-urban communities.

Table 25

Results unique to individual models

Variables	Result	Models
% African American	Higher proportion of African American people in the population is associated with lower unsheltered family homelessness rates and lower family homelessness rates.	Unsheltered Low-poverty areas
% 35-54 who are veterans	Higher proportion of veterans among 35-54 year-olds is linked with greater unsheltered family homelessness and family homelessness.	Unsheltered Low-poverty areas
Unemployment	Unemployment rate is associated with more family homelessness in high-poverty areas.	High-poverty areas
Federal spending on TANF	Greater federal spending on TANF per capita is linked with less family homelessness in non-urban areas.	Non-urban areas
Rate of admission to alcohol treatment programs	Higher rates of admission are associated with higher rates of family homelessness	Non-urban areas
SNAP inclusion rate	The proportion of households in poverty receiving SNAP is a better predictor of homelessness in non-urban areas than the TANF inclusion rate.	Non-urban areas
Owner housing cost burden	Housing costs for owners is a more precise predictor of homelessness than housing costs for renters in non-urban areas.	Non-urban areas

7. Conclusions and Policy Implications

The results of this study address two existing gaps in the literature regarding family homelessness. First, they confirm and extend the findings of previous community-level studies that have focused on homelessness among the general population by showing that housing costs, poverty, and housing affordability are key predictors of homelessness among families. Second, the results show that even when a variety of public assistance programs are measured in multiple ways and included in a model of family homelessness, there are few measures that are significantly and negatively associated with family homelessness rates.

Housing affordability

The results confirm theoretical models of homelessness that highlight the importance of lack of housing affordability, with housing affordability defined as a mismatch between housing costs and household incomes. This is also consistent with results of community-level studies of the total homelessness rate. In the various models developed in this study, housing costs, poverty rate, both variables, or housing-cost burden are significant predictors of homelessness.

The importance of measures that assess housing affordability in various ways, demonstrates that, in general, policies intended to reduce homelessness should be focused on housing affordability, and increasing housing affordability for people in poverty.

Housing Costs

The importance of housing costs in the models – especially in the original model where it is the strongest predictor – highlights the negative implications of changes to local housing markets that result in increases to real-estate values and housing costs, especially rental costs.

These results demonstrate that increased family homelessness rates may be one unintended effect of various private or public actions that contribute to increased housing costs.

Such actions include private development, conversion of units from one building type to another, land use approvals, tax incentives for development, or land-use regulations that increase housing costs by limiting housing density, excluding multi-family housing, or setting minimum requirements for housing size.

Our findings on housing affordability lend general support to a wide range of interventions, from emergency financial assistance to pay rental arrears offered by homelessness prevention programs, to expansion of funding of Housing Choice (Section 8) Vouchers. These programs are designed to mitigate the problems resulting from housing costs that are beyond the reach of poor families.

However, the programs that provide housing subsidies, whether temporary or ongoing, shallow or deep, remain severely limited in their inclusion rates. None of the housing subsidy programs currently operating, such as the Housing Choice Voucher program or homelessness prevention programs that provide temporary rental assistance are entitlement programs. Regardless of the criteria chosen, enrollment in these programs is a fraction of those who demonstrate need, and allocation of low-income housing subsidies within the eligible population is not conducted according to level of need, but on a first-come, first-served basis. Of the population in poverty, a small proportion receives a deep subsidy. Most people who have the lowest incomes receive no subsidy at all, while some people with higher incomes and less severe needs receive a subsidy (Olsen, 2010)

The resulting system, as many have pointed out, results in an incoherent housing subsidy system which is not broadly effective at addressing the population's low-income housing needs or reducing homelessness rates. Olsen (2010) makes a strong case for reforming the U.S. system of housing assistance with the goal of significantly reducing homelessness. His recommendation

is the establishment of an entitlement housing voucher program, which every household that met income criteria would receive. Olsen's strategy for this reform is to maintain the current housing subsidy budget, but to target existing subsidies more narrowly to families with extremely low incomes, which he argues would account for almost all households that become homeless.

However, Olsen's recommendation, while it could be effective in reducing homelessness, would amount to re-allocating an existing number of housing subsidies, and re-allocation could be less effective than expected in reducing homelessness rates. It is difficult to predict what the effect would be of shifting subsidy allocation away from other households in poverty, who are not in extreme poverty, in order to shift vouchers to the lowest-income category. However, Olsen's goal of providing all households that met extremely low income criteria with a housing voucher entitlement could be achieved by expanding the funding of the housing voucher program. If an entitlement program for people in extreme poverty were added to the existing system in which a broader segment of the population in poverty can apply to waiting lists for vouchers, Olsen's goal could be achieved without reducing the number of vouchers available to the general population in poverty.

Based on this study's results that housing costs are a strong predictor of the family homelessness rate, the funding of this program expansion should be designed with consideration of the impact that increasing housing costs have on homelessness rates. By funding a housing voucher entitlement through a progressive tax on residential and commercial real estate transactions, the funds for the expansion could come in greater part from areas in which real estate transactions are frequent and more profitable, which are the areas in which housing costs are high. The impact of real estate transactions on housing costs, and the resulting impact on homelessness rates, could thus be mitigated. While higher real estate values are often viewed as

improvements for communities, the negative impact that they have on the ability of poor households to afford housing should be acknowledged and compensated for by a tax on the transactions that contribute to them.

This study's results could also be used to make improvements to homelessness prevention programs that use short-term rental assistance, rental arrears payments and other services to prevent homelessness, or similar rapid re-housing programs that quickly assist families that do lose housing to find new housing or regain lost housing. These findings suggest that allocation of funds for these programs should be conducted using community- and neighborhood-level measures of rental housing cost, poverty rates, unemployment rates, and the presence of substandard housing to identify areas from which households at risk of homelessness are most likely to be found.

Poverty

The most consistent result of the various models that were created of the family homelessness rate was the positive and significant relationship between poverty and homelessness. The family poverty rate was a predictor in the original multidimensional model of family homelessness, where a 1% increase in the family poverty rate was associated with a 2.8% increase in the family homelessness rate. It became a stronger predictor when shelter beds were added to the model as a control variable, associated with an increase of 4.1% in the homelessness rate. The poverty rate was an even stronger predictor of unsheltered homelessness. In this model a 1% increase in the poverty rate is expected to result in an 8% increase in unsheltered family homelessness.

These findings are consistent with those of individual-level studies, which have shown risk for homelessness to be limited to the population in poverty. They have shown that poverty

is a necessary but insufficient condition for homelessness; in other words, virtually all of those who become homeless are from the population in poverty, but many households who are in poverty do not experience homelessness.

Public Assistance

Given the results of the study that indicate the importance of poverty rates in the model of family homelessness, some of the results for public assistance programs are surprising. Public assistance inclusion and adequacy rates do not appear to have the strong associations with variation in homelessness rates that would be expected from programs that provide supplements to the income of families in poverty.

Given the clear relationship between the family poverty rate and the family homelessness rate, it is surprising that so few public assistance program measures have significant negative relationships with the family homelessness rate. Neither public housing, Section 8, SSI, nor SNAP inclusion rates were significant predictors of homelessness. Adequacy rates for TANF and SSI were not significant. Only two public assistance variables were associated with lower rates of family homelessness: for the total sample of CoCs, SNAP benefit adequacy was a negative predictor, and among non-urban areas, federal spending on TANF cash assistance was a negative predictor.

The limited number of significant results among public assistance variables suggests that some qualities of public assistance programs prevent them from exerting a strong effect on families' risk for homelessness. The unmet potential of public assistance programs to reduce homelessness rates should be a nationally recognized problem addressed by the U.S. Interagency Council on Homelessness (USICH). The USICH is the federal government's vehicle for interagency cooperation on homeless policy, and is made up of the heads of 20 Cabinet-level

departments and agencies, including the Department of Housing and Urban Development, and the Department of Health and Human Services.

Currently, one of the ten objectives in the USICH Federal Strategic Plan to Prevent and End Homelessness is to "improve access to mainstream assistance and services to reduce people's financial vulnerability to homelessness." While this goal recognizes the importance of public assistance for assisting households to avoid homelessness, the implementation of this goal has largely been focused on making use of changes in Medicaid policy instituted by the Affordable Care Act, to obtain better access to medical care for people who are homeless (USICH, 2011).

Priority should be placed on understanding why current U.S. public assistance programs such as TANF and SSI fail to keep approximately 180,000 families from entering shelter over the course of a year, examining benefit adequacy and inclusion rates. The USICH should become a strong advocate for the expansion of public assistance benefits as an important tool in preventing homelessness. Further research could develop understanding of what types of changes to public assistance programs would be most effective in reducing homelessness rates.

Directions for Further Research

Assessing the relationship at the level of an ecological analysis, there remain many questions and there is little information on which to base further conclusions about what qualities of public assistance programs are limiting their effect on the family homelessness rate.

For example, two qualities of public assistance programs could potentially be blamed for a lack of effect on the homelessness rate. First, the rates of inclusion for these programs could be too low to reduce rates of homelessness among people in poverty at a level that can be measured. The one significant negative relationship with a public assistance variable that does appear in the

model supports this argument. There is a negative relationship between the SNAP adequacy rate and the family homelessness rate. This finding contradicts expectations, as adequacy rates for TANF and SSI programs, which pay larger amounts of cash benefits, were not significant, while the adequacy rate for SNAP, a program that pays smaller amounts of non-cash benefits, was significant. One explanation for the significance of SNAP benefit adequacy is that the SNAP program has a higher mean inclusion rate (0.65) than either TANF (0.20) or SSI (0.31).

Another possible explanation for the lack of significant relationships is that the benefit levels for programs such as TANF and SSI are quite low. These programs may not have the potential to increase families' incomes sufficiently to help them avoid homelessness.

This section will describe additional research methods that could be used to provide more insight into why public assistance programs don't exert more influence on family homelessness. First, individual-level, longitudinal study could address some of the gaps in knowledge of the role that public assistance programs play in the housing dynamics of homeless households, and households at risk of homelessness. Second, cross-national comparisons could improve understanding of how the qualities of public assistance programs affect their potential to reduce homelessness rates.

Individual-Level Longitudinal Study. Little is known about how households in poverty who are at risk of homelessness currently use public assistance programs, and how their benefit receipt relates to experiences of homelessness. Different findings at the individual level of study could lead to very different conclusions and policy recommendations. For example, if a longitudinal study of use of public assistance benefits among families at risk for homelessness found that there were high levels of TANF receipt among families who entered shelter, and similar levels among families who did not enter shelter, a logical conclusion would be that the

TANF adequacy rate is too low to be effective in altering families' risk of homelessness. The appropriate policy recommendation would be to increase TANF benefit levels and ensure their value was related to area housing costs.

In contrast, if the same type of study found that TANF receipt was higher among households that did not enter shelter; a better conclusion would be that TANF inclusion rates were too low to assure that most families at risk were receiving TANF benefits. The appropriate policy recommendation and advocacy focus would be increasing TANF inclusion rates.

Finally, longitudinal study at the individual level could address a number of outstanding questions regarding the timing of benefit receipt, benefit loss, and homelessness. For example, if TANF receipt was found to be lower among families when they entered shelter, and higher after they entered homeless shelters, just before they exited shelter to housing, the resulting conclusion would be that a lack of TANF receipt contributed to homelessness risk, that homeless shelter staff were assisting families in TANF enrollment, and that enrollment in TANF then enabled families to exit homelessness and obtain housing. A policy recommendation that grew from this finding would be to improve the performance of TANF program offices in conducting outreach to enroll households at high risk of homelessness, instead of waiting for households to enter shelter before enrolling them.

Cross-national policy comparisons. Existing cross-national literature on social welfare programs suggest two possible explanations for why U.S. social welfare programs may not be able to have much effect on homelessness rate. First, in comparison to other wealthy countries, social welfare benefits in the United States do little to change the rate of poverty among single parents with children. In particular, U.S. taxes and transfers perform very poorly at reducing

poverty for single parents, reducing the poverty rate among this group by only 10%, while the average reduction among other countries studied was 46% (Smeeding, 2006).

A cross-national study of the relationships between national public assistance program characteristics and national homelessness rates is needed. By comparing the performance of nations' programs at reducing poverty among single parents as well as national homelessness rates, the study could identify any cross-national relationship between this program characteristic and homelessness rates.

Another quality that could be investigated using cross-national comparisons is the degree of targeting or universality in social welfare benefits. Brady and Burroway (2010) conduct a cross-national comparison of poverty among single mothers. They compare targeted and universal social welfare benefits in 18 wealthy democratic countries and their impact on the rate of single mothers in poverty, and find that the two measures of universal benefits had stronger negative associations with poverty among single mothers than did the targeting ratio for single mothers.

Similar measures of targeted and universal benefits could be assessed, and used to develop a model of national homelessness rates, to determine whether targeted benefits, universal benefits, or both types, were associated with lower rates of homelessness.

Summary

In summary, the results of this study support the expansion of homeless policies that focus on the problem of housing affordability. Expansion of the existing Housing Choice Voucher program to include an entitlement to housing subsidy for very poor households could be funded through a progressive real estate transaction tax.

Second, the study indicates several community-level rates that should be considered in allocation of funds for homelessness prevention and rapid re-housing programs: poverty rates, rental housing costs, unemployment, and presence of substandard housing units.

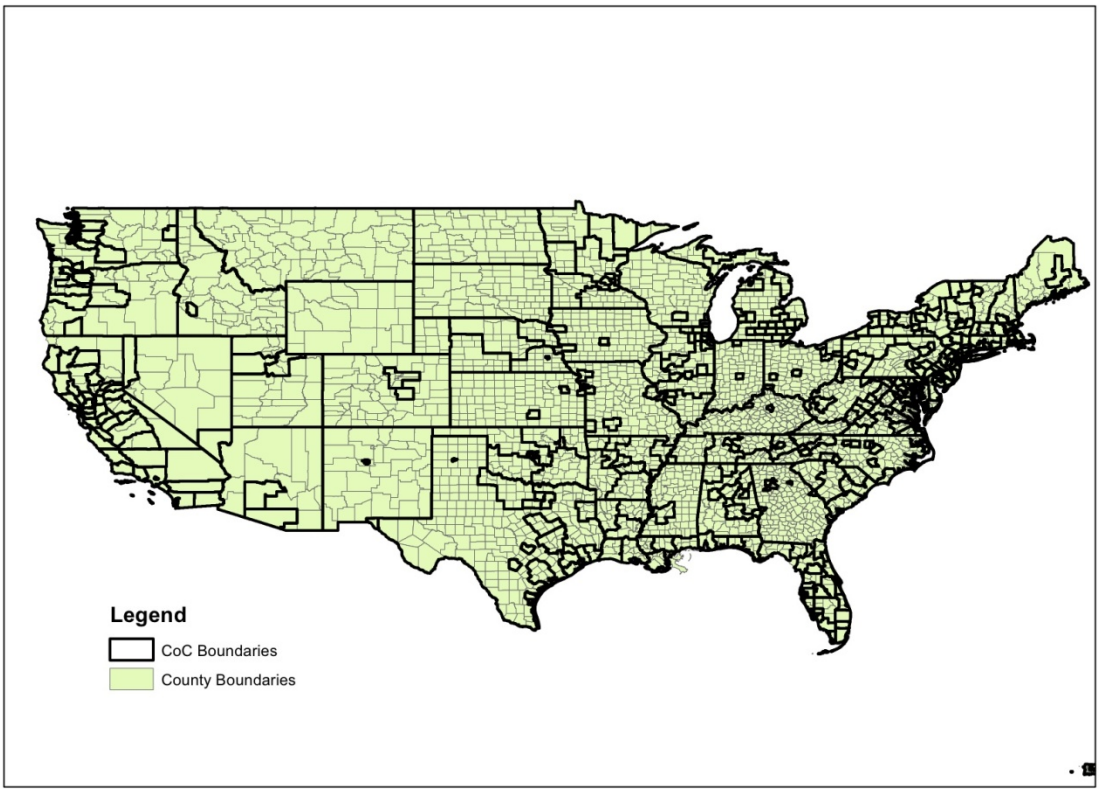
Third, the study suggests that public assistance programs fall short in being able to reduce rates of homelessness. This failure should be acknowledged and investigated by the U.S. Interagency Council on Homelessness, which should advocate for and enact changes to public assistance inclusion rates and/or benefit levels. The exact program characteristics that are limiting their impact on homelessness should be determined through further research. First, individual-level longitudinal study of families' use of public assistance programs and experiences with homelessness would clarify the role that public assistance programs are playing, or not playing, in the dynamics of family homelessness. Second, cross-national comparisons of social welfare policy characteristics and family homelessness rates could show which characteristics of U.S. public assistance programs may be limiting the potential of these programs to reduce homelessness.

8. Appendices

Appendix A: CoC Maps

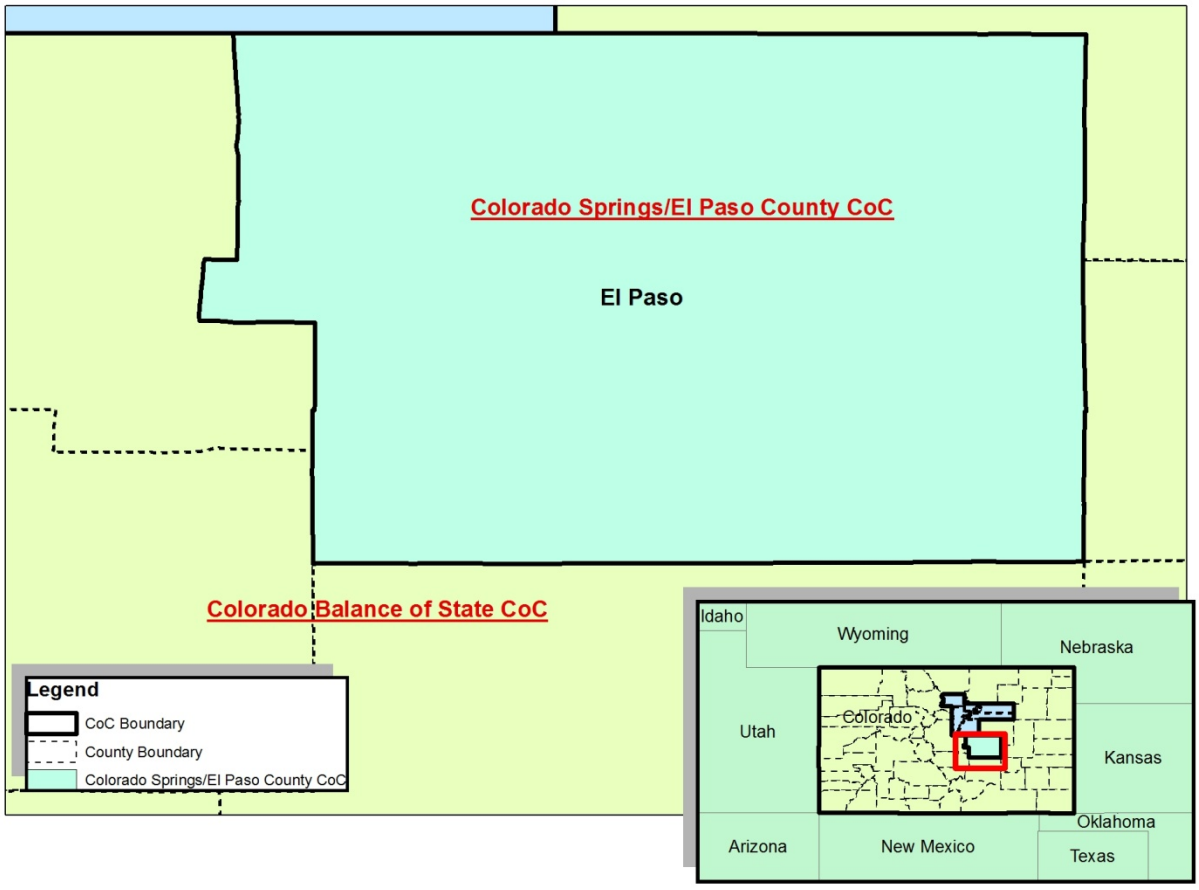
Map 1: *Continua of Care and Counties, United States*

(Map credit: Tom Byrne, National Center on Homelessness among Veterans)



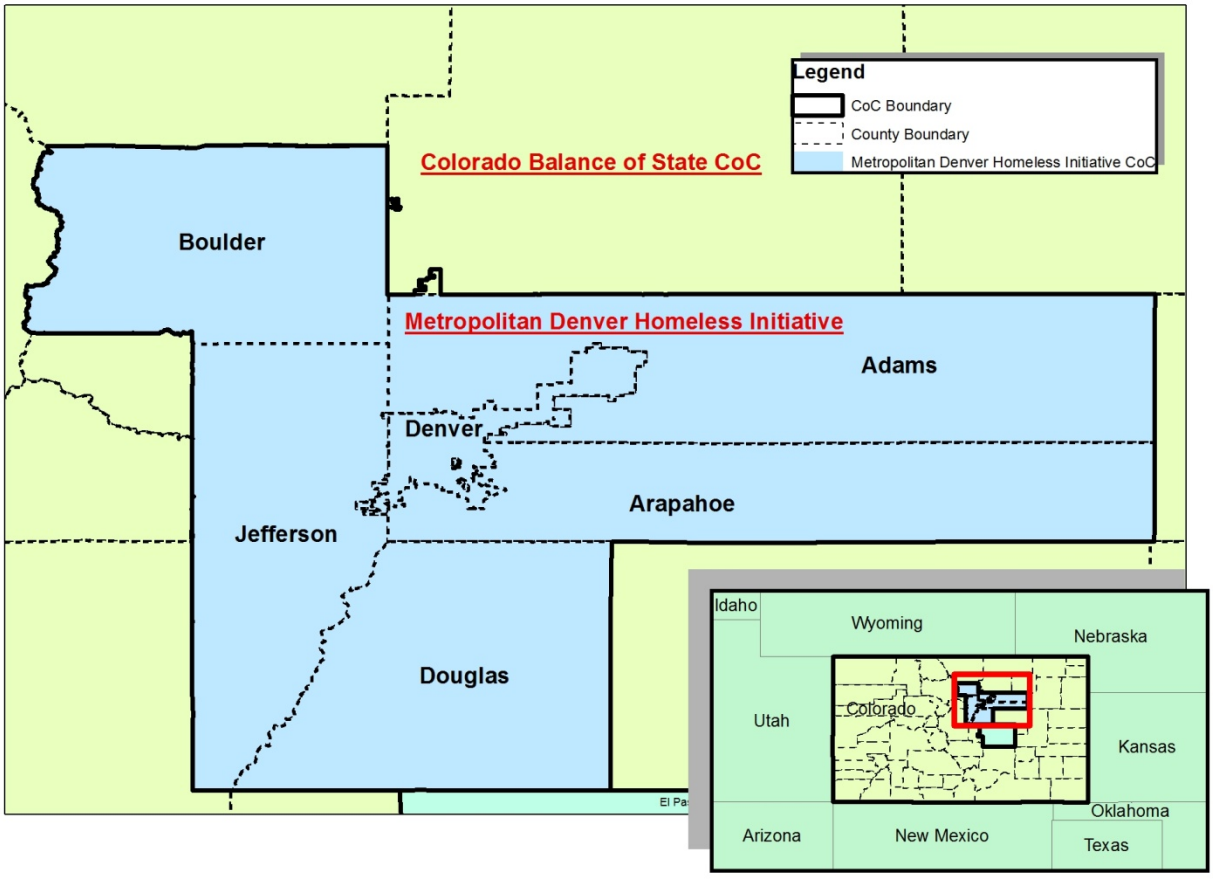
Map 2: *One-to-One Match of CoC to County*

(Map Credit: Tom Byrne, National Center on Homelessness among Veterans)



Map 3: *One-to-Many Match of CoC to Counties*

(Map Credit: Tom Byrne, National Center on Homelessness among Veterans)



Appendix B: *Independent Variables*				
Subject	**Variable Description**	**Data source**	**Geographic Level**	**Date**
Housing				
Median Rent	Median rental costs for housing units of various sizes	American Community Survey (ACS)	County	2005-09
50th Percentile Rents	Estimates of gross rents at 50th percentile of distribution of units for varying sizes	HUD 50th Percentile Rent Estimates	County	2009
Fair Market Rents	Estimates of gross rents at 40th percentile of distribution of units of varying size	HUD Fair Market Rents	County	2009
Overcrowding	Percent of occupied housing units that are overcrowded	ACS	County	2005-09
Vacancy Rate	Percent of housing units that are vacant	ACS	County	2005-09
Tenure	Percents of housing units that are renter-occupied and owner occupied	ACS	County	2005-09
Housing conditions	Percents of occupied housing units lacking complete kitchen facilities and percent lacking complete plumbing facilities	ACS	County	2005-09
Housing cost burden	Percent of owners and percent of renters with housing cost burden over 30% of income	ACS	County	2005-09
HUD Income Limits	Low, very low, and extremely low income limits for housing subsidies, calculated as 80%, 50% and 30% of area median income	HUD Income Limits	County	2009
Median housing costs	Median monthly housing costs for owners and for	ACS	County	2005-09

	renters			
Property Value	Median property value, owner-occupied housing units	ACS	County	2005-09
Residential Mobility	Percent of population that has moved in the past year.	ACS	County	2005-09
Foreclosure	Foreclosure filings and rate of completed foreclosures	Year End Foreclosure Market Report, RealtyTrac	State	2009
Foreclosure	Change in foreclosure rate: 2006-08, 07-08, 07-09, 08-09	Year End Foreclosure Market Report, RealtyTrac	State	2007-09
Economic				
Poverty	Poverty rates for total population, adults, households, families, and individuals	ACS	County	2005-09
Median income	Median household income	ACS	County	2005-09
Very low income	Percent of population with incomes below 50% of poverty threshold	ACS	County	2005-09
Unemployment	Unemployment rate	ACS	County	2005-09
Economic Inequality	Gini Coefficient of Inequality	County Health Rankings (CHR)	County	2007
Demographic				
Race	Percent of population in White, Black, and Hispanic racial/ethnic group	ACS	County	2005-09
Age	Percent of population in each age group: <18, 18-24, 25-34, 35-44, 45-54, 55-64, 65>	ACS	County	2005-09
Nativity	Percents of population and population in poverty that	ACS	County	2005-09

	are foreign born			
Household Type	Percent of housing units that are female headed with no husband present	ACS	County	2005-09
Household Type	Percent of housing units occupied by householder living alone	ACS	County	2005-09
Household Type	Percent of all households that are single-parent	CHR	County	2005-2007
Veteran Status	Percent of each adult age group that are Veterans	ACS	County	2005-09
Foster Care Exits	Youth aging out of foster care as a percent of the population	NAEH State of Homelessness Report	State	2009
Public Assistance Programs				
TANF and GA Inclusion	Percent of households in poverty that received TANF or GA income in past 12 months	ACS	County	2005-09
SSI Inclusion	Percent of households in poverty that received SSI income in past 12 months	ACS	County	2005-09
SNAP Inclusion	Percent of households in poverty that received food stamp (SNAP) benefits in past 12 months	ACS	County	2005-09
Veterans Pension Inclusion	Percent of Veterans that received VA Pension Benefits	Veterans Benefits Administration	County	2008
Medicaid Inclusion	Percent of the population who are Medicaid beneficiaries	Community Health Status Indicators (CHSI)	County	2009
Section 8 Inclusion	Percent of households in poverty that received Housing Choice (Section 8) Vouchers	HUD Picture of Subsidized Households	County	2008
Public Housing	Percent of households in	HUD Picture of	County	2008

Inclusion	poverty that received Public Housing unit	Subsidized Households		
TANF Adequacy	Ratio of maximum monthly TANF payment for family of three with no income to state median rent	Welfare Rules Database (WRD)	State	2009
SSI Adequacy	Ratio of average monthly state supplement to SSI, to state median rent	Social Security Administration Annual Statistical Supplement	State	2009
SNAP Adequacy	Ratio of average monthly SNAP benefit, to state median rent	SNAP Average Monthly Benefits	State	2009
Diversion Payments	Presence of formal diversion payments as an alternative to enrollment in TANF	WRD	State	2009
Job search requirement	Mandatory job search at application for TANF	WRD	State	2009
Maximum Income	Maximum income for initial eligibility for a family of three	WRD	State	2009
Sanction Policy	Percent of benefit reduced by sanction policy for noncompliance with work requirements for single parent	WRD	State	2009
Work Exemption	Age at which child no longer qualifies a parent for exemption from work requirement	WRD	State	2009
TANF spending	State spending on TANF per capita and as percent of total state spending	National Association of State Budget Officers, State Expenditure Report	State	2009
SSI and GA spending	State spending on SSI and GA per capita and as percent of total state spending	National Association of State Budget Officers, State Expenditure Report	State	2009
Medicaid	State spending on Medicaid	National Association	State	2009

spending	per capita and as percent of total state spending	of State Budget Officers, State Expenditure Report		
Public Health				
Alcohol Abuse	Percent of adults who binge drink	CHSI	County	2002-08
Medical Care	Primary Care Providers per 100,000 people	CHSI	County	2009
Medical Care	Dentists per 100,000 people	CHSI	County	2006
Medical Care	Preventable Hospital Stays per 1,000 Medicare enrollees	CHR	County	2005-06
Medical Care	Clinical Care Ranking of County within State	CHR	County	2009
Medical Care	County Designated as a Health Professional Shortage Area	CHSI	County	2009
Medical Care	Percent of 18-65 year olds without health insurance	CHR	County	2005
Mental Health Spending	Spending on State Mental Health Agency per capita	Kaiser State Health Facts	State	2008
General Health	Percent of adults who are obese	CHR	County	2006-08
General Health	Percent of adults with diabetes	CHSI	County	2009
General Health	Percent of population with fair to poor health	CHR	County	2002-08
General Health	Percent of Adults with high blood pressure	CHSI	County	2009
General Health	Percent of Adults reporting no exercise in past month	CHSI	County	2009
General Health	Percent of Adults who Currently Smoke	CHR	County	2002-08
Pre/Neo-Natal Health	Percent of births to women 40-54 years old	CHSI	County	2009
Pre/Neonatal Health	Percent births with low birth weight	CHR	County	2000-06
Pre/Neonatal Health	Neonatal mortality per 1,000 births	CHSI	County	2009

Pre/Neonatal Health	Post-neonatal mortality per 1,000 births	CHSI	County	2009
Pre/Neonatal Health	Teen birth rate per 1,000 women age 15-19	CHR	County	2000-06
Mental Health	Mean Days of poor mental health last month	CHR	County	2000-08
Mental Health	Age-adjusted deaths due to suicide per 10,000 people	CHSI	County	2009
Mental Health	Rates of treatment in mental health facilities	National Survey of Substance Abuse Treatment Services (N-SSATS)	State	2007
Substance Abuse	Rates of illegal drug use and alcohol abuse	National Survey on Drug Use and Health	State	2007-08
Substance Abuse	Rates of treatment for drug and alcohol addiction	N-SSATS	State	2007
Imprisonment	Total imprisonment rate in jails and prisons	Bureau of Justice Statistics (BJS)	State	2009
Releases	Releases from jails and prisons	BJS	State	2009
Miscellaneous				
Climate	January Mean Temperature	Average Mean Temperature Index by Month	State	2009
Emergency Shelter Bed Rate	Number of emergency shelter beds, as proportion of population in poverty	Housing Inventory Chart, Department of Housing and Urban Development	CoC	2009
Transitional Housing Bed Rate	Number of transitional housing beds, as proportion of population in poverty	Housing Inventory Chart, Department of Housing and Urban Development	CoC	2009

Appendix C: *Multilevel Modeling Equations*

I. Intercepts-only Model

The Level 1 and Level 2 equations discussed below together demonstrate how the model, which includes both equations, allows for analysis to occur at two levels of observations and for variance to be calculated separately at each level. The equations for the two levels are connected by the term β_{0j}, which is the group mean or intercept in the Level 1 equation, and the dependent variable of the Level 2 equation.

The Level 1 equation for the intercepts-only model of the family homelessness rate is:

$$Y_{ij} = \beta_{0j} + e_{ij}$$

where Y_{ij} is the rate of family homelessness for CoC *i* in state *j*,
and β_{0j} is the intercept of family homelessness or state mean for state *j*,
and e_{ij} is the random error of prediction for the Level 1 equation, or the Level 1 variance.

The Level 2 equation for the intercepts-only model of the family homelessness rate is:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

where β_{0j} is the rate of family homelessness for CoC *i* in state *j*,
γ_{00} is the overall intercept, or grand mean of the rate of homelessness across all states, and
u_{0j} is the random error for the deviation of the intercept of a group from the overall intercept, or the unique effect of group j on the intercept.

II. Model with a Level 1 Predictor

The equations for the model with a Level 1 predictor closely resemble those of the intercepts-only model, except that the Level 1 equation includes a predictor term, and there are two Level 2 equations, one for each random effect that is included in the Level 1 equation. Both state intercept and state slope are shown as random effects here.

Level 1 equation:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij}) + e_{ij}$$

where Y_{ij} is the rate of family homelessness for CoC *i* in state *j*,

β_{0j} is the intercept of family homelessness or state mean, for state *j*,
β_{1j} is the slope of the relationship between a predictor and the homelessness rate for state *j*,
X_{ij} is the value of the predictor for CoC *i* in state *j*, and
and e_{ij} is the random error of prediction for the CoC, or Level 1 variance.

Level 2 equations:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

where γ_{00} is the average homelessness rate over all states when the predictors are zero,
u_{0j} is the random error for the deviation of the intercept of a group from the overall intercept, or the unique effect of group j on the intercept,
β_{1j} is the rate of family homelessness for CoC *i* in state *j*,
γ_{10} is the overall intercept, or grand mean of the rate of homelessness across all states, and
u_{1j} is the random error of prediction for the state or the Level 2 variance.

III. Model with a Level 2 Predictor

The Level 1 equation remains the same as it was with only a Level 1 predictor. There are again two Level 2 equations, one for each random effect that is included in the Level 1 equation. Only the first equation has changed, adding the slope of the predictor and a predictor value for state *j*.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

where γ_{00} is the average homelessness rate over all states when the predictors are zero,
γ_{01} is the slope of the relationship between the values of the state-level predictor and the intercept of the Level 1 analysis,
W_j is the value of the predictor for state *j*,
u_{0j} is the random error for the deviation of the intercept of a group from the overall intercept, or the unique effect of group j on the intercept,
γ_{10} is the overall intercept, or grand mean of the rate of homelessness across all states, and
u_{1j} is the random error of prediction for the state or level 2 variance.

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