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For my family.

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ABSTRACT

Despite widespread concern about people experiencing homelessness, fundamental questions about this vulnerable and difficult-to-study population are unresolved. This dissertation draws on new data and innovative methods to fill critical gaps in our understanding of homelessness in the United States. The introduction discusses the general problem of homelessness, the state of existing literature, and the contributions and limitations of these essays. The first chapter examines the completeness and reliability of available data sources and develops a new estimate of the U.S. homeless population size. The second chapter examines the level and longitudinal patterns of income and safety net participation for people experiencing homelessness by linking the Census and other datasets to administrative tax and program data. The third chapter provides the first national calculation of mortality for this population, shedding new light on the health disparities associated with homelessness. Taken together, these essays provide researchers, policymakers, and the public with a the first national, close to representative, and rigorously quantitative description of the persistent hardships associated with homelessness while also informing future efforts to aid this population.

CHAPTER 1
THE ISSUE OF HOMELESSNESS

1.1 Introduction

Homelessness is arguably the most extreme hardship associated with poverty in high-income countries. Shelter is a basic human requirement, and the lack of a warm, dry, and safe place to sleep can cause great harm, extending far beyond the direct effects of harsh living conditions to include vulnerability to crime and violence, elevated risks to mental and physical health, stigmatization, and an inability to participate in society and the economy. The personal toll of homelessness is compounded by numerous social costs, including effects on public health, societal cohesion, and public spaces. Homelessness is also a high-profile social problem in the United States, particularly in urban areas, where the difficulties of life at the bottom of the socioeconomic ladder – readily observed in parks and transit stations, in dense encampments along busy streets and under highway overpasses – contrast sharply with the affluence of surrounding neighborhoods.

As with other complex social issues, establishing a firm foundation of understanding is a crucial step towards addressing homelessness. But data challenges have left major gaps in our present knowledge. Researchers' go-to sources for representative information on segments of the U.S. population, household surveys, draw their samples from address lists that, with a few exceptions, by construction exclude people experiencing homelessness. Dedicated efforts to survey this population confront the difficulty of obtaining representative samples and are likely to suffer from bias from non-response and misreporting, issues that may be especially problematic in this setting due to the psychological demands, social stigma, and elevated rates of mental health challenges associated with homelessness. Longitudinal information, which is crucial for learning about the causes and consequences of homelessness, is especially difficult to obtain from people whose living situations are constantly in flux.

Understanding the scope, nature, and causes of homelessness is crucial for designing effective, well-targeted, and adequately scaled policy interventions. If we wish to help those experiencing homelessness, we need to understand who they are – their characteristics, social and economic circumstances, and the life experiences that left them vulnerable to homelessness. If we wish to mount an adequately scaled policy response and evaluate its effectiveness, we also need to know whether available estimates of the homeless population size are accurate and reliable, and we need to understand who is and is not included in our data. Other basic questions that have, to date, lacked answers based on national, representative data include the elevated mortality risks associated with homelessness, patterns of transitions between homelessness, housing, and other living situations, and migration histories. With such fundamental gaps in our present knowledge, it is not surprising that homelessness in the United States appears to have been rising since the mid-2010s, despite billions of dollars in annual public expenditures and intensifying public alarm.

This dissertation draws on new data and innovative linkages to make headway on many of these first-order questions. Chapter 2 examines the completeness and reliability of available data sources and develops a new estimate of the size of the U.S. homeless population. Chapter 3 examines the level and longitudinal patterns of income and safety net participation using linked Census and administrative data, and the Chapter 4 provides the first national calculation of mortality in the U.S. homeless population. These essays provide researchers, policymakers, and the public with the first national, representative, and rigorously quantitative description of key aspects of the U.S. homeless population, while also laying the foundation for future work to learn about the causes and consequences of homelessness and design effective, well-targeted, and adequately scaled policy responses to this longstanding social issue.

1.2 Historical context

Modern homelessness has roots in the age-old intersection of extreme poverty, transience, and social stigmatization (Beier and Ocobock 2008). While the term itself was rarely used before the twentieth century, historical records include many references to what would today be considered homelessness. Laws penalizing vagabondage and vagrancy, widespread in medieval Europe, made their way to colonial America, where assistance to the impoverished was mainly reserved for those with established local residences to the exclusion of the transient poor (Rossi 1989). The nineteenth century phenomena of industrialization, urbanization, and post-Civil War social upheavals produced a class of disaffected, mobile men, often called tramps or hobos, traversing the country in search of work and sleeping in whatever low- or no-cost accommodations they could find (NAS 2018). Homelessness in the early twentieth century was marked by the vast shantytowns and squatter encampments of the Great Depression and Dust Bowl on the outskirts of cities, as well as urban poverty that was increasingly concentrated in slum districts known as skid rows, where down-and-out members of society could find low-cost, single-room apartments or sleep in bare-bones hotels known as flophouses.

The modern era of homelessness began in the 1980s, fueled by a marked increase in the presence of impoverished people, often struggling with mental illness, addiction, and HIV/AIDS, living and sleeping in urban centers (Burt 1992). Explanations put forth for this rise include gentrification and the demolition of skid row housing, the societal movement to deinstitutionalize people with severe mental illness, epidemics of HIV/AIDS and intravenous drug use, and economic factors like unemployment and rising housing prices. Many cities also decriminalized practices like loitering and other so-called "public nuisances" around this time, which in turn may have made pre-existing issues more visible. Whereas historical homeless populations consisted mainly of single, white men, the homeless population that emerged in the 1980s included large shares of Black individuals, women, and children (Lee et al. 2010).

Unlike earlier eras, the so-called "new" homelessness was concentrated not in slum districts or on the outskirts of cities, but in the heart of busy and affluent urban centers. This increased visibility brought homelessness to the forefront of social issues and sparked a new wave of research and policy initiatives, most notably the establishment of federal funding for shelters and other services through the McKinney-Vento Homelessness Assistance Act of 1987 and its subsequent reauthorizations. The modern era of homelessness has also been marked by efforts to improve and systematize the collection of data on people experiencing homelessness, with major initiatives including the establishment of the congressionally mandated Annual Homeless Assessment Reports (AHARs) in 2007 and the creation of Homeless Management Information System (HMIS) databases to record engagement with homeless services. Today, public expenditures on homelessness are substantial, with over $10 billion in direct federal funding allocated in 2024 in addition to significant state, local, and private expenditures that are not tracked in a centralized fashion (USICH 2023). While public interest in this issue has ebbed and flowed since the 1980s, homelessness has once again risen to the top of the policy agenda in recent years. Figure 1, which displays the frequency with which the term "homeless" appears in Google's catalogue of published works between 1960 and 2019, offers one objective measure of how interest in homelessness has changed over time, with a surge in interest between 1980 and 1990 followed by a decline through 2010 and then a steady rise through 2019, the last year for which these data are available. Increased interest over the past decade has coincided with an apparent sharp increase in unsheltered homelessness, particularly in Los Angeles and other West Coast cities. The predominant causes of this recent rise are not understood and remain the subject of much recent debate, as discussed in Section 5.

1.3 Definitions

In the most basic sense, homelessness is a housing status characterized by the lack of a conventional dwelling. The U.S. Department of Housing and Urban Development (HUD) differentiates between sheltered homelessness (sleeping in a facility designated to provide emergency or transitional accommodation to those with no other housed option) and unsheltered homelessness (sleeping at a location not intended for human habitation, like a tent, vehicle, abandoned building, or public place). People residing in such locations are said to be experiencing literal homelessness. Some definitions, such as the one used by the U.S. Department of Education, include people residing in so-called "doubled up" situations of shared, tenuous housing, such as those with a time-limited arrangement to sleep on the couch of a friend or relative. Chapter 2 of this dissertation discusses the merits of different definitions of homelessness, with the key insight being that literal homelessness is a useful category because in most cases it represents a hardship that is more severe than doubling up or residing in low-quality housing.

In practice, many ambiguities may arise when deciding whether to classify a living situation as literal homelessness. There is no single accepted definition of a homeless shelter, and population estimates can vary widely depending on how such definitional ambiguities are resolved in data source. For example, many facilities that HUD classifies as homeless shelters, such as domestic violence shelters, hotel and motel beds paid by vouchers from homeless service providers, and many transitional housing units that provide longer-term residences, were classified in the 2010 Census not as homeless shelters but as other types of group quarters or conventional housing. Unsheltered homelessness is similarly subject to definitional ambiguities, particularly when considering people who live nomadic or itinerant lifestyles either by personal preference, economic necessity, or some combination of the two. For example, some may consider those who reside full-time in Recreational Vehicles (RVs) or boats to be homeless, but others may not consider these living situations to be homelessness unless additional criteria related to the quality of living quarters and the legality of their tenure are met (e.g., a paid campground versus a parking lot). Reasonable observers may similarly disagree as to whether people living in horse-riding stables or traveling with carnivals and circuses for work should be considered homeless.

Many people have strong beliefs about what homelessness is and is not, conceptions that may include criteria not included in official definitions, such as extreme economic deprivation or stigmatization. People residing in temporary shelters due to natural disasters, those who are internally displaced by conflict or seeking asylum, and women residing in shelters after fleeing domestic violence are all disadvantaged groups experiencing severe housing-related hardship, but the pathways to their current living situation likely differ in important ways from most people experiencing homelessness and researchers may wish to consider these groups separately rather than including them in studies of literal homelessness. With so many definitional ambiguities, interpreting the results of any study on homelessness requires a nuanced understanding of the coverage of the underlying data source.

Although some people spend long periods of time without conventional housing, literal homelessness is a transitory status for most people who experience it. Much of the academic literature emphasizes heterogeneity by length of homelessness (Kuhn and Culhane 1998). As researchers, we may be most interested in people who are chronically homeless if we think these individuals form the most deprived segment of this population, if we think that the harm from homelessness is increasing substantially in the length of time spent homeless, or if we think that these individuals are the most difficult to house. On the other hand, we may be more concerned with the incidence of homelessness, i.e., the number of new spells in a period, if we believe that the harm of homelessness is greatest at its onset and diminishes over time. Homelessness, no matter how brief, is also an unambiguous and severe indicator of economic hardship that can help researchers identify the most deprived segment of the U.S. population, which in turn can be useful for learning about the context of extreme poverty within which homelessness arises.

1.4 Causes

To think about how and why homelessness occurs in the course of a person's life, it can be helpful to consider a stochastic model of housing consumption, as applied to this context by O'Flaherty (2010). In such a model, an individual's income consists of a permanent and transitory component, and homelessness occurs when a precipitating event causes income to fall below the cost of the lowest quality housing available to that person. The cost of the lowest quality housing may be determined by local housing markets, household composition, discrimination, criminal records, and credit history, among other factors. The permanent component of income reflects long-term circumstances, such as education and human capital, sustained family support, substance abuse disorders, or physical and behavioral health conditions. The transitory component reflects short-term, unanticipated changes to resources, such as those from a job or benefit loss, a short-term health crisis, or a relationship dispute. Faced with uncertainty, people may smooth their housing consumption through formal or informal saving and borrowing, by drawing on cash or in-kind support from friends and family, or through emergency financial assistance programs for people at risk of homelessness. In this model, an individual's probability of becoming homeless depends on the cost of the lowest-quality housing available to them, the level of their permanent component of income, the volatility of their transitory component, and their ability to smooth housing consumption.

The above-described model assumes that people consider homelessness to be worse than the lowest-quality available housing. But this assumption may not always be satisfied, depending on the attributes of available housing, homeless shelters, and outdoor living options and a person's preferences. Very low-cost housing options might include residing in units that are crowded, unclean, unsafe, located in an undesirable location, or do not allow pets or storage of possessions. Some housing options, including both institutional settings like group homes and shared housing with friends and family, may also come with requirements related to substance use, medical treatment, or other rules like curfews that people find onerous. Attributes of homeless shelters and unsheltered locations also vary substantially. Some homeless shelters provide long-term placements, especially for families with children, that people may find preferable to the extremely low-quality conventional housing available to them. Outdoor locations may similarly be more or less onerous due to factors like weather, the availability of services like meal deliveries and medical care, hygienic facilities, policing and the frequency of encampment sweeps, and local ordinances that criminalize behaviors like sleeping or storing belongings in public areas, substance use, and panhandling. Accounting for people's preferences and the attributes of housed and homeless living situations is increasingly thought to be an important aspect of understanding what types of policies will be most effective in reducing homelessness.

In addition to learning about individual pathways to homelessness, the stochastic model can also be useful for thinking about the determinants of aggregate homelessness and reasons for geographic variation. The minimum housing cost in a locality may be high due to market conditions, regulations that limit the availability of low-quality housing, or policies that make it difficult to evict tenants for non-payment of rent, to name a few factors. The size of the population with low permanent incomes and volatile transitory incomes might depend on the generosity of safety net programs, poverty rates, and the prevalence substance abuse and behavioral health conditions in the population. Policies that facilitate consumption smoothing, such as emergency financial assistance for people at risk of homelessness, and those that affect the quality of housed and homeless accommodations, such as local ordinances criminalizing activities often associated with homelessness, may similarly affect the size of the at-risk population. When seeking to understand aggregate homelessness in a particular area, migration may also be an important consideration, particularly if local attributes or policies make it particularly attractive or undesirable.

The stochastic model of housing consumption sheds light on the proximate causes of homelessness and factors that elevate or reduce risk. Truly understanding the drivers of homelessness, however, means asking why some individuals find themselves with low permanent incomes, volatile transitory incomes, or few resources to smooth housing consumption when met with an unfortunate turn of events. Extreme socioeconomic disadvantage is known to be rooted early in life, and factors like parental investments in development, quality of education, health endowments, neighborhood effects, adverse childhood experiences and discrimination likely play key roles in the human capital processes that leave someone vulnerable to homelessness as an adult. Other adverse experiences through the life course, such as incarceration, may also shift the parameters of the stochastic model of housing consumption to increase the likelihood of becoming homeless.

1.5 Key debates

The preceding section offered a conceptual framework for thinking about the causes of individual and aggregate homelessness without taking a stance on which factors are most important. In practice, policy debates and academic discussions tend to center on two opposing narratives about the primary drivers of homelessness. The first viewpoint maintains that homelessness is fundamentally a problem of housing affordability, while the second emphasizes the failures of existing service networks to meet the needs of people with severe substance abuse conditions and mental illness.

Proponents of the housing-centric viewpoint often illustrate their argument with an analogy to the children's game of musical chairs (Demsas 2023). When there are enough chairs, everyone has a place to sit; but as chairs get removed, the weakest children are left standing. Analogously, the argument goes, the scarcity of low-cost housing options means that inevitably some people will end up homeless, and this population will consist disproportionately of the most vulnerable individuals, including those who grapple with mental illness or addiction. As evidence, they point to elevated rates of homelessness in high-cost cities like Los Angeles and New York, places where policymakers have prioritized the interests of homeowners over renters with regulations like density restrictions and mandatory community input on new developments (Colburn and Aldern 2022). Proponents of this view often cite gentrification's displacement of low-income dwellings like single room occupancy (SRO) units in the mid- to late-twentieth century as a major factor driving the emergence of modern homelessness in the 1980s.

The basic premise of the second, service-centric viewpoint, is that chronic homelessness arises due in large part to failures of the existing support and service systems to meet the needs of people struggling with severe addiction and mental illness, and that some people would struggle to remain housed even if sufficient free or extremely low-cost housing were available (Evans et al. 2019). In this view, simply providing housing without first rehabilitating or ameliorating these disabilities will not be an effective strategy for reducing homelessness. Proponents of this narrative note that addiction and homelessness have always gone hand in hand, even as the predominant substances have changed over time. Proponents also cite the deinstitutionalization movement of the mid-twentieth century, a set of reforms aimed at moving people from public mental hospitals to community-based care, as a predominant cause of the rise in homelessness in the 1980s. This viewpoint, which was widely espoused in the 1980s and 1990s, fell out of favor over the following decades but has reemerged in policy discussions in recent years, prompted by the rise in unsheltered homelessness along with the epidemic of deaths from opioids and other substances and increased adoption of local policies to decriminalize their possession and public usage. As one indication of this shift, in 2023 the state of California and New York City both implemented policies to allow courts and first responders to involuntarily commit people experiencing homelessness with severe mental illness to treatment.

These two viewpoints map closely onto different types of interventions for reducing individual homelessness. The service-centric model emphasizes the progression from treatment programs to permanent housing, often requiring clients to achieve certain benchmarks, like sobriety, on the way. In recent decades, however, service providers have increasingly been shifting towards a housing-centric approach to addressing homelessness, with the reasoning that stable housing is a precondition to addressing disabilities and improving economic prospects. This approach, known as Housing First, seeks to provide stable residences to chronically homeless individuals with few conditions, although wraparound services are typically made available to those who choose to use them. A closely related set of policies that provide emergency cash assistance and housing subsidies have also grown in prominence and seek to keep people housed or rapidly move them back into housing when they become homeless. As summarized in O'Flaherty (2019) and Evans et al. (2019), a growing body of experimental and quasi-experimental studies suggest that housing subsidies, whether temporary or permanent, appear to be more successful at reducing individual homelessness than non-housing interventions.

Most of the empirical evidence on reducing homelessness has centered on interventions aimed at reducing individuals' probabilities of becoming or remaining homeless, but perhaps a more crucial question is what policies can reduce aggregate homelessness (O'Flaherty 2019). Such policies might include federal funding for different types of homeless services such as permanent supportive housing, eviction-related policies like moratoria and free legal representation, measures to alter the desirability of unsheltered accommodations, and changes to the vast array of housing market restrictions that some observers maintain are the fundamental drivers of homelessness. General equilibrium effects like migration to places with more generous safety nets, behavioral responses from tenants and landlords, and the musical chairs-style displacement of one individual from a low-cost housing unit in favor of another, could attenuate or reverse in aggregate the partial equilibrium responses of policies.

Research into policies that can successfully reduce aggregate homelessness remains scarce, however, due in part to the difficulties of obtaining reliable, longitudinal population estimates and in part because it is much more costly to carry out experiments or to find natural experiments to identify the causal effects of large-scale policies.

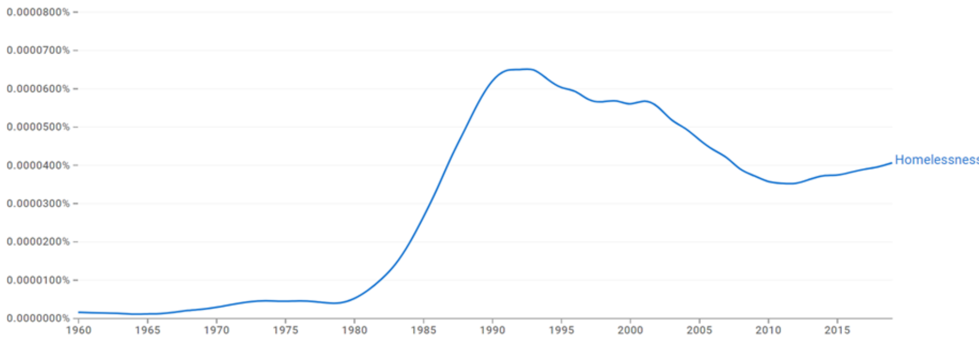
1.6 Contributions

This dissertation's introduction has provided a high-level overview of the issue of homelessness, its historical context, conceptual issues when defining homelessness and contemplating its causes, and ongoing debates about the primary drivers of homelessness and the most effective responses. A recurring theme is the intractability of this issue over time and the major gaps in our present understanding, driven largely by the lack of adequate data.

The three main chapters of this dissertation are the first installment of an ambitious new research agenda that adopts novel approaches to address key data challenges and unlock new insights into the scale, nature, and causes and consequences of homelessness. Our use of large, national datasets, which we link to detailed, accurate, and longitudinal information from administrative data, represents an important departure from prior work and allows us to provide the first rigorously quantitative and national description of the hardships associated with homelessness. These analyses provide valuable new insights into the size of this population, the coverage of available datasets, and the material circumstances and elevated mortality risk associated with homelessness. They also complement prior work by helping to understand the generalizability of studies based on small, localized samples and self-reported information contained in surveys. By demonstrating the usefulness of new data and approaches to study this complex and intractable issue, this dissertation also lays a path for future efforts to unlock new insights into the fundamental, unresolved questions that have animated – and frustrated – policy discussions and social research on homelessness for many decades.

1.7 Exhibits

Figure 1.1: Usage of the Word “Homelessness” in Books Published in 1960-2019



Sources: Google Ngram Viewer. **Notes:** Series height reflects the frequency with which words or phrases appear in published books included in Google's Ngram Viewer's collection.

CHAPTER 2

THE SIZE AND CENSUS COVERAGE OF THE U.S. HOMELESS POPULATION

Abstract

Fundamental questions about the size and characteristics of the homeless population are unresolved because it is unclear whether existing data are sufficiently complete and reliable. We examine these questions and the coverage of new microdata sources that are designed to be nationally representative. We compare two restricted data sources largely unused to study homelessness, the 2010 Census and American Community Survey (ACS), to restricted Homeless Management Information System (HMIS) data, HUD's public-use point-in-time (PIT) estimates, and the Housing Inventory Count (HIC) at the national and individual level. We also develop a new approach to estimating the size of the sheltered homeless population using linked Census and HMIS microdata. Our analyses suggest that on a given night there are about 400,000 people experiencing homelessness in shelters in the U.S. and about 200,000 people sleeping on the streets, with this latter estimate subject to greater uncertainty. More than 90 percent of those in shelters appear to be counted in the Census, although many are classified as housed or in other group quarters, due largely to ambiguity in the definition of a homeless shelter. This paper lays the foundation for pathbreaking future work with these data on the U.S. homeless population.[1]

2.1 Introduction

Despite widespread concern about those experiencing homelessness, many of the most basic questions about this population, including the first-order question of population size,

1. This essay is joint work with Bruce D. Meyer and Kevin Corinth.

are unresolved. Relatedly, the extent to which the Decennial Census and Census Bureau surveys include those experiencing homelessness is unclear in Census documentation and publications, and the empirical extent of coverage has not been examined. In this paper, we compare two restricted data sources that have been largely unused to study homelessness to administrative shelter records and less detailed public data. We also develop a new approach to estimating the size of the sheltered homeless population by linking together Census and administrative shelter microdata, an approach that under our stated assumptions provides a reliable estimate of the true population. We evaluate the usefulness of these datasets to advance our understanding of this difficult-to-study group and lay the foundation for pathbreaking future work using these data.

Efforts to count the U.S. homeless population confront substantial challenges. Because people experiencing homelessness lack a fixed domicile, they cannot be counted using standard address list-based approaches like those most often used in the Census and household surveys. They must instead be counted in the shelters, soup kitchens, encampments, vehicles, or parks where they happen to be staying at a given time. This difficulty is at times compounded by mistrust of authorities, mental illness or substance abuse, involvement in the underground economy, local ordinances that restrict activities associated with homelessness, or other factors that contribute to a desire not to be found (Corinth, 2015, Glasser et al., 2013).

Given these difficulties, the reliability of available estimates, particularly the Department of Housing and Urban Development (HUD)'s point-in-time (PIT) count, is frequently called into question. The PIT is widely cited in the media and often used to allocate resources and inform policy, yet the handful of existing studies on its quality have been limited in geography and scope and are outdated (Hopper et al., 2008; Agans et al., 2014). A 2020 report from the U.S. Government Accountability Office (GAO) determined that the PIT "did not provide a reliably precise estimate of the homeless population," in part, according to the report, because of the decentralized and non-uniform way that local bodies carry out their counting operations. O'Flaherty (2019) observes that PIT data on the unsheltered homeless population are largely gathered by a "loosely supervised army of amateur volunteers" whose "diligence, understanding of the process, and lack of bias are all open to question." The completeness and coverage of shelter-use microdata, which are employed in the PIT's sheltered homeless estimates, have gone largely unstudied. By comparing the PIT's estimate of the U.S. homeless population to independent estimates, this paper provides the most comprehensive assessment to date of the quality of both the aggregate PIT and the microdata underlying its sheltered population estimates.

Our approach draws on restricted microdata from the 2010 Census, the American Community Survey (ACS), and Homeless Management Information System (HMIS) databases from Los Angeles and Houston. The ACS and HMIS include people in homeless shelters, while the Census includes both sheltered and unsheltered homeless individuals. We compare these restricted data to each other and to HUD's PIT estimates and the Housing Inventory Count (HIC). Our restricted data have important advantages over public data. Like the PIT, the ACS and Census are designed to be representative of the entire U.S. homeless population. Unlike the PIT, however, the Census, ACS, and HMIS include individual linkage keys so that the microdata can be linked across sources and to administrative data to examine longitudinally a range of social and economic characteristics. The ACS and HMIS data also in themselves contain a rich set of information about homeless individuals. By examining the coverage and reliability of Census, ACS, and HMIS data, this paper lays the foundation for future work taking full advantage of these datasets to learn about the U.S. homeless population. This paper also provides valuable insight into the coverage of people experiencing homelessness in the Census and household surveys, some of the most fundamental sources of data on the U.S. population.

We begin with an aggregate comparison of unsheltered and sheltered homeless estimates in the Census and PIT. We find that the Census and PIT's unsheltered estimates are quite close to one another, providing encouraging but not definitive evidence of the estimates' accuracy. Moreover, despite what appear at first to be major differences in sheltered homeless estimates, the Census and PIT in fact produce similar estimates once we account for straightforward definitional and weighting differences. Specifically, the PIT's sheltered homeless population estimate includes people in domestic violence shelters, those in voucher-funded hotel and motel rooms, and people in non-shelter facilities, whereas the Census and ACS classify these groups of people as belonging to other, non-homeless statuses. We also describe an aspect of the ACS's weighting methodology that inflates sheltered homeless population estimates by over 30 percent in each year to represent people not included in the survey's scope. Adjusting for straightforward definitional differences and correcting the ACS weighting brings the Census and ACS estimates much closer to the sheltered PIT estimate. The fact that these two sources produce similar estimates despite employing substantially different methods bolsters our confidence in both estimates, although we discuss potential sources of bias relative to the true homeless population that may net out in aggregate comparisons.

Our second set of analyses compare data sources at the person level. We link HMIS shelter use microdata from Los Angeles and Houston to the 2010 Census to learn more about both sources' coverage and to assess the usefulness of Census microdata to study this population. Under stated assumptions and after accounting for likely errors in shelter exit date reporting in the HMIS data, we estimate that about 80–95 percent of people who were indicated as being in HMIS shelters on the date of the Census's homeless counting operation were counted in the Census, although only about 35–45 percent of them were included in the Census's sheltered homeless count, with the rest being counted as housed, unsheltered homeless, or in other types of group quarters facilities. We provide evidence that errors in shelter exit date tracking in HMIS are an important reason for these status discrepancies. We also show that many HMIS facilities, particularly transitional shelters where homeless individuals can reside for up to two years, appear to have been often classified as housing units or other types of group quarters rather than homeless shelters by the Census. Finally, we note that many people may have responded to the Census while housed before entering a shelter or after exiting it during the long window of potential Census response, which ran from mid-March to well into May 2010.

Unexpectedly, our microdata comparisons reveal extensive double-counting of homeless individuals in the 2010 Census. We estimate that 21–24 percent of the sheltered homeless, 45–56 percent of those counted in soup kitchens and while using food vans, and 29–35 percent of those at outdoor locations had at least one housed record in addition to their homeless record in the 2010 Census. We rule out widespread erroneous linkages and misclassification of housed people as homeless and provide evidence that double counting arises primarily when homeless individuals are included on the Census questionnaire of a household where they occasionally reside or where they resided within a few months of the Census's homeless counting operation.

Finally, we develop a new approach to estimating the size of the sheltered homeless population using linked Census and HMIS shelter microdata. This method draws on dual system estimation techniques used frequently in demography and in ecology and allows us to obtain a reliable estimate of the true population under certain assumptions. In brief, we take the share of people in HMIS shelters in Los Angeles and Houston on the Census date who were included in the Census's homeless counting operation as an estimate of the share of the true sheltered homeless population in the Census. We then scale up the Census estimate by the inverse of this share to adjust for under coverage and obtain an estimate of the true sheltered homeless population. This approach does not make assumptions about the completeness of the Census or PIT, but does rely on several assumptions, including the assumption that those counted and uncounted in the Census are equally likely to appear in the HMIS data, an assumption that is plausible but difficult to verify. Using these methods, we estimate the sheltered homeless population size in 2010 to be 367,000–382,000 people, or about 5–10 percent lower than the 2010 PIT estimate and about 27–32 percent larger than the Census count after straightforward definitional adjustments. These analyses suggest that about 93–97 percent of people who were in shelters on the Census date were included in the Census in some status. In addition to providing a new population estimate, this section serves as a blueprint for future researchers seeking to estimate the homeless population as additional data become available.

Our analyses produce several key insights into the size of the U.S. homeless population. We find that, despite what initially appear to be substantial differences between 2010 Census, ACS, and PIT estimates of the homeless population, these sources produce very similar estimates once we account for definitional and weighting differences. We evaluate these aggregate comparisons for the sheltered homeless population with our dual system approach. Taken together, these estimates suggest that on a given night there are about 400,000 people experiencing homelessness in shelters in the U.S. and about 200,000 people sleeping on the streets, with the latter number subject to greater uncertainty. At the same time, our results highlight the fact that there is considerable ambiguity about what types of facilities constitute homeless shelters and that population estimates are sensitive to how these ambiguities are resolved.

Beyond population estimates, this paper also advances our understanding of homeless individuals' coverage in the Census. Our findings suggest that the Census was able to include more than 90 percent of sheltered homeless individuals, although oftentimes it classified them as housed or as residing in non-shelter group quarters facilities. At the same time, widespread instances of double counting of homeless individuals in the Census paint a picture of a highly mobile population that frequently transitions between housed and homeless living situations. These findings suggest that household surveys that rely on Census address lists may incorporate homeless individuals more often than previously thought. By establishing the broad coverage and reliability of the new data sources, this paper lays the foundation for pathbreaking future work using the Census, ACS, and HMIS datasets, including efforts to learn about this population's longitudinal patterns of income and safety net participation and the heightened mortality risk associated with homelessness.

This paper proceeds as follows. Section 2.2 discusses past efforts to estimate the size of the homeless population and summarizes the literature on the quality of available estimates. We also define homelessness and discuss the merits of the definition we use relative to others. Section 2.3 describes our data, including the 2010 Census, ACS, PIT, and related datasets. Sections 2.4 and 2.5 describe our methodology and results for aggregate and microdata comparisons, respectively. Section 2.6 describes our dual system estimate of the sheltered homeless population size. Section 2.7 discusses these findings and Section 2.8 concludes.

2.2 Background and related literature

2.2.1 Prior efforts to estimate the homeless population size

In the 1980s, an apparent rise in homelessness and a surge in media coverage inspired numerous attempts to estimate the U.S. homeless population. Intense controversy surrounded these efforts from the beginning. HUD's first national estimate in 1984 placed the population between 250,000 and 350,000, but their findings were criticized by advocacy groups who maintained that the true number was as high as three million (U.S. General Accounting Office 1985). In a 1992 meta-analysis, Shlay and Rossi (1992) observed that most of the 60 studies they reviewed relied on an unreasonable degree of extrapolation or speculative assumptions and amounted to "sheer guesses" of the homeless population size.

HUD began publishing point-in-time (PIT) estimates in its Annual Homeless Assessment Report (AHAR) in 2007 in response to a directive from Congress. As a national source of longitudinal population estimates, the PIT represents a major advance over previous efforts to count the homeless. It is nevertheless imperfect. HUD engages local homeless service coordinating bodies, known as Continuums of Care (CoCs), to carry out PIT operations and allows them to employ a range of methods. In practice, the techniques used and resources invested vary substantially – as does, presumably, the quality of estimates (U.S. Department of Housing and Urban Development 2014).[2]

A small body of research examines the completeness of unsheltered PIT counts. Several studies have dispatched decoy homeless individuals on the night of the PIT and later reported the share that were included in the PIT. One such study during a 2005 point-in-time count in New York City found that 30 percent of decoys were missed by enumerators (Hopper et al., 2008). The authors also surveyed a sample of homeless individuals about their sleeping arrangements the night of the PIT and estimated that 31–41 percent would not have been visible to counters. In Los Angeles in 2009, Agans et al. (2014) conducted a post-PIT telephone survey asking residents if they knew of homeless individuals who had spent the previous night on private property and would have therefore been missed by that city's PIT. The authors estimated that 20 percent of Los Angeles's unsheltered homeless population would have been missed by the PIT.

The literature pays less attention to the sheltered PIT. These estimates are thought to be more reliable because they are in many cases derived from the Homeless Management Information System (HMIS) database. In practice, HMIS data quality varies between shelters and over time. Cronley (2011) found wide variation in the frequency and thoroughness of HMIS record-keeping among 24 homeless service provides in Michigan and Tennessee during the early years after the system's implementation.

The Census made its first systematic attempt to enumerate homeless individuals during a 1990 operation called Shelter and Street Night (S-Night). S-Night's count of 228,621 individuals fell far below consensus estimates at the time, prompting the Census Bureau

2. The 2009 AHAR, for example, singled out Detroit and New Orleans as having conducted counts of particularly suspect quality that year (U.S. Department of Housing and Urban Development 2010).

to state that "S-Night was not intended to, and did not, produce a count of the 'homeless' population of the country" (Martin 1992). Various S-Night evaluations found that decoys deployed in five cities to act as unsheltered homeless persons were only counted 22 to 66 percent of the time (Wright and Devine 1992).

The Census Bureau aimed to improve on the S-Night methodology with its first Service-Based Enumeration (SBE) in 2000, visiting shelters, food vans, soup kitchens, and a list of pre-identified outdoor locations. This effort produced a count of 280,527 individuals and again received an official caveat: "We cannot be certain that all places were covered or that all people normally using shelters were included in the shelter counts. Nor can our coverage of targeted outdoor locations be considered to have been exhaustive due to the difficulties in mapping such temporary and elusive sites" (Smith and Smith 2001).

The 2010 SBE fared better than the previous two attempts. Meyer et al. (2022) provide a preliminary analysis of the characteristics of those included in the 2010 Census homeless counting operation and demonstrate the types of analyses that can be undertaken once the coverage of this population in the Census is better understood. We discuss the 2010 SBE in depth in Section 2.3 of this paper.

2.2.2 Defining the homeless population

In this paper, we follow HUD's definition of literal homelessness. People are literally homeless if they have "a primary nighttime residence that is a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings, including a car, park, abandoned building, bus or train station, airport, or camping ground" (the unsheltered) or if they are living in "a supervised publicly or privately operated shelter designated to provide temporary living arrangements (including congregate shelters, transitional housing, and hotels and motels paid for by charitable organizations or by federal, State, or local government programs for low-income individuals)." This is the definition of homelessness that guides HUD's point-in-time count and it aligns closely with the population targeted by the Census's homeless counting operation.

We distinguish people experiencing literal homelessness from those who are precariously housed, have low-quality accommodations, or face imminent risk of homelessness for some other reason. Policymakers and researchers are often rightly concerned about hardships faced by people in these categories and at times include them in official definitions of homelessness. The Department of Education, for example, defines homelessness to include children "sharing housing with others due to loss of housing, economic hardship, or a similar reason," otherwise known as doubling up (U.S. Department of Education, 2021).

While such situations often reflect housing-related hardship, we maintain that literal homelessness is the most useful definition for economists. For one thing, literal homelessness indicates a level of material deprivation that in most cases exceeds the hardship experienced by those who are precariously housed or doubled up. The choice of where to live reflects a complex economic calculation by maximizing agents whose choice set typically includes homeless shelters. When shelter beds are available, the decision to share housing or live in subpar accommodations indicates a revealed preference for these living arrangements over literal homelessness.

Moreover, it is not clear that shared housing reflects economic hardship in most cases. There are many reasons why shared housing might be preferable to solo living options, as is well documented in the household formation literature. Reasons include the sharing of quasi-public goods like appliances, bathrooms, and living space and facilitating trades of time, resources, and services like housework or informal caregiving for children or the elderly (Browning et al., 2014). Because it is voluntary, the decision to share living quarters should not be a priori thought of as bad.

As a practical matter, existing data do not allow researchers to identify people for whom shared accommodations reflect extreme hardship. Such a determination would require detailed knowledge of all options in the agent's choice set, including the quality of accommodations, precariousness of tenure, and other factors that could make housing alternatives extremely undesirable (e.g. abuse or neglect at home or unsafe conditions in shelters). For example, when the Department of Education trains educators to identify children who qualify for homeless services due to doubling up, it instructs them to interview parents and/or students extensively to determine whether personal housing is available, whether they left their last housing situation under duress (e.g. were evicted or fled abuse or neglect), and whether their shared housing meets the subjective criteria of being "fixed, regular, and adequate" (U.S. Department of Education, 2021). Educators then make determinations of doubled-up homelessness on a case-by-case basis. As these training materials illustrate, the information requirements for making such a determination go far beyond the questions asked in household surveys.

2.2.3 Time-frame considerations in defining homelessness

We emphasize estimates of the number of people who are homeless at a point in time in this paper. This decision reflects, in part, the availability of comparable estimates in different data sources. While HUD produces estimates of the number of people who used homeless shelters each year, these estimates are not available for the unsheltered and there are no comparable estimates for the sheltered in other data sources. Moreover, HUD's annual estimates are based on data collected by a subset of shelters and then extrapolated to the entire U.S. using assumptions that are difficult to validate.

Relative to interval-based population estimates, cross-sectional estimates include a greater share of people experiencing long-term or repeated homeless spells. This group likely includes people with exceptional difficulty maintaining housing as well as those who have secured extended shelter placements but nevertheless meet the definition of literal homelessness because of how HUD classifies those facilities. As discussed in O'Flaherty (2019), which temporal convention is most appropriate depends on the question at hand and our (as-yet very limited) understanding of how the social and private costs of homelessness vary with time spent homeless. We note, however, that the decision to emphasize the cross-sectional homeless population aligns with the approach used in other literatures, including those that study number of people who are in poverty or unemployed at a point in time.

2.3 Data

This section describes the five sources of data on the homeless population used in this paper: the 2007–2021 HUD PIT and the associated Housing Inventory Count (HIC) dataset, the 2010 Census, the 2006–2018 ACS, and the HMIS microdata from Los Angeles (2004–2014) and Houston (2004–2015).

2.3.1 HUD's point-in-time (PIT) estimates

HUD requires that CoCs produce sheltered homeless population estimates every year and unsheltered estimates at least every other year to maintain federal funding. CoCs' geographic areas can encompass a single city or county, a metro area, a collection of counties, or the so-called "balance of state" outside of one or two major cities. These estimates are known as the point-in-time (PIT) count because they count (or in most cases, estimate) the homeless population on a single night, typically in the last two weeks of January. Each CoC plans and executes its own counting operation using one or more of a set of HUD-approved methods, typically a combination of enumeration, surveys, and extrapolation, occasionally done with the help of outside consultants. Many CoCs rely on volunteers to conduct nighttime canvassing operations, while others conduct multi-day or morning after operations at service locations. CoCs attempt to mitigate double-counting of the same individual using various strategies – for example, by asking homeless individuals whether they have already been counted – but are limited in their ability to de-duplicate unsheltered individuals because they rarely collect identifying information. Sheltered counts often rely, at least in part, on extrapolation from Homeless Management Information System (HMIS) databases.

CoCs also compile an inventory of all beds available for occupancy on the night of the PIT each year. This inventory is published in a separate dataset called the Housing Inventory Count (HIC), which lists the number of beds available on the PIT date, the number of people sleeping there, the target population (e.g., veterans, domestic violence victims, people with HIV/AIDS), and the bed type (e.g., in a shelter, in a non-shelter location, or in the form of vouchers for hotels or motels).

2.3.2 2010 Census Service-Based Enumeration (SBE)

The 2010 Census counted people experiencing homelessness during its Service-Based Enumeration (SBE) operation. Field staff visited emergency and transitional shelters, soup kitchens, food vans, and targeted non-sheltered outdoor locations (TNSOLs, e.g. street intersections or parks where homeless individuals were known to sleep) between March 29 and 31, 2010. The list of shelters and unsheltered locations was built using past Censuses' lists, internet research, and input from local and state governments homeless advocacy organizations, in addition to several advance visit and validation operations. Unlike the PIT, the Census trained enumerators to use uniform methods and apply the same standards nationwide when counting people experiencing homelessness. They also collected name and date of birth when possible.

The Census took several steps to ensure that the same individuals were not counted in multiple locations (Russell and Barrett 2013). People counted at soup kitchens and food vans were asked whether they had a usual home elsewhere and to provide an address. The Census later used a matching algorithm and clerical review to check whether the person was counted at that address and, if so, kept only the housed record. The Census also used this algorithm to de-duplicate person records within the SBE universe. However, the Census did not resolve potential duplicates between homeless shelters and housed or group quarters locations.

A team of non-Census researchers concluded that "there was a high level of cooperation between the homeless service providers such as shelter and day center administrators and the U.S. Census" (Glasser et al., 2013). Nevertheless, the Census Bureau has issued several caveats on the completeness of the SBE's homeless count. An official report noted that "people experiencing homelessness [could] be counted and included in the census via various operations [other than the SBE]," meaning that people in difficult-to-classify situations, such as those precariously housed with friends or acquaintances or residing in motels, might be grouped in with others who are not homeless in published counts (Smith et al., 2012).[3]

2.3.3 2006–2016 American Community Survey (ACS)

The ACS differs from the PIT and Census in that it only counts people experiencing homelessness in shelters, not those on the streets. It relies on random sampling and collects a much larger set of information than the other sources, including self-reported information on demographic characteristics, education, migration, and income and government program receipt. The ACS is conducted throughout the year and thus its population estimates approximate an annual average of point-in-time counts.

The ACS bases its sampling frame on extracts from the Master Address File, which is the Census Bureau's inventory of known housing units, group quarters (GQ) facilities like homeless shelters, transitory locations, and selected nonresidential units. Although the Census Bureau regularly updates this address file, the updating of GQ addresses between Censuses is operationally intensive and lags behind procedures for updating housing unit addresses

3. For example, people residing temporarily in hotels, motels, campgrounds, or other transitory locations may have been counted during the Enumeration at Transitory Locations (ETL) operation, and the Census considers ETL facilities to be a housed status. Some definitions of homelessness also include people who are "doubled-up," i.e. sharing accommodations after losing prior housing or due to economic hardship. Such individuals would have been included on those households' housing unit questionnaires and not included in the SBE.

(National Research Council 2012). As a result, the ACS's shelter inventory consists primarily of information from the most recent Census and likely becomes increasingly outdated in the ten years between Censuses. For example, of the homeless shelters selected for the 2008 ACS sample, about 42 percent no longer existed, were unoccupied, or had been converted into housing units (National Research Council 2012).

2.3.4 Homeless Management Information System (HMIS) data

In addition to the three sources of homeless estimates described above, this paper also draws on administrative shelter-use microdata from the Homeless Management Information System (HMIS) databases in Los Angeles (2004–2014) and Houston (2004–2015). Shelters that receive federal funding are required to track shelter use in an HMIS database, and some shelters that do not receive federal funding elect to do so as well.

Shelter administrators collect several data elements from all clients, including name and date of birth, social security number, and characteristics such as race, ethnicity, gender, veteran status, and disabling conditions. They also track the start and end dates of shelter enrollment and participation in some non-shelter programs like permanent supportive housing, rapid re-housing, and unsheltered outreach. Unlike Census data, HMIS data differentiate between emergency shelters and transitional housing and include shelter names. HMIS data are often used in part to generate CoCs' sheltered homeless PIT estimates, although HUD instructs CoCs to ensure that entry and exit date tracking is reasonably complete and accurate before relying on HMIS-based population totals in the place of canvassing or surveys administered on the night of the PIT operation (HUD 2012).

2.4 Comparisons of aggregate estimates

In this section, we compare aggregate sheltered homeless population estimates in the PIT with those in the Census and ACS. Our goal is to understand how much of the difference between sources can be attributed to straightforward definitional differences and weighting procedures. In doing so, we seek to make the Census and ACS estimates more comparable to the PIT as a precursor to other analyses. Although there are many ways to define homelessness, we make the PIT's definition our target because it is widely used by HUD and service providers.

Figures 2.1 and 2.2 present estimates of the unsheltered and sheltered homeless populations for each year a given source is available.[4] In Fig. 2.1, we see that the 2010 unsheltered homeless population according to the PIT was 233,534, while the Census estimate was about ten percent lower at about 210,000. Fig. 2.2 shows that sheltered population estimates differ more substantially between sources. The sheltered population according to the PIT in 2010 was 403,543, while the Census estimate was 52 percent lower, at about 209,000. The ACS ranges from 41 to 54 percent of the PIT in the years 2006 through 2010 but then jumps to between 67 and 75 percent of the PIT in 2011 through 2016. This jump largely reflects the introduction of a new shelter list and the use of a new population benchmark after the 2010 Census rather than a change in the homeless population size.

2.4.1 Reconciling definitional differences between the PIT count and the Census and ACS

As a first step towards reconciling different estimates in the PIT count, Census, and ACS, we account for a handful of straightforward differences in the way these sources define homelessness. Specifically, the PIT's definition of sheltered homelessness includes people in several types of facilities outside the scope of the Census's Service-Based Enumeration and outside the scope of the ACS's sheltered homeless estimate, including domestic violence shelters, Safe Havens, voucher-funded hotel and motel rooms, and non-shelter facilities with beds for people experiencing homelessness. People residing in these facilities were included in the

4. We exclude PIT and Census totals from U.S. territories in all of these analyses.

Census but classified as being housed or in other types of group quarters. For example, the Census classifies people in domestic violence shelters as being in religious group quarters and does not identify them separately even in restricted data to protect privacy. Safe Havens, which are small-scale facilities for individuals with a history of chronic homelessness and mental illness, are a form of supportive housing and hence classified as housing units in the Census.People residing in hotels and motels, while considered homeless by the PIT if their stays are funded by vouchers, would have been included in the Census during the enumeration of transitory locations, an operation that is separate from the SBE.[5] Beds in non-shelter facilities, which are included in the PIT, would not be included in the Census's SBE unless they had been identified during the Census's address list updating operation and validated as homeless shelters by a facility administrator.

We adjust the aggregate Census and ACS estimates to better align their definition of sheltered homelessness with that of the PIT count. We obtain estimates of the number of people in Safe Havens from published HUD totals. For the other types of facilities, we can either directly calculate or estimate the PIT-only population using information available in the Housing Inventory Count (HIC)'s inventory of shelter beds. In some but not all years, the HIC includes each shelter's PIT count and indicators for whether the facility is a domestic violence shelter, whether it is voucher-based, and whether it is located in a non-shelter facility. For years where the HIC file is incomplete, or where a given data field is not available, we impute values using information in surrounding years.

5. Although the Census definition of emergency and transitional shelters technically includes "hotels and motels used to shelter people experiencing homelessness," in practice these sites would only be included in the SBE if a hotel or motel administrator told Census field representatives that "all of the rooms or units at this building [were] used ENTIRELY to house people experiencing homelessness" (U.S. Census Bureau 2013).

2.4.2 Correcting bias from ACS weighting of the sheltered homeless

We next discuss an aspect of the ACS's weighting methodology that causes upward bias in its homeless population estimates. This bias arises from the ACS's use of population benchmarks in constructing person weights. Specifically, a final step of the ACS weighting methodology scales up person weights so that weighted population estimates match benchmarks produced by the Census Bureau's Population Estimates Program (PEP). For the sheltered homeless, this scaling takes place within a broader class of group quarters types known as Other Non-Institutional (ONI) GQs, a category which also includes group homes, residential treatment centers for adults, workers' group quarters, and religious group quarters. The population benchmark for this group, however, is based on the most recent Census, and in the Census this category includes several additional types of group quarters that are outside the ACS's scope, namely unsheltered homeless locations, domestic violence shelters, and a few smaller categories. Fig. 2.3 provides a graphical representation of the ONI category and the various GQ types. The use of this broader population benchmark in constructing ACS weights means that the sheltered homeless population estimates are inflated to represent people who are not in the ACS's scope.

To correct this bias, we estimate the factor by which the ACS scales up the in-scope population each year by taking the ratio of the 2010 Census population in this ONI category that was in scope for both the Census and ACS to the population that was in scope only for the ACS. Dividing the ACS sheltered homeless estimate by this factor allows us to estimate our target, which is the sheltered homeless population size.

2.4.3 Results from the comparison of aggregate estimates

Fig. 2.4 presents sheltered homeless population estimates with definitional and weighting adjustments. With adjustments, the Census sheltered estimate rises from about 209,000 to more than 290,000, closing nearly half of the prior gap between the Census and PIT.

Table 2.1 displays the year-by-year population estimates for each category of the PIT-only population. Domestic violence shelter occupants comprise the largest group, about 40,000 people each year. Voucher and non-shelter beds each contribute about 20,000 people each year.

Relative to the Census, the adjusted ACS estimates rise by a much smaller amount because the definitional adjustment, which increases the population estimate, is counteracted by the weighting bias correction. Table 2.2 displays the ACS in-scope and out-of-scope ONI populations in the 2010 Census and presents our estimate of the ACS scaling factor of about 1.32. In other words, we estimate that the ACS's person weights inflated the homeless population estimate by about 32 percent to represent people residing in domestic violence shelters, at unsheltered locations, and in other group quarters types outside the ACS's scope.

In the end, we are left with definition- and weighting-adjusted Census and ACS estimates that are about three-quarters of the PIT estimate in each year. We have reconciled about half of the initial gap between the Census and the PIT, representing about 80,000 people. In upcoming sections, we discuss potential explanations for the remaining gap between sources, such as shelter list completeness, ambiguity in the classification of certain facilities, and discrepancies arising from the timing of Census response.

2.5 Comparisons of Census and administrative shelter microdata

In this section, we compare Census and administrative shelter microdata to further explain the gap between the sheltered Census and PIT estimates. Specifically, we link HMIS data from Los Angeles and Houston to the 2010 Census using restricted linkage keys available on both sources. These links allow us to observe whether and in what housing status particular individuals from HMIS data were included in the Census. Because HMIS is a key data source for the PIT, this approach proves informative about the coverage and accuracy of both the Census and PIT.

2.5.1 Assessing HMIS data quality

We begin by assessing the quality of HMIS data with the goal of understanding how accurately these data represent those in shelters at a point in time. Accurate shelter entry and exit dates are critical to this section's analyses because they allow us to identify people who were in HMIS shelters during the Census. Fig. 2.5 displays the average daily shelter occupancy for Los Angeles from January 2009 to December 2013 as implied by HMIS entry and exit dates. We also indicate the number of HMIS beds available (shelter capacity) as indicated by the city's housing inventory count. In Los Angeles, capacity increases each winter as part of the city's Winter Shelter Program, which runs from December 1 to March 15. We extrapolate linearly from one year's point-in-time bed inventory to the next.

Several patterns in the Los Angeles data suggest errors in the exit dates recorded in HMIS in 2009–2011. First, we observe implausibly large increases in occupancy during these years' winter months, leading occupancy to far exceed capacity. We also observe precipitous drops on a handful of days, including March 31 of 2009 and 2010 and June 15 of 2011, suggesting that HMIS administrators conducted a purge of open shelter spells on those dates.[6] Analyses of shelter entry rates and hazard rates for shelter exit suggest that the above-described patterns are driven by incorrect exit dates, not incorrect entry dates.[7]

Fig. 2.6 displays daily occupancy and capacity in Houston HMIS data for 2009–2013. Unlike in Los Angeles data, we do not observe precipitous drops on specific dates or occupancy that exceeds capacity. We do not rule out the possibility of errors in recorded entry

6. Los Angeles' Winter Shelter Program ends on March 15, so large drops on this day, but not other days, are consistent with the closing of seasonal shelters.

7. Table A.4 in the appendix display HMIS shelter entry rates (as a share of the 2010 Los Angeles population) by month for 2009-2013 and HMIS shelter exit hazard rates (i.e. the probability of exiting a shelter in a given month conditional on being in the shelter at the beginning of the month). We observe similar trends in HMIS entry rates by month across years. Shelter exit hazard rates by month, by contrast, differ substantially across years. In 2009-2011, the hazard rate for exit in January or February is very low relative to 2012-2013; in March 2009-2010 and June 2011, in contrast, it is very high relative to those same months 2012-2013. This table suggests that it is the distribution of exit dates, not entry dates, driving excessive occupancy in the winter months of earlier years.

and exit dates in Houston, but we do observe that such errors, if they do exist, appear to arise in a less apparent and systematic fashion than in Los Angeles.

Several other pieces of evidence point to errors in the entry and exit dates recorded in HMIS. During the 2004–2014 period, we find that 21.4 percent of individuals have at least one instance of two or more overlapping emergency and transitional shelter spells, implying an erroneous entry or exit date for at least one of the spells. Moreover, using methods described in the next section, we estimate that 2.3–2.5 percent of people indicated by Los Angeles HMIS data as being in a shelter on April 1, 2010 were counted by the Census in local jails or state prisons on that day, and we take the Census status in these cases to be more reliable.[8][9]

2.5.2 Linking HMIS data to the Census

We link HMIS data to the 2010 Census using Protected Identification Keys (PIKs). The U.S. Census Bureau's Person Identification Validation System assigns PIKs to individuals who appear in survey or administrative data by searching for a matching record by Social Security Number (if available), name, date of birth, sex, and address in a reference file derived from SSA records and augmented with Individual Taxpayer Identification Numbers (ITINs) and other information (Layne and Wagner 2014).

Table 2.3 presents the share of records in our HMIS and Census datasets that are assigned a linkage key. Linkage rates are high for HMIS data because shelters frequently collect SSNs from service users. About 87.9 percent of Los Angeles HMIS shelter users and 95.5 percent of Houston HMIS shelter users in 2010 were assigned a linkage key. Census data

8. HMIS data guide notes that some providers may enter clients into HMIS once they are "accepted" into a program, but prior to placing them in a bed. It also states that HMIS administrators "often forget to enter an exit date in HMIS for a client leaving the program since there is no operational trigger to remind them to do so" (U.S. Department of Housing and Urban Development 2012). The guide further states that some CoCs have a policy of auto-exiting open shelter spells after 90 days.

9. In Houston, in contrast, the Census records less than one percent of HMIS shelter users as being in state prisons and local jails on a date when HMIS data indicated they were in shelters.

do not contain SSNs, so linkage rates depend on the completeness and accuracy of personal information provided to enumerators, the uniqueness of this information, and the coverage of the reference file. Linkage rates for the Census data vary by enumeration site type. The linkage rates in the 2010 Census were 68.6 percent for the sheltered homeless, 42.4 percent for individuals at food vans, 41.8 percent for individuals counted using soup kitchens, and 17.2 percent for individuals at TNSOLs.

We account for incomplete linkage using inverse probability weights, which are estimated by obtaining the predicted probability of being assigned a linkage key in a probit model that accounts for individual characteristics recorded in the Census and HMIS data, including age, gender, race, Hispanic ethnicity. Ideally, we would like to weight our estimates by the inverse of the joint probability of being assigned a linkage key in both datasets, but we cannot directly estimate this target because our data do not allow us to differentiate between HMIS shelter users who do not appear in the Census because they truly were not counted and those who were in fact counted but were not assigned a linkage key. To address this challenge, we estimate bounds on the joint probability of being assigned a linkage key in both sources under the assumption that being assigned a linkage key in one source does not make an individual less likely to be assigned a key the other source. See Meyer et al. (2022) for more extensive discussion of this bounding methodology.

2.5.3 The coverage of HMIS shelter users in the Census

Table 2.4 displays estimated lower and upper bounds on the share of HMIS shelter users counted in various housing statuses in the Census in Los Angeles. We provide bounds on the coverage of all HMIS shelter users in the Census, as well as under three sets of refinements intended to drop individuals with incorrect exit dates. The first refinement drops individuals with an exit date of March 31, 2010, since the shelter occupancy patterns suggest a purge of open spells on that date. The second refinement drops individuals who were in shelters with names indicating participation in the city's winter shelter program, which ended on March 15, 2010. Refinement 3 further drops individuals with shelter entry dates prior to March 1, 2010, which is consistent with our understanding that entry dates recorded in HMIS are more reliable than exit dates. While this last refinement likely drops a large number of people who were truly in shelters on the Census date, we consider a comparison of results under the second and third refinements to be useful check for serious problems in HMIS entry and exit dates.

The share recorded as sheltered homeless in the Census increases with each refinement, suggesting that we have succeeded in better identifying people who were truly in shelters during the Census's homeless counting operation. Refinements 1 and 2 do not cause a large drop in the weighted count of people in Census shelters; most of the individuals dropped by these refinements are people who were counted as housed or had unknown status in the Census. Refinement 3, while allowing us to better identify a set of people who were truly in shelters, also causes the weighted count of people in shelters to drop substantially. We therefore suspect that most of the people dropped by refinements 1 and 2 were not in fact in HMIS shelters on March 30, 2010, whereas refinement 3 dropped many people who were truly in shelters on that date.

Under refinement 2, we estimate that 43–46 percent of HMIS shelter users were recorded by the Census in homeless shelters during the SBE. The range comes from the upper and lower bounds described in Section 2.5. About 8–9 percent were recorded in unsheltered statuses and about 7–8 percent were recorded in other group quarters facilities. About 24–25 percent were recorded as housed, and about 11–18 percent were not recorded in the Census and hence have unknown status. Our results indicate that about 82–89 percent of all people who were in HMIS shelters on that date were counted by the Census in some status.

The last two columns of Table 2.4 display bounds on the share of Houston HMIS shelter users who were recorded in various statuses in the Census. We do not make any refinements because we do not observe obvious, systematic errors in exit date reporting. We see that 35–37 percent of Houston HMIS shelter users were recorded by the Census in homeless shelters. About 4 percent were recorded as unsheltered homeless, 15–16 percent in other group quarters facilities, 22–23 percent in housing, and 21–25 percent with unknown status. These results are similar to those from Los Angeles, but with a few notable differences, including a smaller share recorded as sheltered or unsheltered homeless and a larger share with unknown status or in other group quarters. We also note that the weighted total number of HMIS shelter users was only about 1,500 in Houston, compared to about 5,700 under refinement 2 in Los Angeles.

Explanations for status discrepancies between the Census and HMIS

In this section, we explore potential reasons for discrepancies in individuals' statuses between HMIS data and the Census, including Census classification of certain HMIS shelters as housing units or other group quarters types, discrepancies arising from the timing of Census responses, and residual HMIS exit date errors.[10]

While Section 2.4 discussed straightforward differences in the definition of a shelter across sources, considerable definitional ambiguity remains. In particular, about 40 percent of HMIS shelter users on the PIT date in Los Angeles and Houston were in transitional shelters, which provide people experiencing homelessness a place to stay and supportive services for up to 24 months and typically require that residents possess a lease or occupancy agreement (U.S. Department of Housing and Urban Development 2018). Because these units provide longer-term and more stable tenure than emergency shelters, they are likely candidates for

10. We also consider the possibility that erroneous linkages drive the observed discrepancies. Table A.3 in the appendix displays the share of Los Angeles HMIS shelter users counted in the Census in various statuses who were found by the Census in California and in Los Angeles county. Nearly 90 percent of HMIS shelter users counted by the Census in unsheltered locations or other GQ types were found in Los Angeles, and about 97 percent were found in California. Among those counted by the Census as housed, 74.1 percent were in Los Angeles County and 84.9 percent were in California. These high geographic agreement rates do not suggest widespread erroneous linkages.

classification as housing units in the Census (Smith et al., 2012). Indeed, Table 2.5 shows that about 35–37 percent of people in transitional shelters in Los Angeles were recorded as housed in the Census, compared to just 17–19 percent of those in emergency shelters, with a similar pattern in Houston. Table 2.6 shows that about half of all HMIS shelter users in transitional housing in Los Angeles were in facilities where on average half of the residents were recorded in the Census as housed but none were recorded as sheltered homeless, a finding that further suggests that entire facilities were classified differently in the two sources.

We also find evidence that the Census classified some HMIS shelters as substance abuse treatment centers, group homes for adults with disabilities, or juvenile correctional facilities, discrepancies which may also have arisen from ambiguity in the definition of a homeless shelter. In Table 2.7, we see that of the 7–8 percent of Los Angeles HMIS shelter users recorded by the Census as being in other group quarters, about 43 percent were recorded in residential treatment centers for adults, which "provide treatment on-site in a highly structured live-in environment for the treatment of drug/alcohol abuse, mental illness, and emotional/behavioral disorders." The share of HMIS shelters users in this status rises when we refine our HMIS sample to exclude people with incorrect exit dates, suggesting that ambiguity in these facilities' classification, not incorrect exit dates, explains why shelter users are recorded in this status in the Census. Of the 15–16 percent of Houston HMIS shelter users in other group quarters in the Census, about one-fourth were recorded in group homes intended for adults, defined as "community-based group living arrangements that… provide room and board and services, including behavioral, psychological, or social programs." A key distinction between residential treatment centers and group homes is that the former emphasize substance abuse treatment, while the latter are targeted at people with physical and behavioral health conditions that require a supportive living environment. About 19 percent were recorded in a single correctional facility intended for juveniles, providing further evidence that entire facilities were classified differently in the two sources.

Another possible explanation for discrepancies in HMIS and Census statuses lies in the timing of Census responses from housing units. The SBE recorded individuals' housing status during a three-day window at the end of March, while the Census's housing unit questionnaire asked people to indicate their residence at the beginning of April. While a very small number of individuals may have transitioned from shelters to housing between these dates and hence been recorded as housed, a much larger number might have responded to the Census before entering a shelter or after exiting one during the long window of potential Census response. Census questionnaires were mailed to nearly all housing units on March 15, and by March 30, around half of these questionnaires had been received by the Census Bureau. The window of possible response also extended well beyond April 1, with about 20 percent of households responding during a non-response follow-up operation that began on May 1. Using the distribution of Census response dates and shelter entry and exit patterns, in conjunction with the distribution of Census response dates obtained from various Census press releases and official reports, we estimate that about 5.4 percent of HMIS shelter users might have been counted in housing before entering the shelter and 7.5 percent might have been counted as housed after leaving the shelter.[11] The timing of Census responses could therefore account for as much as half of the 24.4 percent of HMIS shelter users recorded by the Census as being housed.

Finally, some portion of status discrepancies can likely be attributed to remaining errors in HMIS exit dates. Table 2.7 provides some evidence of residual HMIS exit date errors.

11. We use shelter entry and exit rates from 2012 because we are more confident in the accuracy of exit date reporting in this year than in 2010. Specifically, we considered the set of people who were in an HMIS shelter on March 30, 2012 and then for each date between March 1 and March 30, we multiplied the share of this group that entered the shelter on that day by the share of households that had responded to the Census by that day in 2010 according to Census reports. Then for each date March 31 to April 30 (the date after which the Census's non-response follow-up operation wound down) we multiplied the share of this group that exited the shelter on that day by the share of households that responded to the Census on or after that date in 2010 according to Census reports. We then summed these shares across all dates to obtain an estimate of the share of HMIS Census users who would have responded to the Census before entering the shelter or after exiting it. This estimate assumes that those who entered or exited the shelter had the same probability of responding in date range as the broader population.

Under refinement 2, we observe that about 23 percent of the 7–8 percent of HMIS shelter users recorded by Census in other group quarters were found in state prisons and local jails. Because the Census enumeration in prisons and jails relied primarily on administrative records which are likely highly accurate, we interpret this as evidence of incorrect dates in HMIS data.

Caveat on the calculation of housing status probabilities

As a caveat, we note that the preceding analyses rely on the assumption that being assigned a linkage key is random conditional on the covariates in our inverse probability weighting model, meaning that the probability of being assigned a linkage key should be the same for a randomly chosen housed person as for a housed person who was recently homeless, given their covariates. If instead recently homeless individuals were less likely to be assigned a linkage key, then we would underweight those individuals, a tendency which could explain our observation that the share with unknown status (the residual category) decreases with each sample refinement, with each refinement disproportionately dropping underweighted rather than correctly weighted individuals. Recently homeless individuals who transition to housing could be difficult to link for various reasons, including the fact that they are less likely to be associated with their current address in the reference files used for linkage.[12] Recently homeless individuals may also have a tenuous attachment to their living situation, meaning that the person responding to the Census questionnaire might lack complete or accurate information for them. Because about 90 percent of all housed people in the Census were assigned linkage keys, compared to 68 percent of the sheltered homeless, this issue could cause us to understate the count of people in housing and other group quarters by up to one-third and to overstate the count of people in the residual category (those with unknown

12. It is not necessary that the address on a Census record match the reference file for that record to be assigned a linkage key. Having a matching address in the reference file helps, however, because the Census Bureau's PIKing software uses address to narrow the scope of potential matches in the reference file and avoid duplicate matches.

status).

2.5.4 *Double counting of homeless individuals in the Census*

In this section we assess the extent of what turns out to be frequent double counting of homeless individuals in the Census. Table 2.8 displays weighted counts of HMIS shelter users from Los Angeles and Houston whose linkage key appears more than once in various combinations of Census statuses.[13] In Los Angeles, about 800–1,000 people, or 14–17 percent of the 5,800 HMIS shelter users, were counted in multiple statuses in the Census, most frequently in two housed statuses or in one housed and one sheltered homeless status. In Houston, about 10–11 percent of HMIS shelter users had a duplicate record.

Table 2.9 examines double-counting among all individuals counted in homeless statuses in the 2010 Census more broadly. Specifically, this table shows the share of all people counted in homeless shelters and in each of the unsheltered statuses who have at least one housed or other group quarters record in addition to their homeless record, as indicated by the presence of additional records with that same linkage key. We estimate that about 21-24 percent of the sheltered homeless, 45-56 percent of those counted in soup kitchens and food vans, and 29-35 percent of those at outdoor locations had at least one housed record in addition to their homeless record. About 1-3 percent of homeless individuals were included on some other group quarters record in addition to their homeless record. Among those with other group quarters records, the most common facilities were group homes, treatment centers, state prisons, and local jails.[14]

13. In previous analyses, we de-duplicated these records giving preference to sheltered, unsheltered, other GQ, and housed statuses, in that order.

14. Duplication is a non-trivial issue in the Census more broadly. The 2010 Census Coverage Measurement (CCM) study found that about 2.8 percent of all person records in the 2010 Census were likely duplicates. A report from the Department of Commerce's Office of the Inspector General (OIG) described a particularly high risk of duplication for homeless individuals, which they attribute to official guidance that instructed enumerators to count homeless individuals even if they stated they had been previously counted at another service location, although the report also noted that this guidance was frequently ignored by enumerators (U.S. Department of Commerce 2011).

To understand the reasons for double counting, we first explore the possibility of erroneous linkage.[15] Table 2.10 displays agreement rates for age, gender, race, Hispanic ethnicity, and county and state of residence among duplicate record pairs in the Census. Among record pairs where a given characteristic is non-imputed for both records, sex matches in about 94 percent of cases. Agreement rates were also high for age, race, Hispanic ethnicity, and state and county. Several other facts give us confidence that duplication does not reflect widespread erroneous linkages. For one, we observe high rates of duplication even for HMIS shelter users, and we are confident in the high quality of linkage keys assigned to these individuals because their records contain social security numbers. Second, in other work we observe that the sheltered and unsheltered homeless individuals counted in the Census experience persistently low income and high rates of program receipt over the course of a decade, even relative to a comparison group of poor single adults, patterns that we might not expect to see if housed individuals' linkage keys were erroneously assigned to homeless individuals in the Census (Meyer et al., 2022).

Misclassification offers another potential explanation for double counting. It is possible that Census enumerators classified individuals observed in soup kitchens and while using food vans as homeless when in fact those individuals were housed but happened to be using homeless services. However, we maintain that the potential for misclassification is quite low for people who were sleeping in homeless shelters and those counted on the streets at TNSOLs, because these individuals were classified based on where they spent the night. Frequent double counting even of people in these categories suggests that misclassification is not the predominant explanation.

Double counting might also occur if homeless individuals were included on the Census

15. We are unable to directly assess linkage quality because there is no single proxy for linkage error among records assigned a PIK by the Census Bureau's Personal Identification Verification System (PVS) (Abowd et al. 2020). (Layne et al. 2014) estimate aggregate false match rates for PVS, but these differ substantially depending on the nature of the input file and cannot be used to estimate probabilities of correct linkage at the record-to-record level.

form of a housed family member or acquaintance with whom they occasionally resided. As discussed in previous sections, many people likely transitioned between homelessness and housing during the long window of Census response, a finding that could explain some double counting. Moreover, because the 2010 Census questionnaire instructed respondents to count all people "who live and sleep here most of the time," some homeless individuals may have been counted at the residence of a relative or acquaintance where they sometimes reside.

We explore this possibility in Table 2.11, which indicates the household characteristics of homeless individuals who are also included on a housed record. We see that about 19 percent of the sheltered homeless with a duplicate housed record are the only person residing in that housing unit, while the share ranges from 12–27 percent for the unsheltered depending on whether they were counted in a soup kitchen, food van, or TNSOL. The majority of homeless individuals with a duplicate housed record live with family. We also see that while the majority of those with a housed record appear on that record as the household head, a substantial share also appear as the child (typically the adult child) of the household head. Thus we see that in most cases, homeless individuals with duplicate housed records are not living alone and are in fact frequently living with family members. This pattern suggests that much of the observed double counting arises from these individuals' inclusion on the Census form of a family member or acquaintance.

2.6 Dual system estimate of the sheltered homeless population

In this section, we use dual system estimation, a statistical technique widely employed in demography and other fields, to calculate a reliable estimate of the sheltered homeless population under certain assumptions. The U.S. Census Bureau has used dual system techniques to estimate under coverage in Decennial Censuses since 1980.[16] The first system consists of peo-

16. This approach is adapted from a method called "mark and recapture" often used in ecology to estimate the size of animal populations (McCallum 2000).

ple enumerated in the Decennial Census and the second is an independent post-enumeration sample of the U.S. population. The share of people in the post-enumeration sample who were also found in the Census provides an estimate of the Census's coverage rate. Multiplying the Census count by the inverse of this share gives a consistent estimate of the true U.S. population under assumptions we discuss below (Wolter 1986).

In our context, the first system consists of those included in the Census's sheltered homeless count. The second consists of people who were in HMIS shelters on the day of the Census count in Los Angeles and Houston. The share of people in HMIS shelters on the day of the Census count who were found by the Census gives an estimate of the share of the true sheltered homeless found by Census. Multiplying the Census sheltered homeless count by the inverse of this share, we obtain an estimate of the true sheltered homeless population which is consistent if the number of individuals found in both samples is large and certain assumptions are met. As an equation,

$$\text{Sheltered homeless estimate} = \text{Census sheltered homeless count} \times \tag{2.1}$$
$$\frac{\text{HMIS sheltered homeless count}}{\text{Count of HMIS sheltered homeless also found by Census in HMIS shelter}}$$

We define the true sheltered homeless population to be people who were residing in facilities that align with the HMIS definition of a homeless shelter on the date of the Census count, recognizing that this excludes domestic violence shelters. We correct this definitional inconsistency at a later stage by adding an estimate of the population in domestic violence shelters to the estimate obtained from Eq. 2.1.

The Census definition of sheltered homelessness differs somewhat from the HMIS definition as well. In particular, the Census excludes from its sheltered homeless count those in voucher-funded hotel, motel and non-shelter beds and those in other facilities that HMIS classifies as shelters but Census classifies as housing or other group quarters, as suggested by the analyses in Section 2.5. We use (1) to account for these differences. Such individuals are appropriately included in the numerator of the ratio but not in the denominator. Eq. 2.1 also accounts for the extent to which the Census missed individuals in HMIS facilities that the Census defined as shelters.

We draw on results from our linked microdata comparisons in Section 2.5 to estimate the ratio on the right-hand side of Eq. 2.1. A complication in applying this framework is that errors in HMIS tend to prolong individuals' enrollments past their true exit dates. While we excluded some of these errors that were more easily identified in Section 2.5, other errors remain. For example, we believe all those found by the Census in jail or prison but recorded by HMIS as being in a shelter to be exit date errors. Such cases should be excluded from the numerator of the ratio on the right hand side of Eq. 2.1 because they were not in an HMIS shelter on the Census date. We must therefore estimate the number of HMIS observations that are from the time-period outside that of the Census homeless counting operation.

To do so, we estimate the share of those recorded erroneously in HMIS that is consistent with the count found in jail or prison by taking the share of HMIS shelter users found in jails or prisons in the Census and scaling it up by the inverse of the share of those leaving HMIS facilities that end up in jail or prison. We obtain an estimate of this latter ratio using the Census statuses of the sample of those who we identified as having date errors in Section 2.5, a group that we call HMIS shelter exiters. As an equation,

$$\frac{\text{Count recorded erroneously in HMIS shelter}}{\text{HMIS sheltered homeless count}} = \frac{\text{Count found in jail or prison}}{\text{HMIS sheltered homeless count}} \times \frac{\text{Count of HMIS shelter exiters}}{\text{Count of HMIS shelter exiters in jail or prison}} \tag{2.2}$$

As a final step, we must also estimate the count of people recorded erroneously in HMIS that were counted by the Census in non-HMIS homeless shelters. These are people who exited an HMIS shelter prior to the Census date but then entered a non-HMIS shelter and were counted there by the Census. This count, which is a subset of the overall count recorded erroneously in HMIS shelters that we subtracted from the numerator in (1), should also be excluded from the ratio's denominator because these individuals were not in HMIS shelters on the Census date. To estimate it, we take the share of those leaving HMIS facilities that ended up in non-HMIS shelters[17] and multiply this by the estimated count recorded erroneously in an HMIS shelter obtained using Eq. 2.2. We perform analogous calculations for the share that ended up in housing units, other group quarters, and unsheltered statuses and use these estimates to obtain estimates of the counts in these statuses after correcting exit date errors.

Table 2.12 displays counts and shares of the pooled Los Angeles and Houston samples in each Census status. We also indicate the share of HMIS exiters in each status and the HMIS sheltered homeless in each status after the date corrections described in this section. Applying counts in this table to Eq. 2.2, we estimate that about 36–38 percent of the HMIS sheltered homeless were erroneously recorded in an HMIS shelter due to incorrect dates. Scaling down the HMIS sheltered homeless count by 36–38 percent and assuming that these individuals are distributed across statuses in the Census according to the distribution of HMIS exiters' statuses, we obtain a date-corrected estimate of the share of the HMIS sheltered homeless in each status in column (4) of the table.

In summary, we estimate that about 60.8–63.8 percent of HMIS shelter users were found by the Census in shelters. Multiplying the inverse of this share by the Census sheltered homeless estimate of 209,000 as in Eq. 2.1, we obtain a non-domestic violence sheltered homeless estimate of about 328,000–343,000 people. To compare this estimate to the PIT, we add the approximately 39,000 people in domestic violence shelters to obtain a sheltered homeless population estimate of 367,000–382,000 people, or about 90–95 percent of the 2010 PIT count of about 403,500.

17. These shelters are necessarily non-HMIS because these are the people who were not in HMIS shelters at the time of the SBE.

2.6.1 Assumptions of this methodology and caveats

Zhang (2019) formulates the assumptions of the dual system estimator in a setting where the researcher has access to population data from a population dataset (in our case, the Census sheltered homeless count), which is treated as fixed, and a population coverage survey (the HMIS data), which is treated as random.[18] Applying these assumptions to our setting, the dual system estimator from Eq. 2.1 will provide a consistent estimate of the true sheltered homeless population if four conditions are met. First, there must be no duplicated records or erroneous enumerations in either the HMIS or the Census homeless count. Second, the matched records between the HMIS and Census counts must be identified without errors. Third, the average HMIS capture probability for people in our Census dataset should be equal to the average HMIS capture probability for sheltered homeless individuals not in our Census dataset. And fourth, captures in the HMIS must be uncorrelated with one another, aside from intra-cluster correlations, which are permitted.[19]

To address the first assumption, we deduplicate records using linkage keys in both the HMIS and Census data and adjust for apparent exit date errors in HMIS to eliminate erroneous enumerations. After taking these steps, we are confident that the first assumption is reasonably close to satisfied. The second assumption relies on PIK-based linking being accurate which we believe to be a good approximation to the truth. Our inverse probability weights and bounding exercise address account for non-linkage. The fourth assumption, while difficult to test, strikes us as plausible because it allows for intra-cluster correlations

18. By treating the administrative list as fixed, this approach circumvents the problem of modeling the population dataset's potentially complicated data generating process. This approach also allows people who are and are not included in the population dataset to differ systematically from one another. The decision to treat the population dataset as fixed simplifies the assumptions for consistency from the extensive list described in (Wolter 1986).

19. In the most basic formulation of these conditions, the third assumption states that HMIS capture probabilities must be constant for all sheltered homeless individuals and the fourth assumption states that captures in the HMIS must be uncorrelated with one another. Zhang (2019) shows that these assumptions can be relaxed to the formulations described in this text while preserving the consistency of the dual system estimator.

(e.g. people residing in the same shelter may have correlated probabilities of inclusion in the Census).

The third assumption requires further discussion. For this assumption to hold, the average probability of inclusion in Los Angeles and Houston HMIS shelters among those in the Census sheltered homeless count must be equal to the average inclusion probability of all sheltered homeless individuals in the country. In 2010, the Los Angeles CoC estimated that about 40 percent of shelter users were in HMIS-tracked beds. Using the linked microdata, we estimate that 36–39 percent of the Los Angeles Census sheltered homeless were enrolled in HMIS shelters.[20] The similarity of these shares provides support for the third assumption in Los Angeles. Without additional HMIS data, however, we are unable to test this assumption for the U.S. sheltered homeless population more broadly.[21] This remains a caveat on our findings and a potential question for future work linking other localities' HMIS data to the Census.

2.7 Discussion

2.7.1 The size of the U.S. homeless population

A key goal of this paper was to triangulate homeless population estimates across available sources to improve our understanding of the U.S. homeless population size. We did so by comparing aggregate estimates as well as linked microdata and by using dual system methods to obtain a new estimate of the sheltered homeless population that is reliable under plausible assumptions. In this section, we discuss those findings' implications for the size of the U.S.

20. See table A.7 in the Appendix.

21. In Houston, we estimate that about 21-22 percent of the Census sheltered homeless were enrolled in HMIS shelters, a share that is well below the CoC's estimate that 60 percent of beds were tracked through HMIS that year. However, this discrepancy appears to be due in part to some HMIS shelters' exclusion from our internal files and in part to incompleteness in the CoC's inventory of non-HMIS shelters from those years.

homeless population. We also consider potential sources of bias in the Census and the PIT relative to the true homeless population. We discuss how these biases could affect aggregate comparisons and how they might explain differences between the PIT count and Census's sheltered homeless estimates and the dual system estimate.

Unsheltered homeless population size

The 2010 PIT's unsheltered population estimate of 235,000 was similar to the Census's estimate of 210,000 people. We take this aggregate similarity to be encouraging, especially because this is the first time the widely cited PIT estimate has been compared to an independent national estimate. Aggregate comparisons, however, could mask bias in each source relative to the true population, and we are unable to estimate this population using dual system methods because we lack a second source of microdata on these individuals. To address this concern, we discuss potential sources of bias in the Census and PIT relative to the true unsheltered homeless population and how biases might affect their aggregate difference.

We can characterize the relationship between each source's estimate and the true unsheltered homeless population on the PIT date (H_{True}) with the following equations:

$$H_{True} = H_{PIT} + U_{PIT} - O_{PIT}$$
$$H_{True} = H_{Census} + U_{Census} - O_{Census} + S$$

where H_j for $j \in \{\text{PIT}, \text{Census}\}$ is the is the unsheltered estimate in a source, O_j and U_j are counts of people who were undercounted (missed in the PIT or Census) and overcounted (double counted or misclassified as unsheltered), and S is the seasonal difference in true population sizes (at the time of the PIT minus the Census).

Combining these expressions shows that the aggregate difference between the PIT and Census reflects the difference between each source's net error ($U_j - O_j$) and seasonal differences:

$$H_{PIT} = H_{Census} + (U_{Census} - O_{Census}) - (U_{PIT} - O_{PIT}) + S$$

We are interested in the magnitude of each source's net error because this indicates bias relative to the true unsheltered homeless population. An aggregate comparison does not allow us to estimate net error in each source, but it does tell us about the difference of net error. Results based on Meyer et al. (2022), which compares the ratio of Census to PIT counts across CoCs accounting for several measures of temperature and precipitation, suggest that S is small, with reasonable estimates ranging from about -8 to 6 percent of the Census unsheltered count. We therefore emphasize sources of over and undercounting in this section.

Overcounting could arise in either source from the misclassification of housed or sheltered homeless people as unsheltered. Both the Census and the PIT obtain unsheltered estimates in part from counting people using homelessness services. While both sources' methodology documents instruct those doing the count to ask people's unsheltered status, it is possible that the chaotic nature of such locations made it impossible to correctly determine everyone's unsheltered status, leading to misclassification. However, such misclassification appears to be small in the Census. Only 2 percent of the Census unsheltered homeless in Houston and 4–5 percent of those in Los Angeles were enrolled in HMIS shelters on the SBE date, an occurrence that could reflect either misclassification or incorrect HMIS shelter exit dates. We do not have an estimate of misclassification in the PIT.

Overcounting could also arise due to double counting during both sources' multi-day counting operations. This is likely a minor source of bias in the Census because the Census's post processing algorithm deduplicated records within the universe of homeless records using personal information. Table 2.8 shows that it is very rare for someone to be counted multiple times in sheltered or unsheltered homeless statuses in the Census, although a caveat on this is that people who did not provide personal information cannot be deduplicated. CoCs, on the other hand, rarely collect personal information from unsheltered homeless individuals when conducting the PIT counts, so deduplication methods are much less sophisticated, typically consisting of simply asking whether people have already been counted (HUD 2014).

Overall, we suspect that double counting and misclassification are more important sources of bias in the PIT than in the Census because its counting operations often rely on volunteers with minimal training whose understanding of and fidelity to protocols may be limited. Moreover, CoCs apply for funding based on the outcome of the PIT count and hence may not be indifferent to their outcomes. If overcounting is more widespread in the PIT count than the Census, then this would explain some of the aggregate difference between sources.

We also consider potential bias from undercounting in each source. Because both the PIT and Census rely on finding people at service locations and on canvassing outdoor locations at night, both would tend to miss people who do not use services or choose to sleep in isolated or hidden locations, such as vehicles or abandoned buildings. This could lead to correlated undercounting in the sources that would net out in an aggregate comparison. We therefore expect that some amount of undercounting is present and that the magnitude may be similar in both sources, but we are unable to estimate this bias using available data.

In summary, we expect both sources' unsheltered estimates to be biased to some extent by under and overcounting, but these biases are difficult to estimate. We suspect that greater duplication and misclassification in the PIT count could explain some of the aggregate differences between sources. Undercounting may be important in both sources and could net out in aggregate comparisons, but without estimates of overcounting we cannot determine the sign or magnitude of net bias in each source's estimate relative to the true population. Given the substantial difficulties of counting this population and methodological differences between the PIT and Census, the fact that both arrive at similar results provides encouraging evidence that both offer reasonable estimates of the unsheltered population size.

Sheltered homeless population size

Prior to adjustments, the Census's sheltered homeless estimate of about 209,000 people fell far short of the 2010 PIT estimate of about 405,000. The ACS estimate was about half of the PIT in 2006–2010 and about three-quarters of the PIT after 2010. However, we reconciled much of this initial discrepancy by accounting for straightforward definitional differences across sources and bias arising from the ACS weighting methodology. Specifically, we found that the Census SBE's exclusion of domestic violence shelters, voucher-funded hotel and motel beds, and beds in non-shelter facilities explained about half of the initial gap between the 2010 PIT and Census. People in these groups were counted in the Census but not classified as homeless. We also adjusted the ACS upwards to reconcile definitional differences, but then scaled down estimates by about 30 percent to correct bias arising from the ACS's weighting methodology. These straightforward definitional and weighting adjustments closed about half of the initial gap between the 2010 PIT count and the Census, leaving us with a definitionally-adjusted Census estimate of about 289,500.

Using the dual system methodology described in Section 2.6, we obtained a new sheltered homeless estimate of 367,000–382,000 people, or about 5–10 percent lower than the 2010 PIT estimate and about 27–32 percent larger than the adjusted Census count. Because this estimate did not make assumptions on the completeness of the PIT or Census, we maintain that this is a reasonable estimate of the sheltered homeless population size. Our findings in Sections 5 and 6 suggest that much of the gap between the adjusted Census count and the dual system estimate reflects ambiguity in the definition of a homeless shelter leading to a different classification of these structures by the Census rather than their omission. This explanation is consistent with findings in Meyer et al. (2022), which compares CoC-level sheltered population estimates in the 2010 Census and PIT and finds that on average, a given CoC has about three-quarters as many unique shelter addresses underlying its Census estimate as its PIT estimate and differences in facility count explain much of the gap between the aggregate adjusted Census and PIT sheltered population estimates. We next turn to a discussion of potential sources of bias in the sheltered PIT and Census and discuss how bias might explain differences between those sources' estimates and the dual system estimate.

The PIT could overstate the sheltered homeless population due to its reliance on HMIS data, which in the years around the 2010 Census tended to overstate the number of people enrolled in a shelter at a point in time. This issue would be a major concern if CoCs simply extrapolated from HMIS data to obtain their sheltered estimates, but in practice HUD instructs CoCs to implement a series of quality checks before using these data in their counts (HUD 2012). For example, in a 2010 report to HUD, the Los Angeles CoC stated that they compared shelters' capacity and occupancy and corrected counts where necessary when generating their sheltered PIT estimate. Such checks may not have caught all date errors, however, potentially leading to overcounting that could explain why the dual system estimate is lower than the PIT.

Double counting, on the other hand, is less of a concern in sheltered estimates because both the PIT and Census deduplicated sheltered homeless counts using personal information, including name and date of birth in the case of the Census and SSNs recorded in HMIS in the case of the PIT. However, in both sources, incomplete collection of personal information prevents comprehensive deduplication, and some double counting could remain.

Undercounting could have occurred in either source due to shelter list incompleteness. We have also seen that the Census appeared to classify many HMIS facilities as housing or other types of group quarters rather than as homeless shelters, a fact that would lead the Census estimate to understate the population relative to our target definition, which is based on the HMIS and PIT definition. Although we accounted for straightforward definitional differences in aggregate comparisons, microdata comparisons suggest that more subtle differences in classification remain. The combination of Census undercounting and residual classification differences may explain the difference between the Census and dual system estimates, with the latter estimate having corrected for both of these sources of undercounting.

2.7.2 *Completeness and accuracy of available data on homelessness*

The second major goal of this paper was to learn about the completeness and accuracy of available datasets on the U.S. homeless population, particularly the 2010 Census. Overall, we found that the coverage of sheltered homeless individuals in the 2010 Census was surprisingly good. Our dual system estimate implied that about 93–97 percent of people who were in HMIS shelters on the night of the Census's homeless counting operation were included in the Census in some status. Potential bias from the underweighting of people found as housed or in other group quarters, as described in Section 2.5, means that the true share could be even higher. About 61–64 percent were found by the Census in shelters, 19 percent in housing units, and 9 percent in other types of group quarters. The last 4 percent appear to have been misclassified as unsheltered.

As documented in Section 2.5, it appears that many of the HMIS shelter users not found in shelters in the Census were in facilities that the Census classified as housing or other types of group quarters. This pattern in part reflects the straightforward definitional differences identified in Section 2.4. In many cases, however, this pattern also appears to reflect more subtle distinctions in how HMIS and the Census define homeless shelters. For example, we found evidence that the Census classified many HMIS transitional shelters as housing, likely because the people residing there had fairly long-term and stable occupancy agreements. The Census also appears to have classified some HMIS facilities not as homeless shelters but as group homes for adults or residential treatment centers for substance abuse, meaning that those facilities' administrators chose that designation when asked by Census advance visit teams which group quarters type best described their facility. This finding highlights the lack of consensus about what types of facilities constitute a homeless shelter. This ambiguity, in turn, appears to matter substantially for estimates of the sheltered homeless population size.

Unexpectedly, our analyses also uncovered a pattern of frequent double counting of homeless individuals in the Census, often in a combination of housed and homeless statuses. Additional analyses suggested that most double counting arose because people transitioned from being housed to homeless around the time of the 2010 Census or because they were included on the Census form of a family member or acquaintance with whom they sometimes resided. Incorrect linkage and misclassification of housed individuals as homeless may in part explain double counting but do not appear to be its primary causes. These findings illustrate the fluidity of homeless individuals' living situations between housed and homeless statuses.

Finally, our analyses revealed important issues with the quality of exit dates recorded in HMIS data, which are widely used by both program administrators and homelessness researchers. In 2009–2011 in Los Angeles, shelter occupancy, as indicated by HMIS entry and exit dates, far exceeded capacity in winter months and dropped precipitously on a handful of dates, suggesting a purge of open shelter spells. We also found frequent instances of overlapping shelter spells, and we obtained further evidence of errors in the form of individuals who were found in state prisons and local jails during the 2010 Census despite being enrolled in the shelter according to HMIS data. These findings recommend caution for researchers using these data to identify people in shelters at a point in time or to analyze temporal patterns of shelter usage.

2.8 Conclusions

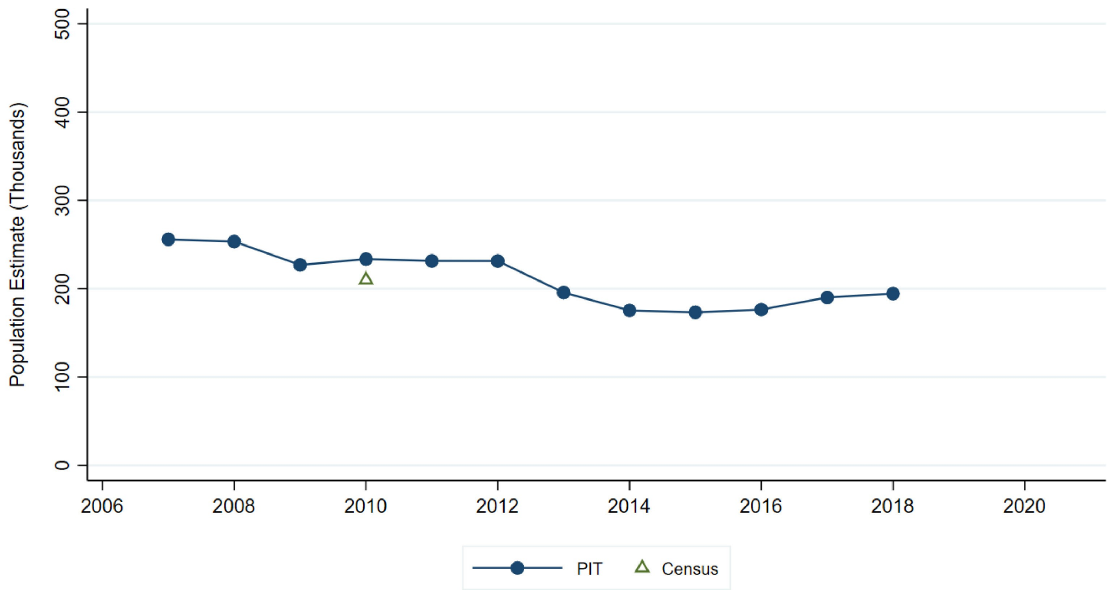
Our work suggests that on any given night, there are about 600,000 people experiencing homelessness in the U.S. and that about one-third are sleeping on the streets and the rest in shelters. We estimate that the 2010 sheltered homeless population was about 367,000–382,000, a range that is slightly lower than HUD's widely cited point-in-time estimate and much larger than the Census's sheltered homeless count, with the latter fact due largely to differences in how HUD and Census defined a homeless shelter. Our work suggests that the Census estimate of 210,000 and the PIT estimate of 235,000 provide a reasonable range for the unsheltered homeless population size, although we acknowledge the possibility of under or over counting in each source. The dual system methods used in this paper may prove useful to other researchers looking to estimate the unsheltered homeless population size, although doing so requires a set of linkable data on the unsheltered population that satisfies the assumptions of this method. Taken together, the findings in this paper lend new credibility to aggregate PIT estimates that had not previously been validated against independent estimates. At the same time, they highlight the fact that there is considerable ambiguity about what types of facilities constitute a homeless shelter and that population estimates are very sensitive to these ambiguities.

Our work also suggests that most homeless individuals were included in the Census, although they were oftentimes counted as housed or in other types of group quarters. Many were counted twice, reflecting frequent transitions between housing status even in a dataset designed to convey a static picture of the U.S. population. This finding has implications for the coverage of homeless individuals in household surveys other than the ACS, like the Current Population Survey (CPS) and Survey of Income and Program Participation (SIPP), which are not intended to represent the homeless population. Given the frequency of double counting, we suspect that homeless individuals may in fact be included in surveyed households' responses more often than previously thought. These findings contribute to a larger emerging picture of the mobility and persistent material deprivation of the U.S. homeless population.

The Census and ACS hold tremendous promise for learning about homelessness. By establishing the broad coverage and reliability of the new data sources, our analyses lay the foundation for pathbreaking work using these data sources to learn about the demographic characteristics, income, safety net program participation, mortality, housing transitions, and migration patterns of those experiencing homelessness, work that promises to advance substantially our understanding of this difficult to study population.

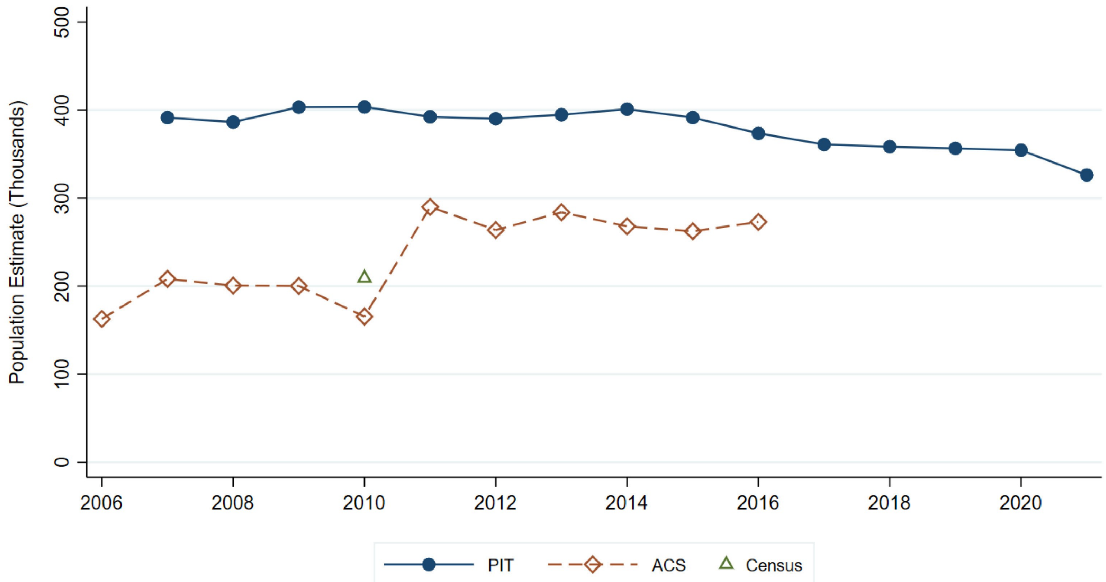
2.9 Exhibits

Figure 2.1: Unsheltered homeless population estimates in the PIT and Census



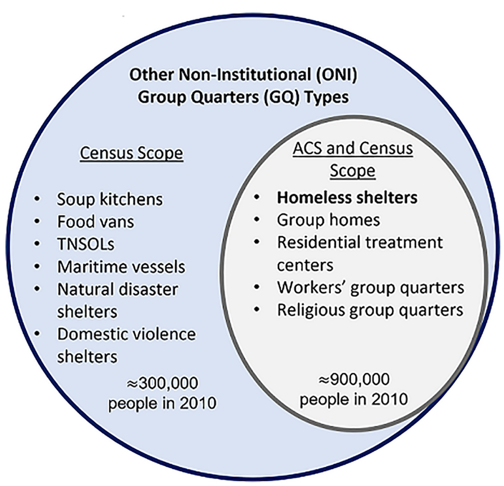
Sources: 2010 Census, 2006-2016 ACS, 2007-2021 PIT Files.
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 2.2: Sheltered homeless population estimates in the PIT, ACS, and Census



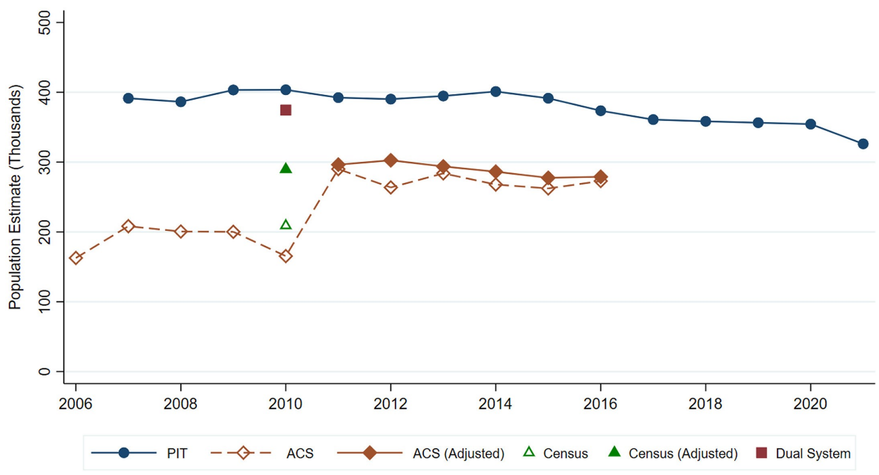
Sources: 2010 Census, 2006-2016 ACS, 2007-2021 PIT Files.
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 2.3: Graphical representation of Other Non-Institutional (ONI) group quarters types



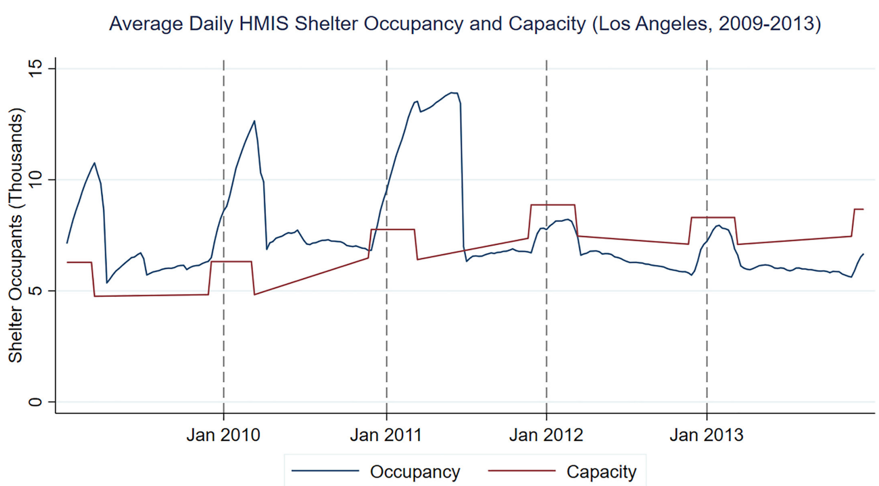
Note: Circles not to scale.

Figure 2.4: Sheltered homeless population estimates in the PIT, ACS, and Census with definitional and weighting adjustments and dual system estimate



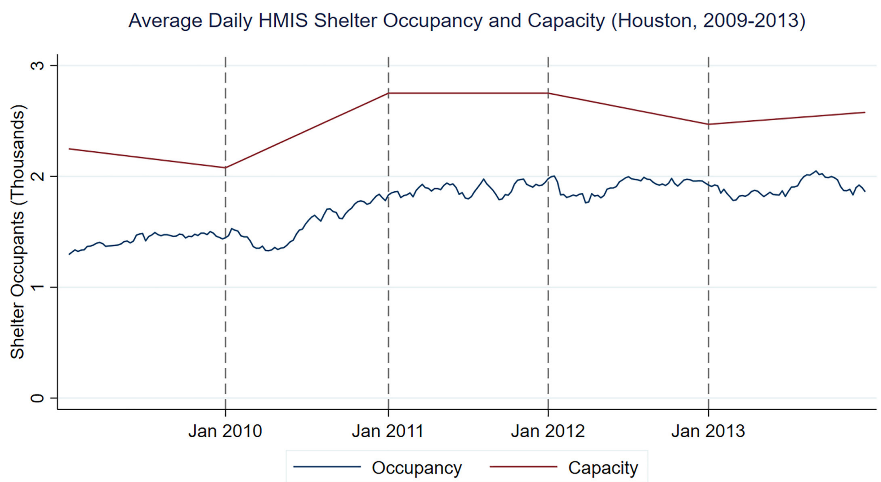
Sources: 2010 Census, 2006-2016 ACS, 2007-2021 PIT Files.
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 2.5: Los Angeles HMIS Data Quality



Sources: 2009-2014 Los Angeles HMIS files.
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 2.6: Houston HMIS Data Quality



Sources: 2009-2014 Houston HMIS files.
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Table 2.1: Homeless Population Estimates

	Unadjusted estimates			PIT-only population estimates				Adjusted estimates		
Year	PIT	Census	ACS	Safe Haven	Domestic Violence	Voucher-Based	Non-Shelters	Census	ACS	Dual Systems
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
2008	386,361	-	162,700	-	39,818	20,854	19,655	-	-	-
2009	403,308	-	208,200	-	39,156	20,902	19,655	-	-	-
2010	403,543	209,000	200,600	1,345	38,704	20,902	19,656	289,607	-	374,500
2011	392,316	-	200,200	1,898	37,127	21,757	16,041	-	296,354	-
2012	390,155	-	165,400	1,991	36,439	44,780	19,775	-	302,606	-
2013	394,698	-	290,000	2,025	35,431	20,602	20,797	-	293,767	-
2014	401,051	-	263,700	2,014	35,118	22,540	23,787	-	286,260	-
2015	391,440	-	283,900	1,861	34,483	20,202	22,387	-	277,495	-
2016	373,571	-	267,900	1,686	34,475	15,551	20,661	-	278,959	-
2017	360,867	-	262,300	1,463	34,241	14,277	27,729	-	-	-
2018	358,363	-	272,900	1,947	34,292	16,428	11,430	-	-	-
2019	356,422	-	-	1,933	34,469	12,636	14,494	-	-	-

Sources: 2008-2019 Official PIT Files, 2008-2019 HIC Files, 2010 Census, 2008-2019 ACS.
Note: Table displays each year's PIT count as well as the number of people identified as being in safe haven beds by the official PIT files. Counts in domestic violence, voucher-based, and non-shelter beds are calculated by summing the PIT counts associated with people in each of these types of facilities in the HIC files. For some CoCs in some years, the internal HIC files lack PIT counts. In these cases, we impute the share of that CoC's PIT count in these types of beds using that CoC's share in the first subsequent year for which data is available. Adjusted Census estimate is calculated by adding PIT-only population estimates to Census total. Adjusted ACS estimate is obtained by adding PIT-only population estimates and then scaling down by the ACS scaling factor to correct weighting bias. Dual systems estimate is obtained using methods described in Section 7 of the text. Estimate reported here is the midpoint of the range of estimates in that section.

Table 2.2: Population of Other Non-Institutional (ONI) Group Quarters (GQ) Types in the 2010 Census

	Population in 2010 Census
A: Census and ACS Scope	
Homeless Shelters	210,036
Group Homes	307,129
Residential Treatment Centers	142,406
Workers' Living Quarters	169,107
Religious Group Quarters (Est.)*	75,684
Total	904,362
B: Census Scope Only	
Soup Kitchens and Food Vans	175,434
TNSOLs	37,502
Maritime Vessels	51,864
Natural Disaster Shelters	26
Domestic Violence Shelters (Est.)*	25,204
Total	290,030
ACS Scaling Factor (total of A plus B, divided by total of A)	1.321

Sources: 2010 Census Service-Based Enumeration Assessment Report, 2010 Census Group Quarters Enumeration Assessment Report.
Note: Table displays the population counts for various ONI GQ types in the 2010 Census, divided into those that are in-scope for both the Census and ACS and those that are in-scope for the Census only. *Indicates that these are estimates, not counts. The Census pools together religious GQs and domestic violence shelters in both public counts and restricted data. In the 2010 Census, this combined group had 100,888 people. We divide the group into a religious GQ estimate and a domestic violence estimate by assuming the ratio of the overall sheltered homeless population to the DV population is the same in the PIT and the Census.

Table 2.3: Linkage (PIK) Rates in Census and HMIS Data

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
HMIS											
Los Angeles[1]	1.000	0.895	0.939	0.945	0.870	0.861	0.879	0.906	0.922	0.923	0.925
Houston[2]	0.800	0.949	0.979	0.967	0.955	0.956	0.955	0.961	0.962	0.965	0.965
Census											
Shelter							0.686				
Soup Kitchen							0.418				
Food Van							0.424				
TNSOL							0.172				

Sources: 2010 Decennial Census, 2004-2014 Los Angeles CoC HMIS Data, 2004-2014 Houston CoC HMIS Data.
Note: Table reports the share of sheltered and unsheltered homeless individuals who are PIKed in the 2010 Census by GQ type. All results were approved for release by the Census Bureau, authorization number CBDRB-FY20-ERD002-004. Los Angeles Housing Management Information System (HMIS) data contains demographic and shelter use information for individuals who enrolled in emergency or transitional shelters in the Los Angeles CoC in 2004-2014. This CoC encompasses shelters in Los Angeles excluding Glendale, Long Beach, and Pasadena. Houston Housing Management Information System (HMIS) data contains demographic and shelter use information for individuals who enrolled in emergency or transitional shelters in the Houston CoC in years 2004-2015. This CoC encompasses shelters in Houston, Harris, Fort Bend, and Montgomery Counties.

Table 2.4: Coverage of Los Angeles and Houston HMIS Shelter Users in the 2010 Census

	Los Angeles								Houston	
	All Records		Refinement 1: Excluding 3/31 Exits		Refinement 2: Excluding 3/31 Exits and Winter Shelter Program		Refinement 3: Excl 3/31 Exits, WSP, Entries Before 3/1		All Records	
Census Status	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Sheltered	0.273	0.299	0.367	0.398	0.428	0.464	0.497	0.539	0.351	0.371
Unsheltered	0.106	0.119	0.105	0.116	0.085	0.092	0.156	0.170	0.035	0.037
Other GQ	0.077	0.088	0.068	0.076	0.071	0.079	0.047	0.054	0.151	0.160
Housed	0.267	0.292	0.236	0.253	0.236	0.252	0.193	0.205	0.218	0.226
Status Unknown (not in Census)	0.202	0.277	0.158	0.225	0.114	0.181	0.032	0.107	0.207	0.245
Unweighted Total	10500		7000		5800		1300		1400	
Share and PIKed in HMIS	0.876		0.886		0.897		0.923		1.000	
Share PIKed and in HMIS and Census	0.522		0.548		0.577		0.583		0.536	
Weighted Total	10420		6901		5738		1258		1480	

Sources: LA (CA-600, 2004-2014) HMIS administrative data, Houston (TX-700, 2004-2015) HMIS administrative data, 2010 Census.
Note: Table displays the weighted share of individuals who were present in an emergency or transitional shelter in HMIS data on March 30, 2010, according to HMIS records, who appeared in the 2010 Census in various GQ types or as housed. Where exit dates were missing in HMIS data, we imputed an exit date based on the median stay length for users of that shelter type. Lower and upper bound weights calculated using methods described in the text. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table 2.5: Coverage of HMIS Shelter Users in the 2010 Census by HMIS Program Type

	Los Angeles (Refinement 2)				Houston			
	Emergency Shelters		Transitional Housing		Emergency Shelters		Transitional Housing	
Census Status	*Lower*	*Upper*	*Lower*	*Upper*	*Lower*	*Upper*	*Lower*	*Upper*
Sheltered	0.399	0.438	0.481	0.512	0.349	0.370	0.353	0.371
Unsheltered	0.108	0.118	0.041	0.045	0.062	0.065	0.020	0.021
Other GQ	0.070	0.080	0.072	0.076	0.011	0.012	0.225	0.237
Housed	0.172	0.185	0.351	0.372	0.143	0.151	0.260	0.269
Status Unknown (not in Census)	0.177	0.248	-0.006	0.055	0.402	0.435	0.102	0.143
Weighted Total	3697		2042		533		948	

Sources: LA (CA-600, 2004-2014) HMIS administrative data, 2010 Census.
Note: Table displays the weighted share of individuals who were present in an emergency or transitional shelter in HMIS data on March 30, 2010, according to HMIS records, who appeared in the 2010 Census in various GQ types or as housed. Where exit dates were missing in HMIS data, we imputed an exit date based on the median stay length for users of that shelter type. Lower and upper bound weights calculated using methods described in the text. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table 2.6: HMIS Sheltered Individuals by Share Sheltered in Census and Census Status (Los Angeles)

			Share of People in Census Status				
HMIS Shelter Type	Census recorded share in shelter	Bound	Shelter (1)	Housed (2)	Other Census (3)	Status Unknown (4)	Total People (5)
Emergency	0	Lower		0.163	0.363	0.435	80
		Upper		0.146	0.419	0.475	
Transitional		Lower		0.537	0.113	0.336	850
		Upper		0.548	0.116	0.350	
Emergency	0 to .5	Lower	0.231	0.170	0.161	0.417	2700
		Upper	0.240	0.174	0.169	0.437	
Transitional		Lower	0.363	0.152	0.136	0.335	350
		Upper	0.369	0.153	0.143	0.349	
Emergency	0.5 to 1	Lower	0.811	0.016	0.047	0.115	550
		Upper	0.819	0.016	0.051	0.125	
Transitional		Lower	0.874	0.031	0.007	0.083	600
		Upper	0.880	0.030	0.006	0.089	

Sources: 2010 Census, 2004-2014 Los Angeles HMIS data.
Note: Sample is restricted to shelters with greater than ten occupants. Lower and upper bound weights calculated using methods described in the text. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table 2.7: Distribution of GQ Codes for HMIS Shelter Users Appearing in "Other GQ" Types in Census

		Los Angeles			Houston
		All records	Refinement 1: Excl 3/31 exits	Refinement 2: Excl 3/31 exits and WSP	All records
GQ Code	Category				
103	State Prisons	0.130	0.106	0.093	-
104	Local Jails	0.313	0.253	0.228	-
301	Nursing Facilities	0.063	0.073	0.089	-
203	Correctional Facilities for Juveniles	-	-	-	0.191
801	Group Homes for Adults	-	-	-	0.261
802	Residential Treatment Centers for Adults	0.278	0.407	0.430	0.513
-	All Other GQ Codes	0.217	0.161	0.160	0.035
Overall share in Other GQs (midpoint of bounds)		0.083	0.072	0.075	0.155

Sources: L.A. and Houston HMIS administrative data, 2010 Census.
Note: "HMIS shelter user" is defined as an individual who was in an HMIS shelter on March 30, 2010, according to HMIS administrative records. Dashed lines indicate categories that have been included in the "All Other GQ Codes" category due to the small number of observations in that category. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table 2.8: HMIS Shelter Users with Multiple Statuses in Census

		Housed +				Sheltered +			Unshel. +	More than two	Other combination	Shelter Users with Duplicate Records	Total Records
		Housed	Sheltered	Unshelt-ered	Other GQ	Sheltered	Unshelt-ered	Other GQ	Unsheltered				
Los Angeles	All records												
	Lower bound	247	376	131	144	19	37	86	16	91	24	1172	10500
	Upper bound	289	479	188	199	20	57	134	19	139	48	1570	10500
	Refinement 2												
	Lower bound	78	351	61	69	13	34	82	-	79	16	782	5800
	Upper bound	83	448	84	87	14	51	126	-	120	26	1037	5800
Houston	All records												
	Lower bound	22	67	-	19	-	-	-	-	-	31	139	1400
	Upper bound	23	71	-	20	-	-	-	-	-	32	147	1400

Sources: Los Angeles HMIS data (2004-2014), Houston HMIS data (2004-2015).
Note: Table displays weighted counts of unique HMIS shelter users (as of 3/30/2010, without any restrictions) found in multiple statuses in the Census. In Los Angeles, in about 80% of cases the individuals' ages matched exactly, and about 90% of cases the individuals ages matched within five years. In about 95% of cases the individuals' sex matched. In about 92% of cases both individuals lived in California, and in about 88% of cases both individuals lived in L.A.county. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization numbers CBDRB-FY2022-CES005-006 and CBDRB-FY2022-CES005-008.

Table 2.9: Homeless with duplicate housed or other GQ records in Census

	All people		Has at least one housed record			Has at least one other (non-homeless) GQ record		
Homeless type	Number of Records	Unique PIKs	Unique PIKs	Weighted population estimate		Unique PIKs	Weighted population estimate	
				LB	UB		LB	UB
Shelter	209,000	143,000	26,500	43,280	49,020	1,400	2,235	3,002
Soup Kitchen	162,000	67,000	29,000	72,670	84,800	1,200	2,924	4,078
Food Van	11,500	4,900	2,300	5,588	6,399	80	229	305
TNSOL	36,500	6,300	1,900	10,660	12,830	100	586	835
Homeless type				Share of all records			Share of all records	
				LB	UB		LB	UB
Shelter				0.207	0.235		0.011	0.014
Soup Kitchen				0.449	0.523		0.018	0.025
Food Van				0.486	0.556		0.020	0.027
TNSOL				0.292	0.352		0.016	0.023

Sources: 2010 Census.
Note: Upper and lower bound weights estimated using methods described in the text. Among those with duplicate records in other GQ types, the most common GQ types for the sheltered homeless are state prisons (9.2%), local jails (23.1%), group homes (15.4%), and residential treatment centers (23.1%). The most common GQ types for the unsheltered homeless are state prisons (7.7%), local jails (23.1%), group homes (30.7%), and residential treatment centers (15.4%). All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization numbers CBDRB-FY2022-CES005-006 and CBDRB-FY2022-CES005-008.

Table 2.10: Agreement Rates for Characteristics of Duplicate Housed/Homeless Pairs in 2010 Census

	Imputed and Non-Imputed		Non-Imputed Only		Non-Imputed Only		Non-Imputed Only	
	All records		All records		Same sex duplicates		Different sex duplicates	
	Share	N	Share	N	Share	N	Share	N
Same sex	0.937	59500	0.939	57000		53500		3500
Age exactly same	0.709	59500	0.775	53000	0.819	47500	0.099	3100
Age within one year	0.756	59500	0.811	53000	0.855	47500	0.120	3100
Age within five years	0.867	59500	0.903	53000	0.942	47500	0.299	3100
Same race	0.812	59500	0.851	51000	0.862	46000	0.670	2800
Same Hispanic status	0.874	59500	0.890	48000	0.900	43500	0.762	2800
Same state	0.893	59500	0.893	59500	0.893	53500	0.890	3500
Same county	0.806	59500	0.806	59500	0.805	53500	0.808	3500

Sources: 2010 Census.
Note: Table displays the share of duplicate housed/homeless pairs of records in Census for which the given characteristic is the same (or within a given interval) for both records. "Non-imputed" is defined here as having a flag indicating that a given characteristic was preserved "as reported" - i.e. not altered in any way (edited for consistency, allocated from hot deck). Sample includes only duplicate pairs where all characteristics are non-missing in both sources. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-008.

Table 2.11: Household Characteristics of Homeless Individuals with a Duplicate Housed Record in 2010 Census

Record Type	Relationship to household head: Household head	Spouse or partner	Child (adult or minor)	Other relative	Other nonrelative	Household type: Lives alone	Lives with family	Lives with non-family	N
Shelter	0.382	0.095	0.318	0.125	0.080	0.185	0.728	0.087	26500
Soup Kitchen	0.516	0.120	0.183	0.100	0.081	0.268	0.616	0.117	29000
Food Van	0.483	0.161	0.197	0.096	0.063	0.198	0.713	0.089	2300
TNSOL	0.386	0.146	0.271	0.111	0.086	0.115	0.790	0.095	1900

Sources: 2010 Census.
Note: Sample includes all homeless individuals from 2010 Census with a single duplicate housed record. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-008.

Table 2.12: Weighted Counts and Shares of HMIS Shelter Users by Census Status (Los Angeles and Houston Pooled)

A: Weighted counts								
	All records		All records minus first set of those with exit date errors		First set of those with exit date errors		Records with correct dates	
	(1)		(2)		(3)		(4)	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Sheltered	3,368	3,660	2,976	3,212	392	448	2,750	2,966
Unsheltered	1,157	1,294	537	584	620	710	180	194
Other GQ								
Non-Jail and Prison	673	749	500	542	173	207	400	428
Jail and Prison	357	408	131	145	227	264	0	0
Housed	3,101	3,373	1,674	1,778	1,427	1,595	852	902
	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Status unknown	3,243	2,414	1,400	957	1,843	1,457	338	157
Total	11,899	11,899	7,218	7,218	4,681	4,681	4,521	4,648

B: Weighted shares								
	All records		All records minus first set of those with exit date errors		First set of those with exit date errors		Records with correct dates	
	(1)		(2)		(3)		(4)	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
Sheltered	0.283	0.308	0.412	0.445	0.084	0.096	0.608	0.638
Unsheltered	0.097	0.109	0.074	0.081	0.132	0.152	0.040	0.042
Other GQ								
Non-Jail and Prison	0.057	0.063	0.069	0.075	0.037	0.044	0.089	0.092
Jail and Prison	0.030	0.034	0.018	0.020	0.048	0.056	0.000	0.000
Housed	0.261	0.283	0.232	0.246	0.305	0.341	0.188	0.194
	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Status unknown	0.273	0.203	0.194	0.133	0.394	0.311	0.075	0.034
Total	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Sources: 2010 Census, 2004-2014 Los Angeles HMIS datasets, 2004-2015 Houston HMIS datasets.
Note: Table indicates weighted counts in Census statuses, calculated as the sum of weighted totals from Los Angeles and Houston HMIS datasets. Columns (2) indicate bounds on the sum of Houston and L.A. weighted totals under Refinement 2. Columns (3) indicate bounds on the the difference between (1) and (2). Columns (4) scales down the weighted total from (2) by one minus estimated share counted erroneously in an HMIS shelter (share in jail or prison in Columns (2) times the inverse of the share in jail or prison in Columns (3)), and then distributes these deletions according to the distribution of statuses in Columns (3).

CHAPTER 3

HOMELESSNESS AND THE PERSISTENCE OF DEPRIVATION: INCOME, EMPLOYMENT, AND SAFETY NET PARTICIPATION

Abstract

Homelessness is arguably the most extreme hardship associated with poverty in the United States, yet people experiencing homelessness are excluded from official poverty statistics and much of the extreme poverty literature. This paper provides the most detailed and accurate portrait to date of the level and persistence of material disadvantage faced by this population, including the first national estimates of income, employment, and safety net participation based on administrative data. Starting from the first large and nationally representative sample of adults recorded as sheltered and unsheltered homeless taken from the 2010 Census, we link restricted-use longitudinal tax records and administrative data on the Supplemental Nutrition Assistance Program (SNAP), Medicare, Medicaid, Disability Insurance (DI), Supplemental Security Income (SSI), veterans' benefits, housing assistance, and mortality. Nearly half of these adults had formal employment in the year they were observed as homeless, and nearly all either worked or were reached by at least one safety net program. Nevertheless, their incomes remained low for the decade surrounding an observed period of homelessness, suggesting that homelessness tends to arise in the context of long-term, severe deprivation rather than large and sudden losses of income. People appear to experience homelessness because they are very poor despite being connected to the labor market and safety net, with low permanent incomes leaving them vulnerable to the loss of housing when met with even modest disruptions to life circumstances.[1]

1. This essay is joint work with Bruce D. Meyer, Gillian Meyer, Alexa Grunwaldt, and Derek Wu.

3.1 Introduction

Homelessness is an inordinately severe hardship. A long history of qualitative research and abundant anecdotal evidence suggest that people will go to great lengths to avoid becoming homeless when confronted with an unfortunate turn of events like a job loss, health crisis, eviction, or relationship dispute, leaving only those with the fewest resources – those without savings or credit to procure temporary lodging, those without the possibility of emergency assistance from friends and family, those with health challenges or addictions that impair decision-making and tax their psychological reserves – to end up sleeping on the streets or in a homeless shelter. As Peter Rossi (1989) wrote in his seminal work Down and Out in America: The Origins of Homelessness, homelessness is "the most aggravated state of a more prevalent problem, extreme poverty" (p.8).

Yet while the association between homelessness and severe economic disadvantage is apparent in a general sense, obtaining a detailed and accurate picture of the material circumstances of people who have experienced this hardship in the United States is challenging. Without a fixed address, these individuals are largely excluded from the household surveys that typically inform our understanding of poverty and well-being, and they have consequently been understudied in the extreme poverty literature. The most recent national survey to examine income and program receipt for people experiencing homelessness, the National Survey of Homeless Assistance Providers and Clients (NSHAPC), dates back nearly three decades to 1996 (Burt 2001). Recent studies linking homeless shelter microdata and administrative employment records offer important insights but are limited to a handful of cities and a single income source, earnings (Metraux et al. 2018; von Wachter et al. 2020). Numerous ethnographic studies and geographically narrow surveys offer nuanced and detailed information on the material circumstances of the individuals they represent, but their results may not generalize, and they typically lack longitudinal information. Such studies also rely on self-reported information that even when obtained from rigorously tested surveys of the housed have been shown to be substantially biased (Meyer et al. 2015; Meyer and Mittag 2019; 2021).

Understanding the income, employment, and safety net participation of people who have experienced homelessness is crucial for the design and targeting of policy interventions. Such knowledge can, for example, suggest the degree of income-related deprivation that puts someone at risk of homelessness, which can in turn improve the targeting of prevention efforts, shed light on the size of the at-risk population, and inform the scale of interventions needed to significantly reduce aggregate homelessness. Understanding the persistence or transience of deprivation can also direct policymakers towards the most appropriate prevention strategies, which might consist of measures aimed at raising permanent incomes, reducing housing costs, or mitigating income volatility.

This paper advances our understanding of the conditions in which homelessness arises by providing the most detailed and accurate portrait to date of income, employment, and safety net participation for a cross-section of the U.S. homeless population. Our main sample consists of 139,000 adults who were recorded as homeless in the 2010 Census, of which 89,500 were residing in homeless shelters and 49,500 were living in unsheltered situations. These data provide by far the largest and most representative samples ever used to study these questions, particularly for unsheltered homeless individuals, a group that has never before been linked to administrative data beyond a handful of localized studies with small convenience samples and limited outcome measures. We link these individuals to administrative tax and program records to provide the first national calculations of formal employment, income, and safety net participation in this population and compare these outcomes to a demographically similar sample of people who were poor but conventionally housed. We examine differences by sheltered status, race, gender, family status, Hispanic ethnicity, and geography and demonstrate the robustness of our findings to alternative linkage methods and data sources, including samples drawn from several cities' Homeless Management Information System (HMIS) shelter-use databases and nationally representative samples of those in homeless shelters from the American Community Survey (ACS).

Our approach benefits not only from large samples that are designed to represent national homelessness patterns, including people living in unsheltered situations, but also from a wealth of accurate income and safety net information from administrative records. Using confidential personal identification keys, we link individuals experiencing homelessness to Internal Revenue Service (IRS) microdata on taxable income and employment from Forms 1040, W-2s, and 1099-Rs, as well as data on numerous state and federal safety net programs, including the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps), Medicaid, Medicare, Temporary Assistance for Needy Families (TANF), General Assistance (GA), Supplemental Security Income (SSI), Social Security Disability Insurance (DI), rental assistance from the Department of Housing and Urban Development (HUD), and service-connected disability payments from the Department of Veterans Affairs (VA). We account for mortality in our analyses using Social Security Administration (SSA) records of death dates.

We learn that people experiencing homelessness are surprisingly well-connected to formal employment and the safety net, in contrast to earlier years' depictions of a population "unconnected to the world of work" with "no safety net of entitlements" (Rossi 1989, p.9). Nearly all sheltered homeless adults in our sample (97 percent) and the vast majority of unsheltered homeless adults (93 percent) were formally employed or enrolled in at least one safety net program in 2010, the year they were observed as homeless. A substantial share of these individuals were drawn from the ranks of the working poor: about half of those in shelters and 40 percent of those at unsheltered locations had formal employment in 2010, albeit with low median annual earnings (about $8,300) suggesting low-wage, sporadic work. SNAP enrollment was especially high, with about 77 percent of all adults in our sample enrolled in this program in 2010. These employment and program receipt rates understate true rates as we lack information on informal work and rely on incomplete program records. Connections to formal work and the safety net coexisted with deep poverty for this population, however. The median value of our most comprehensive resource measure, which adds to cash income the value of in-kind transfers from SNAP and HUD, was $7,500 for those in shelters and $5,500 for those in unsheltered living situations in 2010. Our findings are qualitatively similar across sub-populations defined by demographic characteristics and geography, although patterns by gender and race may hold clues into differences in the predominant pathways to homelessness between groups. Taken together, these findings suggest that people experience homelessness not because they are estranged from formal income and programs, but because they are very poor despite being highly connected to work and the safety net.

Turning to longitudinal patterns, our calculations reveal persistent, severe deprivation, with incomes remaining low for the decade surrounding an observed period of homelessness. Median annual income, including in-kind transfers, never exceeded $10,000 in the sheltered homeless sample and $8,000 in the unsheltered homeless sample in the decade surrounding 2010. We observe only a small dip in employment and earnings relative to the long-term trend preceding an observed period of homelessness, suggesting that large shocks to employment and earnings are not the predominant precipitating event for most spells of homelessness. Reliance on the safety net was also persistently high over the ten years of our study, although receipt of SNAP and TANF/GA – benefits typically understood to be temporary – peaked in the year observed as homeless, perhaps due in part to service providers' and homeless shelters' efforts to facilitate enrollment in these programs. We see a long-term pattern of declining employment that is accompanied by increasing enrollment in disability programs, with receipt of SSI or DI increasing from 19 to 34 percent for the sheltered homeless and 29 to 40 percent for the unsheltered homeless between 2010 and 2016. These longitudinal patterns suggest that homelessness tends to arise in the context of severe long-term deprivation, alongside steadily declining employment and increasing disability assistance receipt, rather than large shocks to income.

The absence of major disruptions to long-term trends surrounding an observed period of homelessness is even more striking because a large body of prior work suggests that most spells of homelessness are short, meaning that most people in our sample were likely conventionally housed for much of the study period (HUD 2010, Lee et al. 2010). Our findings are therefore informative not just about material circumstances during a period of homelessness, but also about the long-term conditions faced by the exceptionally disadvantaged and housing insecure segment of the U.S. population that is vulnerable to literal homelessness. The work of Meyer et al. (2023b), which links this same Census homeless sample to administrative mortality records, further underscores the extent to which time spent homeless is not an aberration in long-term trajectories. These individuals face nearly four times the mortality risk of a housed person with the same characteristics over that study's twelve-year period, with no discernable jump in the years immediately following an observed period of homelessness. Put differently, we learn that people who experience homelessness are enduring not just an exceptionally difficult year, but an exceptionally difficult decade – and perhaps in many cases, an exceptionally difficult life.

Our analyses also reveal important similarities between the material circumstances of people recorded in homeless shelters during the Census and housed individuals in poverty who share their demographic profile. This poor housed comparison group consists of unmarried individuals who we weight to have the same characteristics as the homeless, a group that is predominantly male, between the ages of 40 and 59, and disproportionately Black relative to the overall population. These individuals had a median income, including the value of in-kind transfers, of about $9,900 in 2010, compared to the median of $7,500 among those who were in homeless shelters during the Census. By some measures, the housed poor appeared to be somewhat more deprived than sheltered homeless individuals: they were slightly less likely to be employed in 2005 through 2010 and slightly more likely to receive SSI in 2010. These results underscore the dire economic circumstances faced by this segment of the housed poor population, a group that tends to be neglected in policy discussions on poverty relative to single mothers and children. In this way, our paper complements the Meyer et al. (2021) work on extreme poverty in the U.S., which finds that after accounting for misreporting of income and program receipt in surveys, the only households who cannot be ruled out as being extremely poor are those consisting of a single, childless adults. Our findings suggest that this overlooked segment of the population, which appears to be exceptionally vulnerable to homelessness and likely other severe hardships as well, may merit more attention in national discussions of poverty alleviation.

At the same time, we caution that similarities in formal income and program receipt between the housed poor and Census homeless do not necessarily imply a similar degree of disadvantage in these groups. Homelessness itself is detrimental to well-being, and the fact of having experienced homelessness likely indicates – either through causation or correlation – exceptional disadvantage in other areas of life. Indeed, sheltered homeless individuals surveyed in the ACS indicate substantially elevated rates of functional limitations relative to the housed poor, and Meyer et al. (2023b) find that the Census homeless face about seventy percent greater mortality risk than a poor housed person of the same age and gender, with this disparity persisting well past an observed period of homelessness (Meyer et al. 2021, Meyer et al. 2023b).

Our findings help explain several patterns that have emerged in the recent literature on homelessness prevention. For example, a growing number of experimental and quasi-experimental studies find that providing small emergency payments to people at risk of losing housing, often on the order of one month's rent or less, can significantly reduce their probability of entering a shelter (Rolston et al. 2013; Evans et al. 2016; Phillips and Sullivan 2023). The effectiveness of small-scale emergency payments accords with our finding that homelessness tends to arise in the context of persistent, severe deprivation rather than major disruptions to income: just as a small loss of resources may be enough to trigger a spell of homelessness for those with the most precarious circumstances, a small boost to income may be enough to prevent it. Yet our results also underscore the likely continued vulnerability to homelessness of those who receive small, one-time payments through such programs. Indeed, these prior studies have found that the effect of emergency financial assistance on shelter entry attenuates over time, suggesting that some of the people for whom a spell of homelessness was initially averted eventually end up homeless – an outcome that is consistent with the persistently low incomes documented in this paper. A small emergency payment may be enough to prevent a singular instance of homelessness but may not make a dent in the long-term deprivation that leaves people vulnerable to the loss of housing.

Our findings are also consistent with prior work indicating the exceptional difficulty of predicting who will become homeless and targeting prevention efforts towards them. Indeed, while recent literature finds that emergency payments reduce the risk of homelessness, these studies also find that the vast majority of those who do not receive payments also do not end up entering a homeless shelter. Other theoretical and empirical work has similarly emphasized the difficulty of predicting homelessness (O'Flaherty 2011; Shinn et al. 2013; von Wachter et al. 2021). Difficulties in predicting homelessness and targeting prevention resources are consistent with our finding of substantial overlap between the economic circumstances of people in homeless shelters and the housed poor who share their demographic profile. Even detailed and accurate information about someone's long-term trajectory of income and safety net participation is unlikely to yield strong predictors of homelessness because of the substantial overlap in the material circumstances of those who do and do not become homeless.

We probe the strength of the evidence for our main findings through a series of extensions and robustness checks. These additional analyses not only demonstrate the robustness of our main findings to different data sources and methodological approaches, but also give us confidence our that our results are representative of people experiencing literal homelessness in the United States, including people living in unsheltered living situations. We first examine misreporting in the ACS's homeless samples by comparing survey-reported measures of demographic characteristics, income, and safety net participation to values from linked administrative data. We find that, as with surveys of people who are housed, surveys of people experiencing homelessness are subject to considerable misreporting and benefit from the improved accuracy offered by administrative data. We then demonstrate the robustness of key findings to alternative time-based sampling approaches, data sources, and years. First, we use HMIS data, which indicate dates of shelter enrollment and exit, to compare key results based on cross-sectional samples (as in our main Census results) to samples of people whose first recorded homeless shelter enrollment in the history of the HMIS data occurred during a focal year (allowing for a substantial look-back period, a widely used approach in the literature). The former samples contain a larger share of people with extended and repeated spells of shelter enrollment than the latter samples, which are weighted more towards people with short spells. We find a striking degree of similarity in the levels and longitudinal patterns of employment, earnings, and benefit receipt between these two sampling approaches, which in turn suggest that our main, Census-based results would change little even under a hypothetical alternative sampling approach that gave more weight to people with short spells of homelessness or if we examined income and program receipt relative to an individual's first shelter enrollment. We next check the robustness of key findings to different data sources and years by comparing results based on those recorded as homeless in the Census to results based on those enrolled in HMIS shelters and those surveyed in homeless shelters in the ACS. We find our results are once again largely robust to the use of different data sources and years, although we note the potential for some differences between the Census and HMIS data that appear to stem from differences in the way these sources define a homeless shelter. The final set of analyses compare our main findings to alternative Census samples designed to address potential bias from non-linkage, misclassification, and the incomplete geographic coverage of our SNAP datasets, which could result in bias due to migration.

The analyses in this paper shed new light on a highly disadvantaged segment of the U.S. population, those for whom extreme poverty means vulnerability to homelessness when met with even modest disruptions to their life circumstances. The rest of the paper proceeds as follows. Section 3.2 discusses related prior work, Section 3.3 describes our data, and Section 3.4 describes our methodology, including a discussion of how we define homelessness and link datasets. Section 3.5 presents our main results, as well as analyses of heterogeneity by demographic characteristics and geography and Section 3.6 presents extensions and robustness checks, including an analysis of demographic and income misreporting in household surveys and calculations of key outcomes using alternative data sources, sample definitions, and linkage methods. Section 3.7 compares our findings to prior work and Section 3.8 concludes.

3.2 Connections to Prior Work

Concerted efforts to learn about the income, employment, and safety net participation of people experiencing homelessness in the U.S. began in the 1980s, when an alarming and highly visible rise in homelessness drew renewed attention from researchers and the broader public. Rossi (1989) reviewed this early literature in his seminal ethnographic work, with an emphasis on his own surveys of Chicago's homeless population, which were innovative in their efforts to obtain representative samples. These early studies depicted an extremely deprived and disconnected population, heavily reliant on donations of meals and clothing and informal income from activities like panhandling and peddling. Rossi's surveys found that just one in four homeless Chicagoans received food stamps and that one in three had been employed in the previous month. Interviewees reported mean monthly income equivalent to about \$375 in 2018 dollars, or \$4,500 in a year.

The 1996 National Survey of Homeless Assistance Providers and Clients (NSHAPC) built on this early work to provide the first – and, until the present study, the only – estimates of the income, employment, and safety net participation using a sample designed to be nationally representative (Burt 1989; Burt et al. 1999). The NSHAPC, which was carried out by the Census Bureau on behalf of numerous federal agencies, collected detailed information from 4,200 users of homeless services around the country to learn about their characteristics, material well-being, health, and life circumstances. This survey painted a picture of severe deprivation in the U.S. homeless population that was somewhat less grim than Rossi's. Survey respondents reported average monthly income of $590 in 2018 dollars, corresponding to annual income of $7,080, slightly less than half of the corresponding federal poverty threshold for a single individual. Forty-four percent reported having worked in the previous month, and 37 percent said they received food stamps. NSHAPC also estimated the receipt of SSI (11 percent), Medicaid (30 percent), and General Assistance (GA) plus Aid to Dependent Families with Children (AFDC, the precursor to TANF) (19 percent). Taken together, about 40 percent of those experiencing homelessness received at least one benefit according to this survey.

While NSHAPC remains the most recent national survey of the U.S. homeless population, two studies have since revisited the question of employment among people experiencing homelessness using administrative data by linking individuals from Homeless Management Information System (HMIS) databases to data on employment and earnings (Metraux et al. 2018, von Wachter et al. 2020). Linked administrative data permit longitudinal analyses and provide more accurate information on employment and earnings, which are frequently misreported in surveys and perhaps especially so for those experiencing homelessness, as we show in Section 3.6.

These two studies suggest lower employment than NSHAPC, even more so as their estimates are for any employment over a year, which would mechanically tend to be higher than NSHAPC's monthly estimate. They also offer some evidence of disruptions to employment and earnings preceding homelessness. Metraux et al. (2018) find that about 42 percent of adults in New York City homeless shelters received wage income in the year they first enrolled in a shelter, a drop of about 6 percentage points relative to average employment rates over the preceding decade. They also observe an average $3,000 drop in mean earnings conditional on working relative to the preceding decade. Von Wachter et al. (2020) estimate that just 29 percent of Los Angeles shelter users were employed in the year before shelter enrollment, although this share may be biased towards zero because it is based only on California state earnings records. They observe very little drop in employment in the year preceding the first shelter enrollment in the full sample, although mean earnings do fall among those who work. While these studies produced new insights into the level and longitudinal patterns of employment in this population, their findings are limited to homeless shelter users New York or Los Angeles and may not generalize nationally or to those experiencing unsheltered homelessness. Moreover, these studies examine just one income source, earnings, and therefore provide a limited view of individuals' financial resources.

In this paper, we advance this literature by providing the most comprehensive, accurate, and detailed calculation of the income, employment, and safety net participation for the U.S. homeless population to date. We build upon prior work by using national samples of the homeless population, including those residing at unsheltered locations, and linking these individuals to administrative records that encompass a more comprehensive set of income sources. Administrative data allow us to obtain more detailed and accurate information on income and safety net receipt than in the NSHAPC and other surveys and permit longitudinal analyses. In Section 3.7, we compare our results in detail to the studies described in this section and discuss how our findings advance and revise our understanding of the level and persistence of deprivation faced by those experiencing homelessness in the United States.

3.3 Data

3.3.1 2010 Census Data on the U.S. Homeless Population

Our main analysis sample consists of people who were recorded as experiencing sheltered or unsheltered homelessness during the 2010 Census. The Census collected information on this population through its Service-Based Enumeration (SBE) operation on March 29-31, 2010. SBE enumerators interviewed people in homeless shelters, users of soup kitchens and mobile food vans, and people spending the night at pre-identified outdoor locations known as targeted non-sheltered outdoor locations (TNSOLs), such as vehicle and tent encampments.[2] People using soup kitchens and food vans were only included in the unsheltered homeless count if they did not indicate a valid residential or shelter address. The Census homeless sample therefore consists of a cross-section people who were experiencing literal homelessness in early 2010 – i.e., people residing in homeless shelters and those with a primary nighttime residence not meant for human habitation. In Section 3.4, we discuss the merits of this definition of homelessness relative to other definitions, for example those that include people who are "doubling up" or involuntarily sharing housing.

The Census built its list of service providers and outdoor locations for the SBE through a series of research and validation operations, including internet research, queries to local government officials, advocacy organizations, and other local partners, and numerous advance visit and validation operations (Russell and Barrett 2013). Enumerators across the country received several days of uniform training that included a sensitivity component to teach them how to approach people experiencing homelessness and how to work with people suffering from psychological health concerns. At many locations, the Census engaged local "culture facilitators" to aid in interviewing people experiencing unsheltered homelessness.

2. The SBE did not include people residing in domestic violence shelters. These individuals were included in the Census through a different counting operation and are not identified even in restricted-use data due to privacy concerns, so we do not include them in our study.

Enumerators were instructed to collect names and dates of birth from all interviewees, but in practice many individuals were enumerated by sight without providing this personal information because they were asleep or because interviews were not feasible at bustling of service locations. We discuss the implications of such nonresponse and our methods of accounting for the resulting non-linkage in Section 3.4.

Meyer et al. (2023a) established the broad coverage and reliability of the 2010 Census as a source of data on the U.S. homeless population, estimating that more than 90 percent of people residing in homeless shelters (as these facilities are defined by HUD) were included in its count. However, these individuals were at times classified as residing in housing or other types of congregate facilities due largely to ambiguities in the definition of a homeless shelter.[3] The completeness of the Census's unsheltered count is less certain, but the similarity of unsheltered estimates between the Census and HUD's point-in-time (PIT) count – despite substantial differences in the sources' methodologies – suggests that the Census covered this population reasonably well.

3.3.2 American Community Survey (ACS) Data on the Sheltered Homeless

We use additional data on those experiencing sheltered homelessness from the ACS to test the robustness of our findings to different samples, linkage methods, and years. The ACS interviews about 2,500 to 3,500 people in homeless shelters each year but excludes people experiencing unsheltered homelessness. Its shelter list is based on the most recent Census, with limited updates during the intercensal period. Unlike the Census, which collects only basic demographic characteristics, the ACS collects a wealth of information about shelter users' characteristics, geographic mobility, physical and cognitive difficulties, and self-reported income and program receipt. Meyer et al. (2021) provide a detailed description of these

3. We test the robustness of our findings to differences between the Census and PIT definitions of a homeless shelter in Section 3.6 by comparing results based on Census sheltered homeless in Los Angeles and Houston to those based on HMIS sheltered homeless samples in these cities, with the definition of a homeless shelter in these latter sources aligning closely with HUD's definition.

characteristics for sheltered homeless individuals interviewed in the 2006-2018 ACS. Despite offering large, nationally representative samples of the sheltered homeless population, the ACS has been largely unused to study this population in the past because shelter users are not identified in public-use versions of the data.

3.3.3 Homeless Management Information System (HMIS) Data

In addition to the Census and ACS, we obtain administrative data on people experiencing sheltered homelessness from Homeless Management Information System (HMIS) databases from Los Angeles (2004-2014), Houston (2004-2015), and Chicago (2014-2019). These databases contain individual records of homeless shelter entries and exits covering a large share of these cities' sheltered homeless populations. All federally funded shelters are required to track clients' program use in HMIS and many others elect to do so.

Although HMIS data are limited geographically, they allow us to examine heterogeneity across subsets of this population and to check the robustness of our results to alternative sampling schemes. Unlike the Census and ACS, the HMIS data group individuals into family units and can thus be used to examine differences in key outcomes by family type that is often emphasized in the literature. Moreover, HMIS-recorded shelter entry and exit dates permit analyses of income and program receipt relative to an individual's first observed shelter enrollment. This feature allows us to compare results based on different temporal conceptions of the homeless population (e.g., those who were homeless at a point in time versus those with a first shelter enrollment during a period). Finally, because shelter administrators record the Social Security Numbers (SSNs) of clients in HMIS databases, these microdata can be assigned linkage keys at higher rates than the Census and ACS, which rely only on name, date of birth, gender, and geographic location to assign linkage keys. We leverage these high linkage rates to examine whether incomplete linkage leads to bias in the results based on Census and ACS samples (Section 3.6).

3.3.4 Administrative Records on Incomes and Program Receipt

We link homeless individuals from the Census, ACS, and HMIS to an extensive collection of administrative records on formal income, employment, and safety net participation from federal and state agencies. We obtain information on taxable sources of money income from Internal Revenue Service (IRS) Forms 1040, W-2, and 1099-R.[4] These records track the universe of formal employment (specifically wages) in the entire United States, with Form 1040 providing information for people who file taxes and Form W-2 adding wage amounts for those who do not. We have further information on retirement distributions from Form 1099-R. We obtain information on food assistance from five states' Supplemental Nutrition Assistance Program (SNAP) enrollment records and on cash assistance from New York State's Temporary Assistance for Needy Families (TANF)/General Assistance (GA) enrollment records.[5] We obtain national administrative data on housing assistance from the Department of Housing and Urban Development (HUD)'s Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification System (TRACS) files, which cover nearly all public and subsidized housing assistance programs under this agency's jurisdiction. We utilize Medicare and Medicaid enrollment records from the Centers for Medicare and Medicaid Services (CMS). We also obtain data on three sources of disability benefits: the Veterans Benefit Administration's USVETS data on service-connected disability compensation, a universe file on receipt of Supplemental Security Income (SSI), and an indicator for Disability Insurance (DI) receipt in Medicare records. Finally, we obtain birth and death dates from the Social Security Administration (SSA)'s Numident file to account for mortality when calculating income and program receipt.

These datasets cover most formal sources of income and the most important means-tested safety net programs in the United States. Formal income sources not covered by these data

4. IRS 1040 records are available for 2003-2016, W2s for 2005-2016, and 1099-Rs for 2003-2016.

5. The states and years for which we have SNAP data are the following: Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016).

include DI amounts, Unemployment Insurance (UI) among people who do not file 1040s, and workers' compensation. We also emphasize that our data are limited to formal income and do not include income from informal employment or private transfers. Information earnings and transfers from family, friends, and private charity – which could consist of cash assistance or in-kind transfers via housing, food, clothing, or other goods – are undoubtedly important for many people experiencing homelessness but are outside the scope of the present analysis.

3.4 Methods

3.4.1 Defining Homelessness

The Census homeless sample consists of people experiencing what HUD defines as "literal homelessness." People are literally homeless if they have "a primary nighttime residence that is a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings" or if they are living in "a supervised publicly or privately operated shelter designated to provide temporary living arrangements" (HUD 2022).[6] As documented in Meyer et al. (2023a), the Census definition of a homeless shelter differs in several straightforward ways from HUD's definition, with the latter including people in domestic violence shelters, those in hotel and motel beds funded by homeless service providers, and people sleeping in non-shelter facilities with temporary homeless accommodations. The Census also appears to have classified some HUD-designated shelters, particularly those where individuals can reside for extended periods of time, such as transitional housing, as conventional housing or other types of congregate facilities rather than homeless shelters. In Section 3.6, we test the robustness of our findings to HUD's broader definition of a homeless shelter by comparing results based on the Census's homeless population to those residing in HMIS

6. For programmatic purposes, HUD also classifies among the "literally homeless" people exiting certain institutions, such as prisons and hospitals, where they have resided for 90 days if they were residing in a homeless shelter or at unsheltered locations immediately before entering the institution. Our definition does not include such individuals.

shelters, which follow the HUD definition.

Literal homelessness does not include people residing in low-quality or shared housing or with tenuous attachment to their current residence. While such living arrangements reflect housing-related hardship in many cases and may indicate heightened risk of homelessness, we limit our attention in this paper to those experiencing literal homelessness for several reasons. First, literal homelessness typically indicates a degree of housing-related hardship that exceeds that associated with precarious or shared housing, as evidenced by individuals' revealed preference for such accommodations over literal homelessness. Moreover, it is not clear that shared housing reflects hardship in most cases, as is well-documented in the household formation literature (e.g., Browning et al. 2014). Furthermore, the data requirements needed to identify those individuals for whom shared or low-quality housing represents hardship as extreme as literal homelessness far exceed the information available in household surveys and administrative data. Meyer et al. (2023a) provide further discussion of the merits and data limitations associated with different definitions of homelessness.

3.4.2 Constructing Homeless and Housed Comparison Samples

We limit our samples to people who were between the ages of 25 and 59 in 2010 and keep only those assigned an anonymized unique identifier by the Census Bureau's linkage software. Our primary homeless samples consist of 89,500 linked individuals who were residing in homeless shelters during the Census (the sheltered homeless) and 49,500 linked individuals who were counted at soup kitchens, food vans, or overnight at outdoor locations and indicated no valid usual address elsewhere (the unsheltered homeless). We also calculate key outcomes for two comparison groups of housed adults drawn from the first six months of the 2010 ACS.[7] Our main comparison sample consists of 55,000 housed, unmarried individuals with self-reported incomes below the federal poverty threshold. To permit more direct comparisons, we reweight

7. The timing was chosen to be as synchronous as possible with the Census operations counting and interviewing the homeless at the end of March 2010.

these individuals' demographic characteristics to match those of the pooled sheltered and unsheltered homeless sample. We also calculate key outcomes for the 994,000-person ACS sample of housed individuals surveyed during the first six months of the 2010.[8]

3.4.3 Linking Across Datasets

We link datasets at the individual level using Protected Identification Keys (PIKs), unique anonymized identifiers assigned by the Census Bureau's Personal Identification Verification System (PVS). This software assigns linkage keys by matching the personal information provided to Census enumerators – including name, date of birth, and gender – against a reference file based on Social Security Administration (SSA) records and enhanced with address information from other administrative records (Wagner and Layne 2014). In the restricted 2010 Census microdata, this software assigned a linkage key to 69 percent of people in homeless shelters, 42 percent of those counted at food vans and soup kitchens, and 17 percent of those counted at targeted non-sheltered outdoor locations (TNSOLs). According to the Census's official SBE assessment report, item nonresponse was the proximate reason for most of this non-linkage (Russell and Barrett 2013). Such non-response was highest at TNSOLs, where about 56 percent of records contained incomplete names and 49 percent lacked year of birth, followed by soup kitchens and food vans (27 and 25 percent, respectively) and shelters (15 and 10 percent, respectively). Item nonresponse was especially high at TNSOLs because canvassing operations took place overnight and enumerators were instructed not to wake or disturb people who were asleep or covered up to collect information from them. Similarly, many people were also enumerated by sight at bustling soup kitchens or food vans. Linkage rates were highest at shelters, on the other hand, because in many cases enumerators were able to use administrative records to obtain complete information about the people staying

8. For analyses using SNAP and TANF/GA data, we restrict our sample to people residing in states for which these administrative data are available (only New York state in the case of TANF/GA). We examine the potential bias from migration due to the limited geographic coverage of SNAP datasets in Section 3.6.

there.

Incomplete linkage would lead to bias in our results if the outcomes of unlinked individuals differed systematically from linked individuals. We address this concern by applying inverse probability weights (IPWs) to linked individuals, where weights are obtained by estimating a probit model of linkage status as a function of age, race, gender, Hispanic origin, state, and homeless location type.[9] The key assumption for this IPW adjustment to eliminate bias from non-linkage is that outcomes are uncorrelated with linkage status conditional on the characteristics included in the IPW model. This assumption would be violated if, for example, unlinked individuals with a given set of characteristics had lower incomes or fewer connections to the safety net than linked individuals with those same characteristics. We assess the potential for such bias through a series of checks in Section 3.6, including comparisons of key results using Census data and the HMIS and ACS samples. Comparisons of Census to HMIS data are informative because the latter include social security numbers and hence have very high linkage rates (more than 90 percent in most years). Comparisons of Census to ACS data are informative because the latter contain a much richer set of covariates for the linkage probability model, including self-reported measures of the income and program receipt outcomes of interest. As described in-depth in Section 3.6, these comparisons attenuate concerns about bias from non-linkage and bolster our confidence in the representativeness of results based on the IPW-adjusted Census samples.

3.5 Results

This section contains our main results. We start with summary statistics for our homeless samples and comparison groups, before showing how employment, income, and program participation evolved in the years preceding and following an observed period of homelessness

9. Given exceptionally low linkage rates at TNSOLs, we exclude people recorded at these locations from our main results, although we show in Section 3.6 that our findings are robust to their inclusion.

during the 2010 Census.[10] We next discuss comparisons of key outcomes between those who are homeless and the demographically comparable sample of the single housed poor population. The last set of results describes differences among the homeless and comparison groups by gender and family status, race and ethnicity, and geography and discusses possible reasons for these differences.

3.5.1 Characteristics of the Homeless and Housed Comparisons Samples

Table 3.1 presents descriptive statistics for the Census homeless samples and ACS housed comparison groups used in our main analyses. Relative to housed adults (Column 4), sheltered (Column 1) and unsheltered (Column 2) homeless individuals are much more likely to be male (67 and 74 percent, respectively, compared to 49 percent of the overall housed) and much more likely to be Black (40 and 38 percent, compared to 13 percent). They are similarly likely to be Hispanic (14 and 15 percent, compared to 15 percent) and are slightly older (43.5 and 44.4 years old, on average, compared to 42.4), conditional on being between the ages of 25-59 in 2010.

As noted in Section 3.4, we reweight the single housed poor sample to match exactly the distribution of demographic characteristics in the pooled sheltered and unsheltered homeless samples. The characteristics of the single housed poor indicated in Column 3 are therefore equal to a weighted average of the characteristics in Columns 1 and 2 by construction. This reweighting ensures that any subsequent comparisons are not confounded by demographic differences between those experiencing homelessness and single poor housed individuals. Such comparisons should be interpreted as between those experiencing homelessness and a demographically comparable segment of the poor population, i.e., a segment that is unmarried and more likely to be male, Black, and in their 40s and 50s than the typical single

10. We inflation-adjust all amounts to 2018 dollars using the Chained Consumer Price Index for All Urban Consumers (C-CPI-U) and report individual income and program receipt at the annual level. The notes in Appendix A.2 contain detailed information about the definitions and methodology underlying income and program receipt measures.

housed person living in poverty in the United States.

3.5.2 Employment, Income, and Safety Net Participation in the Year Observed as Homeless

We begin by summarizing levels of employment, safety net participation, and material deprivation in the year individuals were observed as homeless, before turning to a discussion of longitudinal patterns of income, employment and earnings, disability program receipt, and receipt of other benefits in the years preceding and following an observed period of homelessness. Key results are indicated in Tables 3.2 and 3.3.[11]

Connections to Formal Employment and the Safety Net

Figure 3.1 displays the share of the Census homeless population and single housed poor comparison group receiving various benefits and earnings in 2010.[12] We find that homeless individuals are highly connected to formal employment and the safety net, with 97 percent of those in shelters and 93 percent of those at unsheltered locations receiving at least one government benefit and/or having been formally employed in 2010. The vast majority received at least one safety net benefit (89 percent of the sheltered and 80 percent of the unsheltered), and about 52 percent of sheltered homeless individuals and 40 percent of unsheltered

11. Detailed additional results are available in the Appendix.

12. The lack of a residential mailing address can create complications in applying for benefits, satisfying recertification requirements, and receiving regular payments, but people experiencing homelessness address these barriers in various ways. Some homeless shelters, churches, and social service sites offer mail service to people experiencing homelessness, and many individuals receive mail at the address of friends or family. Moreover, most benefits are provided through direct deposit to a bank account or Electronic Benefit Transfer (EBT) card, circumventing the need for a mailed check (IOM and NRC 2013; SSA 2024). In some instances, the eligibility criteria for programs are less onerous for people experiencing homelessness. For example, under federal SNAP regulations (7 CFR 273.2(f)(l)(vi)), homeless households are exempt from residency verification requirements and can use the address of an authorized representative, shelter, or SNAP local office as a place to receive mail from SNAP (USDA 2013). People experiencing homelessness are also exempt from work requirements and time limits that some states impose on able-bodied SNAP recipients without dependents.

homeless individuals had formal employment, albeit with low earnings (a median of $8,300 among workers) that suggest sporadic and/or part-time work at very low wages.[13]

Receipt of all non-disability benefits was higher among people experiencing sheltered rather than unsheltered homelessness, but this latter group was more likely to receive disability benefits from SSI or DI. About 83 percent of those in homeless shelters and 70 percent of those at unsheltered locations received SNAP in the year they were observed as homeless. About 45 and 41 percent of those experiencing sheltered and unsheltered homelessness, respectively, were enrolled in Medicaid, and TANF/GA receipt was 58 and 30 percent for these groups, respectively, in New York. A moderate share received disability benefits in 2010, with 14 and 21 percent of the sheltered and unsheltered homeless, respectively, received SSI, 9 and 14 percent received DI, and 3 and 2 percent received service-connected disability payments from the VA, respectively. A small share (10 percent of the sheltered and 9 percent of the unsheltered) received HUD housing assistance for at least some portion of 2010, although the mean months of receipt drop in 2010 relative to surrounding years, suggesting disruptions in housing benefit receipt that are consistent with having been homeless for some portion of that year.

Income and the Value of In-Kind Transfers

We also calculate the median and 75th percentile of our most comprehensive resource measure, money income plus in-kind transfers, for our homeless and 2010 housed comparison samples (Figure 3.2). This income measure includes most sources of taxable income reported on 1040s or in W-2s and 1099-Rs, as well as (non-taxable) cash transfers from SSI and VA payments and the value of in-kind transfers from SNAP and HUD. Despite the high degree of connection to employment and the safety net indicated in Figure 3.1, we find that people experiencing homelessness have extremely low incomes, indicating severe material de-

13. For comparison, a full year of work at the prevailing federal minimum wage of $7.25 corresponded to about $15,000 of annual earnings.

privation. The median value of income including in-kind transfers was about $5,500 for the unsheltered homeless and $7,500 for the sheltered homeless in 2010. These annual incomes fell well below the official poverty threshold of about $12,000 for a single-person household, despite including the value of in-kind transfers that are not included when calculating official poverty status.[14]

At the same time, we note that material deprivation would have been even more extreme in this population without certain safety net programs. For example, median income fell to about $750 for those in shelters and to $0 for the unsheltered homeless population when we excluded the value of transfers from SSI, SNAP, and housing assistance (Appendix A.2). The safety net appears to provide crucial assistance to many people experiencing homelessness.

Comparisons to the Single Housed Poor

Figures 3.1 and 3.2 also allow us to compare the material circumstances of those experiencing homelessness and single housed poor individuals who share their demographic profile. We find that single housed poor individuals were less connected to formal employment and the safety net, with just 89 percent employed and/or receiving at least one benefit in 2010, compared to 93 and 97 percent in the homeless samples. Among the single housed poor, the share with formal earnings (48 percent) fell between that of the sheltered homeless (52 percent) and unsheltered homeless samples (40 percent), with the median value of earnings conditional on working of about $12,200, compared to $8,300 among homeless individuals with formal employment.[15] W-2 records offer suggestive evidence of slightly elevated employment instability in the homeless population, with sheltered and unsheltered homeless

14. We reference the 2018 federal poverty threshold because we measure incomes in 2018 dollars. Although we compare income to the poverty threshold for a single individual, we note that some people in our samples, particularly those recorded in homeless shelters in the Census, were likely accompanied by children and would hence be subject to even higher poverty thresholds.

15. Although relatively small, differences in employment rates between the sheltered homeless and single housed poor samples are statistically significant and change sign after 2010, reflecting a more persistent decline in employment for the former group after that year.

workers both having an average of 1.6 distinct jobs (as proxied for by the number of W-2 forms) in 2009, compared to 1.4 among the single housed poor (Appendix A.2). The single housed poor were less likely to receive SNAP, TANF/GA, Medicaid, and VA disability benefits than those experiencing homelessness, but were more likely to receive housing assistance. They received DI at similar rates to unsheltered homeless individuals, and their receipt of SSI (16 percent) was between receipt rates for the sheltered homeless (14 percent) and unsheltered homeless samples (21 percent).

Turning to comparisons of the median and 75th percentiles of income including the value of in-kind transfers in Figure 3.2, we observe a striking degree of similarity between those experiencing homelessness and single housed poor individuals who share their demographic profile. The median single housed poor individual had about $9,900 in income after in-kind transfers in 2010, only $2,400 higher than the median sheltered homeless individual. There is also a substantial amount of overlap between these samples' income distributions. At least one-quarter of those experiencing homelessness had higher incomes than most single housed poor adults: the 75th percentiles of income for the unsheltered and sheltered homeless were about $14,300 and $15,100, respectively, compared to the median value of $9,900 for the single housed poor. In other words, those experiencing homelessness, particularly sheltered homelessness, look very much like single housed poor adults who share their demographic profile in terms of their incomes, employment, and safety net participation.

3.5.3 Longitudinal Patterns of Employment, Income, and Safety Net Participation

Persistence of Deprivation

Moving beyond static levels of deprivation, Figure 3.3 examines longitudinal patterns of median income including the value of in-kind transfers from SNAP and HUD between 2005 and 2016. The solid lines indicate the value of income from all sources except SSI, which we only incorporate starting in 2010 (as reflected in the dashed lines) when our administrative SSI records begin. This figure illustrates the stark persistence of material deprivation for this population, with incomes remaining very low over the four years prior to and six years after an observed period of homelessness. We find little evidence of major disruptions to income in the years leading up to 2010, a finding that contrasts with anecdotal narratives emphasizing major and abrupt deteriorations in material circumstances preceding homelessness. This figure illustrates our key finding that people experiencing homelessness appear to be enduring not just a difficult year or two, but rather a decade or more of exceptional material hardship.

Longitudinal Patterns of Earnings and Employment

We next turn to longitudinal patterns of employment (Figure 3.4) and median earnings among those who are employed (Figure 3.5) to examine the magnitude of disruptions to these outcomes relative to their long-term trend in the years preceding and following an observed period of homelessness.[16] All homeless and housed comparison groups see a pattern of declining employment between 2005 and 2016, consistent with aging, but the proportional decline in employment is greatest for the unsheltered homeless (39 percent), followed by the sheltered homeless (30 percent), single housed poor (20 percent), and the overall housed population (7 percent).

Because we condition on being observed as homeless or poor in early 2010, we might expect any loss of earnings that led to homelessness or poverty to appear in 2009 tax records. Indeed, we observe a drop in employment and earnings in 2009 for the homeless and single housed poor groups relative to their long-term trends, but the magnitude of the drops is small. Conditional on working, the earnings of sheltered homeless workers were about $1,500to$1,700

16. In addition to the single housed poor comparison group, this figure also includes a series for the overall housed population to help distinguish longitudinal patterns among the homeless and single housed poor from secular trends in employment for this age cohort during this period, which includes the Great Recession.

lower in 2009 relative to the two surrounding years, and for unsheltered homeless workers it was 500*to*1,000 lower. These disruptions are modest relative to the overall trend of declining employment between 2005 and 2016 and are similar in magnitude to the drop in earnings and employment observed among the single housed poor.

Longitudinal Patterns of Safety Net Participation

Disability program receipt increased for all three groups between 2010 and 2016, but the rate of increase was higher among those experiencing homelessness than in the single housed poor sample (Figures 3.6 and Figure 3.7). Between 2010 and 2016, SSI receipt increased from 14 to 23 percent for those in shelters, from 21 to 27 percent for those at unsheltered locations, and from 16 to 17 percent for the single housed poor. DI receipt increased from 9 to 17 percent, 15 to 19 percent, and 14 to 18 percent for these groups, respectively, over the same period. This pattern of accelerating disability program receipt following an observed period of homelessness, a novel finding in research on this population, merits additional exploration. Future work could examine, for example, whether this pattern indicates an association between the onset of disability and the onset of homelessness (with causality potentially running in both directions), or, alternatively, whether interactions with homeless service providers help connect people to disability programs for which they were already qualified. This latter hypothesis would be consistent with concerted efforts by the Social Security Administration (SSA) to increase access to SSI and DI among eligible people experiencing homelessness.

Figures 3.8 and 3.9 display longitudinal patterns in the receipt of other safety net programs among sheltered and unsheltered homeless individuals, respectively, between 2003 and 2016. Patterns differ across benefits, with receipt of SNAP and TANF/GA – benefits typically understood to be temporary – peaking in the year observed as homeless relative to surrounding years. These peaks occur for both the sheltered and unsheltered homeless but are more pronounced in the sheltered homeless population.[17] Medicaid receipt increases steadily through 2013 for both homeless groups, before increasing sharply in 2014 after many states expanded eligibility under the Affordable Care Act (ACA). Receipt of HUD housing benefits appears to dip slightly in 2009 for the sheltered homeless population before increasing through 2016, but the overall level of housing assistance receipt remains low (below 20 percent) for both groups over this entire period.

We find that people who were residing in homeless shelters during the 2010 Census have persistently higher rates of enrollment in non-disability safety net programs than those who were experiencing unsheltered homelessness, despite facing somewhat better material circumstances overall, as indicated by their higher incomes.[18] This pattern appears to reflect, at least in part, differences in family structure between these groups, because adults with accompanying children are more likely to reside in shelters than at unsheltered locations and also to qualify for safety net programs. Different rates of program receipt could also reflect selection into sheltered or unsheltered status related to one's underlying propensity to use services, as we might expect that people who elect to use shelters – essentially a safety net service – will be more likely to take up other safety net programs, as well.

In addition to demographic differences and selection, sheltered homeless individuals may have higher program receipt because shelters facilitate the enrollment in and continued receipt of safety net benefits. We investigate this potential explanation for shelter users' higher program receipt using HMIS data, which unlike the Census indicate precise dates of shelter entry and exit. Figure 3.10 displays monthly SNAP enrollment among Chicago HMIS users

17. Some of this peak is likely due to migration between states for which we do and do not have SNAP data, but our checks described in Section 3.6 suggest that most of the rise preceding 2010 and fall after 2010 reflect true changes in SNAP receipt.

18. The unsheltered homeless are more likely than the sheltered homeless to be enrolled in Medicare, but this is largely because eligibility for DI leads to eligibility for Medicare (in most cases after a two-year qualifying period).

relative to their first observed shelter entry.[19][20] SNAP enrollment remains steady at about 46 percent over the two years prior to shelter entry, with a slight (3 percentage point) increase in the three months preceding shelter enter. Receipt abruptly increases to nearly 60 percent in the month of first observed shelter entry, and then peaks at 63 percent in the third month after shelter entry before declining to about 51 percent after a year has passed. While not establishing a causal relationship, the jump in SNAP enrollment in the month of shelter entry is consistent with shelters facilitating SNAP enrollment for new clients, while conversely, the timing of the subsequent fall in SNAP receipt is consistent with people becoming disenrolled at the time of their six-month recertification. These findings suggest that work to establish a causal relationship between shelter entry (exit) and SNAP enrollment (disenrollment) could produce useful insights into the factors that facilitate and impede connections to the safety net among those experiencing homelessness.

3.5.4 Differences Across Demographic Groups and by Geography

Having discussed static and longitudinal patterns in economic conditions for the overall homeless population, we now turn to differences across policy-relevant sub-groups defined by gender and family status (i.e., the absence or presence of accompanying children), race and ethnicity, and geography (i.e., California, New York, and the rest of the U.S.).[21]

19. See Appendix A.2

20. People experiencing homelessness are eligible for SNAP even if they lack a permanent address or have limited documentation to prove residency. SNAP allow such individuals to use the address of a shelter or some other authorized representative to receive official correspondence, and funds are made available through Electronic Benefit Transfer (EBT) cards that are automatically refilled once a month (U.S. Department of Agriculture 2013).

21. See Appendix A.2

Family Status and Gender

We first examine differences in in longitudinal patterns of income and safety net participation by gender. In the year they were observed as homeless, women were more likely to be employed (Figure 3.11) and had higher average earnings conditional on working (Figure 3.12) than men with the same sheltered status. Longitudinal patterns also differed by gender, with men experiencing larger and apparently more persistent disruptions to employment and earnings surrounding an observed period of homelessness. Sheltered homeless women were also about 6 percentage points more likely to receive any benefit than sheltered homeless men in 2010, while unsheltered homeless women were 3 percentage points more likely to receive benefits than their unsheltered male counterparts.

One potential explanation for higher incomes and greater program receipt among homeless women relates to family status, a dimension of heterogeneity that is emphasized in much of the homelessness literature, including HUD's annual national reports on homelessness. Data from HUD's 2022 report suggested that about 40 percent of sheltered homeless adult women had accompanying children, compared to just 10 percent of sheltered homeless adult men (HUD 2022).[22] Housing may be more expensive to maintain when children are present, which in turn could lead to homelessness even at higher levels of income and hence higher average income among sheltered homeless women. Moreover, many programs consider household size in determining income thresholds or other aspects of eligibility, which could in turn also explain greater benefit receipt among homeless women than men.

While Census and ACS data do not report household structure for those experiencing homelessness, we examine differences in key outcomes by family status using cross-sections

22. The HUD reports do not contain separate cross-tabulation of gender and family status for adults and children, which are needed to estimate the share of women and men with accompanying children. The reports do, however, include cross-tabulations of gender and family status and age and family status. We assume that children are equally likely to be male and female and subtract these estimated counts from the overall cross-tabulations by gender and family status to obtain the necessary cross-tabulation of gender and family status among homeless adults.

of individuals indicated as being enrolled in HMIS shelters in Los Angeles and Houston on March 30 of 2012 and 2013.[23] Adults in both types of households experienced a drop in employment similar in magnitude to the drop among the Census homeless, but employment rates for those without children continued to decline after an observed period of homelessness, while employment among adults with accompanying children recovered almost to its initial level, consistent with the gender-based differences described above (Figure 3.13).

In summary, our findings suggest that homeless women are more connected to employment and the safety net than men who share their sheltered status, and that homelessness appears to be associated with smaller disruptions to employment for women than for men. Differences by gender are likely closely associated with differences by family status, where we find that homeless adults with accompanying children (predominantly women) are more connected to employment and the safety net than those without children (disproportionately men).

Race and Hispanic Ethnicity

We next turn to analyzing differences by race (Figure 3.14) and Hispanic ethnicity (Figure 3.15). Compared to white individuals of the same sheltered status, Black individuals experiencing homelessness had higher rates of employment and benefit receipt, including disability benefits. Hispanic homeless individuals had higher employment and lower disability program receipt than non-Hispanics with the same sheltered status. Overall benefit receipt was higher for sheltered homeless Hispanics than for sheltered homeless non-Hispanics, but the reverse was true among the unsheltered homeless, with Hispanics having lower overall benefit receipt than non-Hispanics.

23. We use 2012 and 2013 reference years, rather than 2010, because we are more confident in the quality of HMIS shelter entry and exit date reporting in these years, for reasons explained in Meyer et al. (2023a). We condition our sample on shelter enrollment on March 30 because this date aligns with the mid-point of the Census's homeless counting operation and hence ensures that our results are robust to any seasonal changes in shelter enrollment.

Differences by race are of policy interest because Black individuals are overrepresented among those who experience homelessness relative to their share in the broader population in poverty, raising concerns about equity. Meyer et al. (2021) find using the ACS that 47 percent of people in homeless shelters are Black, compared to 30 percent of single housed poor adults. As with gender-based differences, differences in income and program receipt by race may suggest differences in the predominant pathways to homelessness across groups. As with women (who often have accompanying children) relative to men, it may be the case that Black individuals face a higher cost of maintaining housing due to discrimination or the effects of racial disparities in the criminal justice system. Black individuals may also have access to fewer resources from their family and social networks to insure against homelessness. If Black individuals face a higher minimum housing cost or are less able to insure against income shocks at a given income level, they could in turn experience homelessness even when they are somewhat less deprived, on average, than poor white individuals, resulting in the observed differences in income, employment, and safety net participation across racial groups.

California, New York, and Other States

Policy discussions on homelessness in the U.S. often center on two states: California, which is home to the largest unsheltered homeless population, and New York, which is home to the largest sheltered homeless population. We therefore examined income and safety net participation in these states separately and compared them to those experiencing homelessness in the rest of the country. As shown in Figure 3.16, employment rates were lowest in California (47 percent among the sheltered, 35 percent among the unsheltered), followed by New York (50 percent among the sheltered, 37 percent among the unsheltered) and all other states (53 percent among the sheltered, 42 percent among the unsheltered). At the same time, Figure 3.17 demonstrates that median earnings among homeless workers in California and New

York (about \$10,000 to \$11,000) were somewhat higher than those in other states (about \$7,500), a difference that could once again reflect differential housing costs by state. We also observed slightly higher rates of disability program receipt in California and New York relative to other states (Figure 3.18). In summary, although we found somewhat lower employment and higher disability program receipt in New York and California, these differences were relatively small and suggest a high degree of similarity in the material circumstances of people experiencing homelessness across the United States as a whole.

3.6 Extensions and Robustness Checks

This section contains extensions of our main analyses and robustness checks. We begin by examining the accuracy of self-reported income and benefit measures and demographic characteristics among those surveyed in homeless shelters in the ACS and housed comparison groups through comparisons of survey and administrative responses. We do these comparisons to examine whether recorded answers can be trusted for items where we must rely on surveys and to see the improvement in accuracy through replacing survey responses where we can with administrative values. Our second sets of analyses use HMIS data, which indicate the date of shelter enrollment and exit, to compare key results based on cross-sectional samples (as in our main Census results) to samples of people with a first homeless shelter enrollment in a year (a widely used approach in the literature). These analyses facilitate comparisons to prior work and shed light on the extent to which key outcomes differ by length of time spent homeless. Our third set of analyses check the robustness of key findings to different data sources and years by comparing results based on those recorded as homeless in the Census to results based on those enrolled in HMIS shelters and those surveyed in homeless shelters in the ACS. Analyses using HMIS data allow us to examine the sensitivity of key results to definitional differences between the Census and HMIS, as described in-depth in Meyer et al. (2023a), while analyses using the ACS allow us to examine whether our findings change when we use samples of people experiencing homelessness in years other than 2010. Analyses using the ACS and HMIS also serve as checks on potential bias from non-linkage in the Census because both sources have higher linkage rates than the Census and include a richer set of covariates for inclusion in our model to account for non-linkage using inverse probability weights. The final set of analyses test the robustness of key findings to alternative Census samples designed to address potential bias from non-linkage, misclassification, and the incomplete geographic coverage of our SNAP datasets, which could result in bias due to migration.

3.6.1 *Misreporting of Income, Benefit Receipt, and Characteristics in the ACS*

Our first extension examines the extent to which demographic characteristics, income, and program receipt are misreported in the ACS by those experiencing homelessness and housed comparison groups. These analyses illustrate the importance of administrative data and provide estimates that may help researchers and service providers to understand the accuracy of self- and interviewer-reported information contained in the ACS and other surveys of this population.

Household surveys suffer from widespread underreporting of income and safety net benefit receipt in general, and self-reported measures may be especially inaccurate among those with very low and very high incomes (Meyer et al. 2015; Bollinger et al. 2019). Misreporting of income and benefit receipt among those experiencing homelessness is of particular interest because nearly all existing work on this population relies on self-reported measures of these outcomes. It is not clear, however, whether we should expect the quality of self-reported information among those experiencing homelessness in the ACS to be higher or lower than those who are housed. On the one hand, homelessness is associated with substantial psychological burdens and elevated rates of cognitive limitations, which could in turn affect interviewee's ability and willingness to provide accurate survey responses. Nearly one-quarter of sheltered homeless adults in the 2011-2018 ACS reported difficulties with memory and decision-making, compared to just 12 percent of the single housed poor and 4 percent of the overall housed population (Meyer, et al. 2021). The myriad of programs and services targeted at those experiencing homelessness may also contribute to confusion between federal, state, local, and private programs that could result in less accurate survey responses. At the same time, we might expect the quality of self-reported information in the ACS to be higher for those experiencing homelessness because information from these individuals is collected via in-person interviews with field representatives, unlike housing unit surveys, which are typically completed through mail or electronic submission.

We start by assessing the misreporting of date of birth, place of birth, gender, and citizenship status in the 2011-2018 ACS (Table 3.4). We take characteristics indicated in the Social Security Administration (SSA)'s Numident file to represent the truth and calculate the share of individuals reporting a different response in the survey. People experiencing homelessness are slightly more likely to misreport the exact day, month, or year of their birth, but only a small share (3.5 percent) report a date of birth that is three or more years away from the true date. These shares differ only slightly from misreporting rates for this characteristic among the single housed poor (4 percent) and overall housed populations (3.7 percent). In addition, homeless individuals are slightly more likely to misreport their state or country of birth (7.4 percent) than the single housed poor (5.1 percent) and overall housed populations (4.9 percent), but they are less likely to misreport their gender. Citizenship misreporting rates are similar (3 to 3.7 percent) for all three groups. In summary, the demographic information provided by people experiencing homelessness in the ACS appears to be generally quite reliable and only slightly less accurate than the information provided by housed individuals.

We next summarize the misreporting of wage and salary income, SNAP, Medicaid, and

Medicare in the 2011-2016 ACS, where we take values from administrative datasets to be the truth (Table 3.5).[24] Among those experiencing homelessness, 43.2 percent of wage earners fail to report any wages in the survey, which is higher than the corresponding false negative rates for the single housed poor (28 percent) and overall housed population (7.7 percent).[25] Among true SNAP recipients, those experiencing homelessness are slightly more likely to falsely report no receipt (20.5 percent) than the single housed poor (15.8 percent), but less likely to do so than the overall housed population (29 percent). On the other hand, false positive rates for SNAP receipt are substantially higher in the homeless sample than in the single housed poor and overall housed populations (30.7 percent, compared to 6.3 percent and 1.2 percent). The three groups have similar (and low) rates of false positives and false negatives for Medicare receipt. Finally, for Medicaid receipt, those experiencing homelessness have slightly lower false negative rates (16.5 percent, compared to 18.6 and 27.6 percent of the single housed poor and overall housed, respectively) but substantially higher false positive rates (20.4 percent, compared to 13.2 and 3.7 percent).

Thus, we find that people experiencing homelessness are slightly more likely than the housed population to underreport certain sources of income and benefits (e.g., wage and salary income, SNAP) but may be less likely to underreport receipt of other benefits (e.g., Medicaid). At the same time, high rates of false positives for program receipt (e.g., SNAP and Medicaid) appear to be a greater concern for this population, perhaps reflecting misunderstanding about these programs vis-a-vis other types of food and medical assistance that they may receive. In summary, survey responses in the homeless sample suffer from substantial error, but they are not clearly worse than the responses for the housed. Both

24. We limit the sample to ACS data through 2016 for income and safety net misreporting analyses because these are the years for which we have access to administrative data.

25. We note that our administrative earnings data indicate only formal wage and salary income, so false negative rates should be interpreted as false negatives for formal wage and salary income. Because people may report informal income in the survey that would not be recorded in the tax data, false positive rates should be interpreted with more caution.

show sufficient error for income sources that a reliance solely on survey responses is likely to lead to substantial bias.

3.6.2 Robustness to Different Time-Based Sampling Approaches

Our next set of analyses compare key findings across two different time-based approaches to selecting a sample of those experiencing homelessness. The first approach, which is analogous to our main Census sample, takes a cross-section of those experiencing homelessness at a point in time. The second, which is widely used in the homelessness literature, takes a sample of people with first shelter enrollments in a year. These comparisons shed light on the extent to which key outcomes appear to differ by length of time spent homeless, facilitate comparisons to prior work, and allow us to see how income and program receipt change longitudinally relative to the first observed homeless shelter enrollment.

Much of the prior literature on homelessness emphasizes differences in characteristics, life circumstances, and pathways to homelessness between people with different patterns of time spent without conventional housing (Lee et al. 2010; Kuhn and Culhane 1998). Such differences are also important for programmatic purposes, with eligibility criteria for some HUD assistance programs being contingent on exhibiting "chronic" homelessness (i.e., having extended or repeated spells of homelessness alongside a disabling condition). The timeframe across which samples are selected creates an implicit set of weights related to an individual's length of time spent homeless. Our main Census sample consists of a cross-section of people experiencing homelessness at a point in time, which in turn should provide a spell length-weighted sample of people who are ever homeless if the size of the population and distribution of spell lengths are constant over time. While such a weighing scheme is sensible in many ways and consistent with how samples are typically drawn in the broader literature on poverty, we may also be interested in summary statistics based on samples using other time-based approaches. For example, von Wachter et al. (2020) and Metraux et al. (2018) use samples of people with a first observed shelter enrollment in a year, an approach which applies equal weight to all individuals in the sample regardless of the length of time spent homeless. This latter approach also allows researchers to examine changes in key outcomes in the time preceding and following the onset of homelessness.

A key limitation of the Census and ACS data is that they do not indicate the start and end dates of spells of homelessness, which in turn limits our ability to compare key results across different time-based approaches to sampling using these data. We turn instead to HMIS data from Los Angeles and Houston, which indicate individuals' shelter entry and exit dates, to examine the sensitivity of key findings to different time-based approaches to sampling. The first approach, which provides a sample that is analogous to the Census samples in our main results, takes a cross-section of those enrolled in these shelters on March 30 of 2012 or 2013.[26] The second approach, which aligns more closely with samples used in key prior studies, including von Wachter et al. (2020) and Metraux et al. (2018), takes individuals with their first observed HMIS shelter enrollments in 2012 or 2013. By construction, the cross-sectional samples place greater weight on people with longer or more frequent spells of homelessness, while the samples of first enrollments apply equal weight to all individuals regardless of length of time spent homeless. Indeed, summary statistics reveal much longer average lengths of shelter enrollment for people in the cross-sectional samples (319 days in Los Angeles and 280 days in Houston) than in the samples of first enrollments in a year (70 days in Los Angeles and 30 days in Houston).

In Los Angeles, we observe remarkably similar levels and longitudinal patterns of employment (Figure 3.19), median earnings conditional being employed (Figure 3.20), and benefit receipt (Table A.31) in the cross-sectional sample and the sample of people with first enrollments in a year. Over the seven years before and four years after an observed period of

26. We use 2012 and 2013 for these analyses, rather than the Census year of 2010, to ensure that we have several years of preceding high-quality HMIS data, which in turn increases our likelihood of having identified an individual's first shelter enrollment. See Meyer et al. (2023a) for a discussion of HMIS data quality improvements over time.

homelessness, employment in the sample of first enrollments differed from the cross-sectional sample by -0.3 to 3.7 percentage points, corresponding to a -1 to 11 percent difference. Median earnings conditional on being employed differed between the sample of first enrollments and the cross-sectional sample by -$1,000 to $900 (-13 to 9 percent difference), Medicaid enrollment differed by -4 to 3.5 percentage points (-5 to 13 percent difference), and disability program receipt differed by -4 to 3 percentage points (-14 to 13 percent difference).

Compared to Los Angeles, differences in the levels of employment and benefit receipt – but not longitudinal patterns – were more pronounced between the two samples in Houston. The sample of first enrollments had lower employment than the cross-sectional sample (3 to 9 percentage points lower, or a 5 to 14 percent difference), higher rates of Medicaid enrollment (2 to 7 percentage points higher, or a 14 to 31 percent difference), and higher rates of disability program receipt (5 to 8 percentage points higher, or a 30 to 180 percent difference). Median earnings conditional on working were not consistently higher or lower in the sample of first enrollments however, ranging from $2,400 lower to $2,100 higher than the cross-sectional sample, with the proportional difference ranging from -24 to 21 percent. Longitudinal patterns of employment and benefit receipt were similar in the two samples, however. In in the sample of first enrollments, the average year-to-year changes in employment, Medicaid enrollment, and disability program receipt were -1.4, 2.5, and 1.6 percentage points, respectively, compared to -1.2, 1.9, and 2.0 percentage points in the cross-sectional sample.

Taken together, these results highlight a striking degree of similarity in the levels and longitudinal patterns of employment, earnings, and benefit receipt between cross-sectional samples and samples consisting of people with their first shelter enrollment in a year. These similarities are even more notable when we consider that the cross-sectional samples consisted of individuals who spent 4.6 (Los Angeles) and 9.3 (Houston) times as many days in the shelter, on average, as the samples of first enrollments. Considering key outcomes relative to the onset of homelessness rather than an observed period of homelessness with unknown start date makes little difference in longitudinal patterns. These analyses suggest that our main, Census-based results would change little even under a hypothetical alternative sampling approach that gave more weight to people with shorter spells of homelessness. More broadly, these analyses further illustrate our key finding that the year someone is observed to be experiencing homelessness does not appear to be a major aberration in long-term trajectories characterized by persistent, severe material deprivation.

3.6.3 Robustness to Different Data Sources and Years

This section examines the robustness of our main results to different data sources and years. We first compare key outcomes for samples of people who were enrolled in HMIS shelters in Los Angeles and Houston on the Census date to the subset of the Census sheltered homeless from those same cities. We then calculate key outcomes for individuals surveyed in homeless shelters in the 2010-2014 ACS and compare these to our main results to see whether findings differ for people who were homeless in years other than 2010.[27] Both sets of analyses also serve as checks on potential bias from non-linkage because HMIS data have high linkage rates (over 90 percent in most years) and because the ACS includes a rich set of covariates for inclusion in our inverse probability weighting model, including self-reported measures of some of the same income and program receipt outcomes we are estimating with administrative data.

We are interested in the comparability of Census and HMIS data because the latter are frequently used in homelessness research and official HUD reports and there are important differences in the way that these sources define a homeless shelter, which in turn could result in different patterns of income and program receipt. Meyer et al. (2023a) highlight straightforward definitional differences between these sources as well as ambiguities that lead

27. This date range has been selected to allow several years of administrative data to calculate longitudinal outcomes in surrounding years.

the Census to classify some HMIS facilities as conventional housing or other types of group quarters rather than homeless shelters. For example, unlike HMIS, the Census appears to have classified many transitional housing units not as shelters but rather as conventional housing, most likely due to the extended residency (up to two years) and formal tenancy agreements that these facilities entail.

To assess the comparability of these data sources, we calculate key outcomes for Los Angeles and Houston HMIS shelter users with entry and exit dates indicating enrollment during the Census's homeless counting operation as well as Census sheltered homeless individuals from these cities.[28] Figures 3.21 and 3.2 illustrate employment and median earnings conditional on working, respectively, for the Census and HMIS samples. In Los Angeles, both the levels and longitudinal patterns of employment and earnings were similar for the two data sources, with employment differing by at most 4 percentage points and median earnings conditional on working differing little between the samples in most years. In Houston, the HMIS sample had higher employment (by about 7 to 10 percentage points) but similar earnings conditional on being employed, with similar longitudinal patterns for both outcomes in both samples.[29]

Similarities between the Census and HMIS samples are broadly encouraging, but employment differences in Houston suggest that the level of deprivation may be sensitive to the choice of data source in some localities. In the case of Houston, the Census appears to have identified a more deprived set of individuals than HMIS, which in turn may reflect greater misalignment in the two sources' definition of a homeless shelter in Houston than in Los

28. Following Meyer et al. (2023a), we exclude from the Los Angeles sample people whose HMIS-recorded exit dates appear to be erroneous, i.e., those with exit dates of March 31, 2010 (the date of an apparent administrative closure of numerous spells with missing exit dates), as well as those who still had open spells on March 30 despite being enrolled in Los Angeles's Winter Shelter Program, which ended on March 15.

29. Table A.32 presents the share with disability program receipt and the share enrolled in Medicaid for the Census and HMIS samples. The trend in both outcomes is similar in both cities and the levels are similar in Los Angeles, but Medicaid enrollment and disability program receipt are higher in the Houston's Census sample than its HMIS sample.

Angeles. Prior work by Meyer et al. (2023a) suggests that a larger share of Houston's HMIS shelter users were in facilities classified by the Census as housing, with about 37-39 percent of Houston's HMIS shelter users being in facilities classified by the Census as conventional housing or other group quarters, compared to 31-33 of Los Angeles's HMIS shelter users. In addition, about two-thirds of Houston's HMIS sample in the present analysis were enrolled in a transitional housing facility, compared to just one-quarter in Los Angeles. Because about one-half of all sheltered homeless individuals in the United States in 2010 were enrolled in transitional housing, we might expect the degree of definitional misalignment between Census and HMIS data nationally to fall somewhere between that of Houston and Los Angeles (HUD 2010). Moreover, because transitional housing offers a more stable living situation than emergency shelters, we might expect HMIS samples to include individuals who are slightly less deprived, on average, than the Census when such facilities are prevalent.

We next compare key results for the sheltered homeless in the Census and 2010-2014 ACS. In addition to checking the robustness of our results to another data source, these analyses allow us to examine the degree to which our main findings hold true when we study people who were homeless in years other than 2010. We may be concerned, for example, that our main results reflect prevailing macroeconomic conditions 2010 and the surrounding years rather than more general trends that tend to precede or follow homelessness. Comparisons of Census to ACS data are also informative about the extent of bias from non-linkage in our main Census results because the ACS allows us to estimate an IPW model that includes a much richer set of covariates than those available in the Census, including self-reported measures of income and program receipt. As we saw in Section 3.6, self-reported values of income and program receipt, while sometimes misreported, are nevertheless highly correlated with true values.[30] Including these self-reported measures in the IPW model should therefore account for most of any unobservable characteristics that are potentially associated with the

30. Table 3.5 shows that sheltered homeless individuals' survey reports are accurate 78, 78, 82, and 95 percent of the time for having formal employment, and receipt of SNAP, Medicaid, and Medicare, respectively.

outcomes. The similarity of the estimates from the two samples suggests that there is at most a small bias resulting from non-linkage conditional on the Census's more limited set of demographic and geographic variables.

Figures 3.23 and 3.24 illustrate employment and the share of individuals with disability program receipt, respectively, for the 2010 Census and 2010-2014 ACS sheltered homeless samples. In Figure 3.23, we observe similar levels and longitudinal patterns in employment over the two years preceding and two years after an observed period of homelessness in both samples, suggesting that declining employment preceding homelessness is not specific to the Great Recession years. Disability program receipt is 2-5 percentage points higher in the Census sample than the ACS, but the longitudinal pattern is once again similar across the two data sources. Table A.33 presents numerous additional outcome measures for the ACS sheltered homeless samples, all of which have similar levels and longitudinal patterns to our main Census sheltered homeless sample. Taken together, these results suggest our main findings are not specific to people who experienced homelessness in 2010, but rather reflect more general trends surrounding an observed period of homelessness.

In summary, the analyses in this section demonstrate that our results are largely robust to the use of different data sources and years, although we note the potential for some differences between the Census and HMIS data stemming from differences in the way these sources define a homeless shelter. The similarity of results from different data sources also lends confidence to our non-linkage corrections using inverse probability weights.[31]

31. While these checks on our linkage methods were carried out using comparisons of sheltered homeless samples, we consider them to be informative about the accuracy of the very similar non-linkage corrections for the unsheltered homeless sample as well. Transitions between sheltered and unsheltered statuses are common, suggesting that the distinction between these groups may not be pronounced. In the 1996 NSHAPC survey, 11 percent of respondents had slept in both shelters and at unsheltered locations during the week of the survey (Burt et al. 2001). Similarly, about 10-11 percent of people indicated as being enrolled in HMIS shelters in Los Angeles and Houston on the Census date were recorded by the Census as unsheltered homeless, suggesting transitions between these statuses within a short window of time (Meyer et al. 2023a). Finally, our finding of high rates of connection to the safety net even among the unsheltered homeless is consistent with Metraux et al. (2016)'s analysis of homeless decedents in Philadelphia, which found that three-quarters these individuals had prior contact with homeless services.

3.6.4 Robustness to Alternative Census Samples

This section contains additional robustness checks using Census data to address concerns about our sample selection criteria, the potential for misclassification of housed individuals as homeless in the Census, and potential bias in SNAP receipt due to migration between states for which we do and do not have administrative data on this outcome.

We first calculate employment and benefit receipt for a version of the Census unsheltered homeless sample that includes those counted at outdoor locations (TNSOLs). These analyses serve as a check on our decision to omit this group from our main results due to low linkage rates and concerns about non-randomness of linkage conditional on observed characteristics. We next calculate key outcomes for subsets of the sheltered and unsheltered homeless Census samples that exclude people who were recorded in housing units as well as being counted as homeless in the 2010 Census. These analyses are intended to address concerns about potential misclassification of housed people as homeless, concerns that stem from the finding in Meyer et al. (2023a) that about 40 percent of the unsheltered population and 20 percent of those in shelters were also counted as housed in the Census. Figures A.1-A.4 (Tables A.34and A.35) contain these results. Our findings are largely robust to these alternative sample choices. Despite concerns about low linkage rates for people located at TNSOLs, the decision to exclude these individuals appears to have little effect on our results. We note that people who were double-counted during the Census appear slightly more likely to be employed and slightly less likely to receive benefits, differences which may reflect a small degree of misclassification, but which could alternatively reflect heterogeneity between people with strong and weak connections to housed friends or family.

We conduct a final series of checks to address concerns over potential bias in longitudinal SNAP receipt that could arise from migration and the incomplete geographic coverage of our administrative datasets for this program. In our main results on SNAP receipt and outcomes that incorporate SNAP, like income including in-kind transfers, we restrict the sample in year t to people who in 2010 lived in a state for which we have SNAP data in year t. People who migrate between states for which we do and do not have SNAP data during the study period could incorrectly be identified as non-recipients, leading to downward bias in our results. To estimate the extent of such bias, we calculate longitudinal SNAP receipt for the subset of the 2010 homeless population that links to the 2000 Census and resided in the same state in both 2000 and 2010. We call this our migration-adjusted sample because we consider these individuals to be less likely to have resided in other states in years between 2000 and 2010. As expected, the peak in SNAP receipt surrounding 2010 is attenuated in the migration-adjusted sample, but the qualitative pattern of sharply increasing SNAP receipt preceding 2010 and somewhat decreasing SNAP receipt after 2010 remains intact. Our findings are similar when we examine migration-adjusted SNAP receipt in the unsheltered homeless and single housed poor samples, suggesting that the peak in SNAP receipt in the year observed as homeless is a real phenomenon, not the result of bias due to incomplete coverage of SNAP datasets.

3.7 Comparisons to Past Work

We compare our findings to three key prior studies of the income, employment, and safety net participation of the U.S. homeless population: the NSHAPC survey, Metraux et al. (2018), and von Wachter et al. (2020). The NSHAPC survey interviewed a random sample of 4,200 users of homeless services in 1996, including people who were homeless at the time of the interview and some who had recently been homeless (Burt et al. 2001). Its advantages lie in its intention to be nationally representative and its detailed self-reported income and program receipt measures. However, three decades have passed since this survey was conducted. More recently, Metraux et al. (2018) base their analyses on a sample of 161,000 New York shelter users with first observed HMIS enrollments in 1990-2002 and von Wachter et al. (2020)'s sample consists of 137,000 Los Angeles shelter users with first observed HMIS enrollments in

2010-2018. Metraux et al. (2018) link their sample to Social Security Administration (SSA) earnings data and von Wachter et al. (2020) link their sample to California Unemployment Insurance (UI) wage records. These studies benefit from large samples and accurate earnings data but are limited to a single income source (earnings – and only in-state wages in the latter study). They do not include people who were experiencing unsheltered homelessness and may not generalize outside of the cities in which they were conducted.

Table 3.6 summarizes the main findings from these studies alongside the most comparable estimates available in our study. They include estimates for the pooled Census sheltered and unsheltered in Column (1) to facilitate comparisons with NSHAPC and estimates for the sheltered homeless only in Column (3) to facilitate comparisons with Metraux et al. (2018) and von Wachter et al. (2020). We also indicate employment rates and Medicaid receipt for single adults and those in families (from our pooled Los Angeles and Houston HMIS samples) to compare differences by family status to the results in prior work. We report all cash amounts in 2018 dollars. While we have so far emphasized percentiles of income in this study, in this section we report mean income amounts to align estimates based on the Census homeless with prior studies' results.

Our estimates of formal income and earnings in the year observed as homeless exceed the estimates in prior studies. Mean pre-tax cash income for the pooled Census sheltered and unsheltered homeless, including the value of SSI payments, is about \$10,900, nearly \$4,000 greater than the inflation-adjusted \$7,100 average income reported in NSHAPC.[32] We also calculate mean annual earnings among workers to be nearly \$6,000 higher than in Metraux et al. (2018) and \$3,500 higher than in von Wachter et al. (2020), differences that could reflect the studies' different timeframes, geographic coverage, or sample selection. We also find higher rates of employment in the sheltered homeless population than those suggested

32. In New York, where we have access to TANF/GA data, we estimate mean pre-tax cash income including these cash benefits to be about \$12,700. We note, however, that New York's cash assistance programs tend to be more generous than in other states.

by Metraux et al. (2018) and von Wachter et al. (2020). Fifty-two percent of the Census sheltered homeless were employed in the year observed as homeless, compared to just 42 percent of shelter users in Metraux et al. (2018) and 29 percent of those in von Wachter et al. (2020). Low employment rates in this latter study may in part reflect the incomplete coverage of their earnings data, which consist of Unemployment Insurance (UI) wage records exclusively from California.

Comparisons with prior work also suggest a possible reversal in employment rates between single homeless adults and homeless adults with partners or children over the past three decades. Both NSHAPC and Metraux et al. (2018), studies that relied primarily on homeless samples from the 1990s, found substantially higher employment among unaccompanied adults than those with partners or children, with the first group being predominantly male and the latter group consisting primarily of single mothers. In contrast, our estimates based on 2012-2013 HMIS data from Los Angeles and Houston and von Wachter et al. (2020)'s estimates based on Los Angeles HMIS data from 2010-2018 indicate substantially higher employment for adults in families than for unaccompanied adults. The reversal in employment rates by family status between the 1990s and 2010s may reflect the well-known increase in employment among single mothers, especially those with low education, since the 1990s (Han et al. 2021).

Finally, we compare safety net participation in our study to that reported in the NSHAPC.[33] Pooling the sheltered and unsheltered Census samples, we estimate that about 86 percent of those experiencing homelessness in 2010 received at least one benefit that year, including about 77 percent of people who received SNAP. In NSHAPC, just 40 percent of those experiencing homelessness reported receiving at least one benefit, including 37 percent receiving SNAP. We find higher receipt rates for all benefits: 24 percent were enrolled in SSI (compared to 11 percent in NSHAPC), 46 percent were enrolled in Medicaid (compared to

33. A caveat is that the NSHAPC reports contemporaneous program receipt at the time of interview, while our estimates indicate program receipt at any point in the calendar year.

30 percent in NSHAPC), and 48 percent were enrolled in in TANF or GA in New York (compared to 19 percent of the U.S. homeless population enrolled in in AFDC in NSHAPC). Some of these differences are likely driven by the underreporting of benefit receipt in the survey as discussed in Section 3.6, but under-reporting in other surveys tended to be less pronounced back in the 1990s. Furthermore, our annual measures of benefit receipt are higher by construction than NSHAPC's contemporaneous receipt measures, but such time-frame misalignment is unlikely to explain all of the differences we observe. Higher program receipt in the 2010 Census homeless population appears to reflect, at least in part, a true increase in connections to the safety net for this population since the 1990s as eligibility for many of the programs has broadened.

In summary, our analyses are qualitatively consistent with past studies in demonstrating the dire economic circumstances of people experiencing homelessness. At the same time, we show that these individuals have somewhat greater incomes, employment, and connections to the safety net than previously understood. Differences between our estimates and those in prior work likely reflect some combination of true changes over time – including an apparent rise in employment among homeless mothers and increasing program receipt in recent decades – as well as the improvements to accuracy that come from using administrative data rather than self-reported outcomes, as has been established in the broader literature on poverty measurement (e.g., Meyer and Mittag, 2021). At the same time, we caution that these findings do not necessarily mean that this population is less deprived than previously thought. Homelessness itself is an unambiguous indicator of severe hardship, so there can be no doubt that people experiencing homelessness are deprived. Rather, these comparisons underscore that people experience homelessness because they are unable to negotiate their dire circumstances despite being connected to formal work and the safety net, not because they are disconnected from these sources of income.

3.8 Conclusions

This paper provides the most detailed and accurate description to date of the level and persistence of material deprivation among people experiencing homelessness in the United States, including the first-ever national estimates of income, employment, and safety net participation based on accurate administrative data. We find that these individuals are highly connected to work and the safety net, with nearly all sheltered homeless adults (97 percent) and the vast majority of unsheltered homeless adults (93 percent) having received at least one benefit or been formally employed in the year they were observed as homeless. Pooling together the sheltered and unsheltered samples, we find that half of these individuals (46 percent) had formal employment in the year they were observed as homeless, more than three-quarters received food assistance from SNAP (77 percent), and many were enrolled in Medicaid (43 percent) or received disability assistance through SSI or DI (24 percent). While higher than prior estimates, these rates understate true employment and program receipt given that our data are not complete. At the same time, formal incomes were very low: the median annual value of our most comprehensive resource measure – cash income plus the value of in-kind transfers from SNAP and HUD – was just $7,500 for the sheltered homeless and $5,500 for the unsheltered homeless in 2010. As these findings illustrate, people with very low incomes remain vulnerable to homelessness even when they are connected to formal labor markets and the social safety net. Relatedly, connecting people to formal employment and these social safety net programs are unlikely to be sufficient policies for preventing or reducing homelessness.

Our longitudinal analyses reveal highly persistent deprivation, with little change in median incomes over the four years prior to and six years after an individual is observed to be homeless. Employment declines steadily between 2005 and 2016, with only a small and transitory drop relative to this long-term trend in the years leading up to 2010. Long-term declines in employment are accompanied by increasing disability program receipt, with enrollment in SSI or DI increasing from 24 to 37 percent between 2010 and 2016. Because we expect that most of the people in our sample were housed for much of this longitudinal period, we interpret these findings to be informative not just about material circumstances during a period of homelessness, but also about the long-term life circumstances within which homelessness arises. Our results suggest that homelessness tends to arise in the context of long-term, severe deprivation, including declining employment and increasing disability program receipt, rather than large and sudden losses of employment or benefit income. Put differently, for these individuals, extremely low permanent incomes translate into heightened vulnerability to homelessness, leaving them with few resources to buffer against the loss of housing when met with even a relatively modest disruption to their income or life circumstances.

Perhaps surprisingly, we observe a high degree of similarity in the material circumstances of people experiencing sheltered homelessness and unmarried poor individuals who are housed but share their demographic profile (i.e., disproportionately male, Black, and in their 40s and 50s). Both groups have persistently very low incomes and high benefit receipt. Although median annual incomes are higher among the housed poor, there is substantial overlap between these groups' income distributions, with at least a quarter of sheltered homeless adults having incomes that exceed the median income in the housed poor comparison group. Adults in our sheltered homeless sample even had slightly higher rates of employment than the single housed poor in the years leading up to 2010. These analyses highlight the severe income-related deprivation faced by this segment of the housed population, a group that tends to receive less attention in academic and policy discussions about poverty alleviation than single mothers and children.

At the same time, substantial overlap in the economic circumstances of sheltered homeless and housed poor individuals raises the question of what factors, unobserved in our data, cause some individuals to become homeless while others remain housed. With only about

600,000 people experiencing literal homelessness in the U.S. at a point in time (Meyer et al. 2023a), homelessness remains a rare event even among those who are very poor. Differences in permanent incomes and connections to formal work and the safety net do not appear to be the predominant factors distinguishing those who experience homelessness from the single housed poor. Alternative explanations may center on the role of behavioral health conditions and substance abuse disorders, the strength of social ties and affluence of one's social network, and the bad luck of experiencing non-income shocks to life circumstances. Understanding what non-income factors raise or lower an individual's probability of becoming homeless can shed light on the most effective prevention measures and inform the targeting of such interventions. Extreme poverty appears to be just one part of the broader puzzle of what put someone at risk of homelessness.

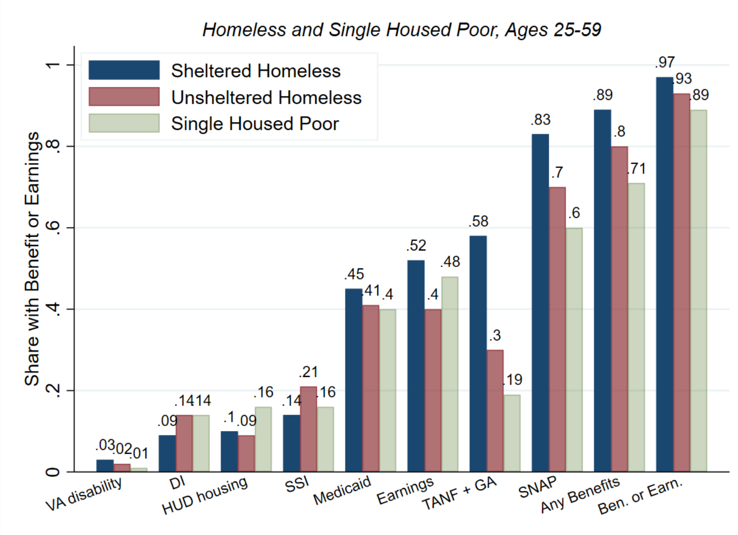
An important caveat on our longitudinal analyses is that we describe patterns in the central tendencies of income, employment, and safety net participation in the U.S. homeless population over time, but we do not examine individual dynamics in these outcomes. This approach yields useful summary measures of the level of deprivation in this population and how this level changes on average across years, but it does not allow us to describe individual-level variability in these outcomes. In future work, we plan to examine individual income dynamics surrounding an observed period of homelessness to characterize the extent of income volatility associated with homelessness and to understand heterogeneity in dynamic patterns. These analyses will shed light on whether policies aimed at increasing permanent incomes (or, equivalently, lowering housing costs) or policies aimed at reducing the volatility of income (or, equivalently, reducing the volatility of housing costs) will be more effective prevention measures.

Another limitation of our study is that we do not observe the duration of spells of homelessness for those in our Census samples. HUD's best estimates, which are based on surveys of likely uneven quality conducted by local service providers, suggest that only about one-quarter of people who are literally homeless at a point in time face extended or repeated long-term spells of homelessness (HUD 2022). In other words, we expect most people in our Census sample to have been housed for much of the decade surrounding 2010. Yet our findings do not suggest that 2010 was major aberration in these individuals' long-term economic trajectories; they face similar levels of material deprivation even in years where we expect most of them to have been housed. Moreover, our analyses using HMIS data demonstrate the remarkable robustness of key findings to the use of samples designed to include a smaller share of those with longer or more frequent spells of homelessness. Literal homelessness is a severe hardship that rightly draws widespread concern, but the context of persistent, extreme poverty within which homelessness arises – poverty that is less visible than literal homelessness, and hence less likely to capture the attention of policymakers – may be nearly as alarming and deserving of our concern.

This paper adds to an emerging portrait of the life circumstances of people who experience homelessness in the United States based on large, national samples linked to administrative data. Recent work has documented the substantially elevated mortality risk associated with homelessness (Meyer et al. 2023b), and ongoing analyses seek to understand homeless individuals' patterns of housing status transitions, migration histories, and the effects of safety net programs on health and wellbeing. These pathbreaking analyses are informing efforts to understand the causes and consequences of homelessness and to identify the most effective strategies for improving the lives of this exceptionally deprived and ill-understood segment of the U.S. population.

3.9 Exhibits

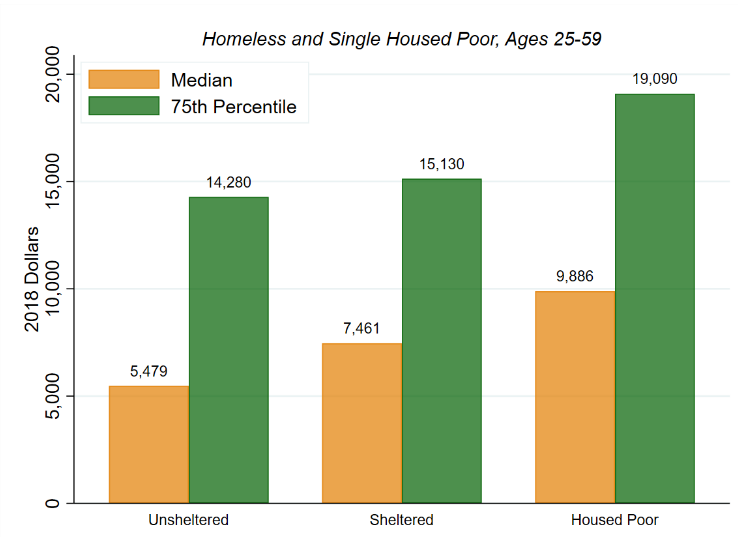
Figure 3.1: Benefit Receipt and Earnings in 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

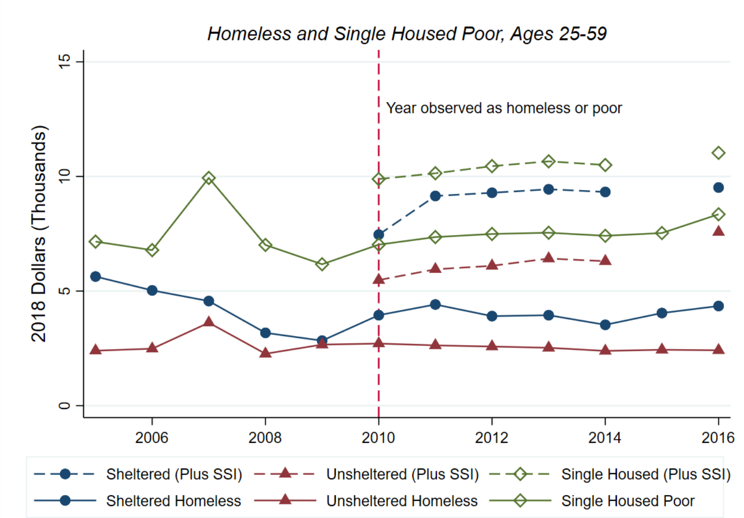
Figure 3.2: Income Including In-Kind Transfers in 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

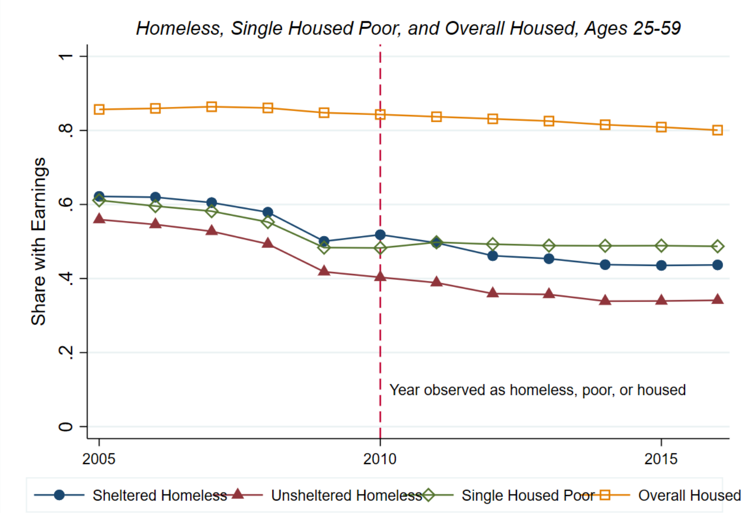
Figure 3.3: Median Income Including In-Kind Transfers in 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

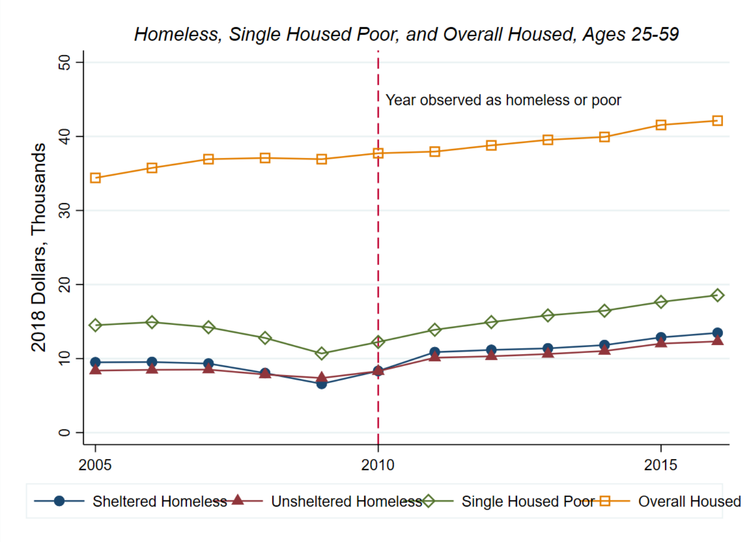
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 3.4: Share with Earnings, 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS. **Note:** Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

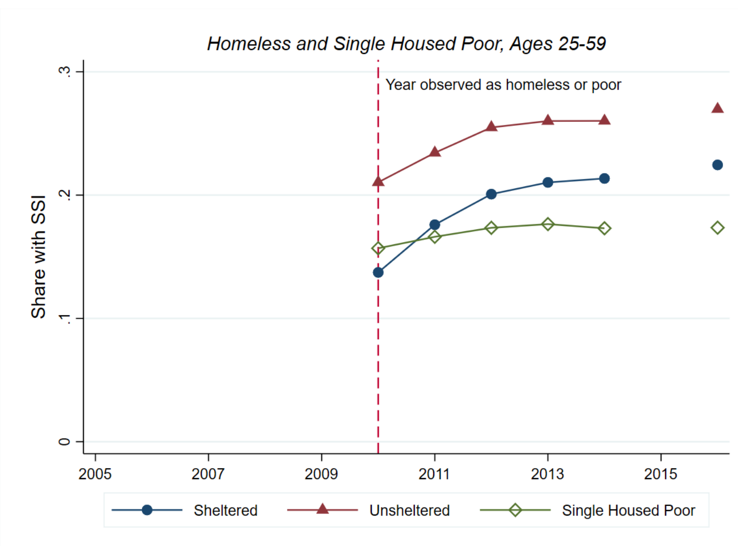
Figure 3.5: Median Earnings (Conditional on Working), 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

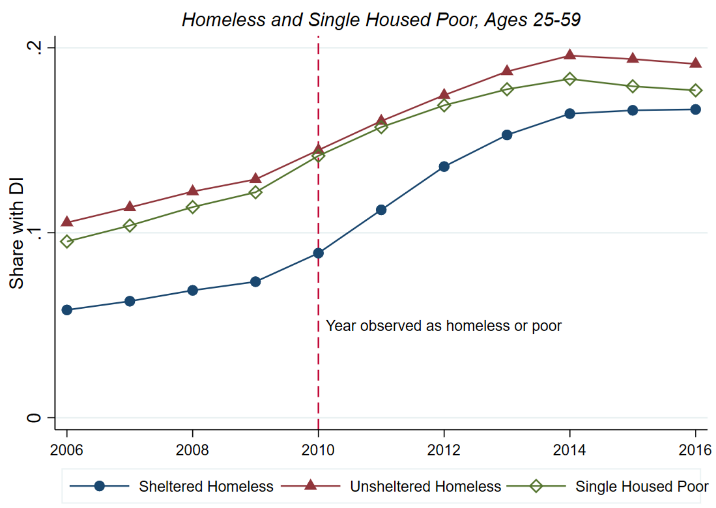
Figure 3.6: SSI Receipt, 2010-2016



Sources: SSI Datasets (2010-2014, 2016), 2010 Census, 2010 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

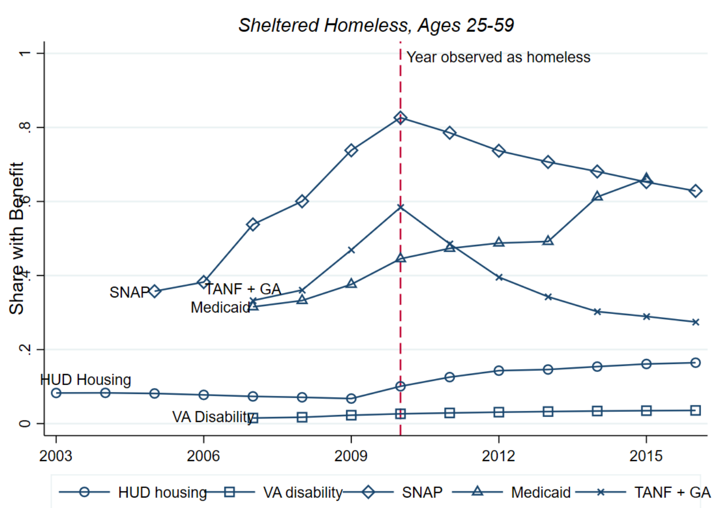
Figure 3.7: DI Receipt (According to Medicare Records), 2006-2016



Sources: 2006-2016 Medicare Datasets, 2010 Census, 2010 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

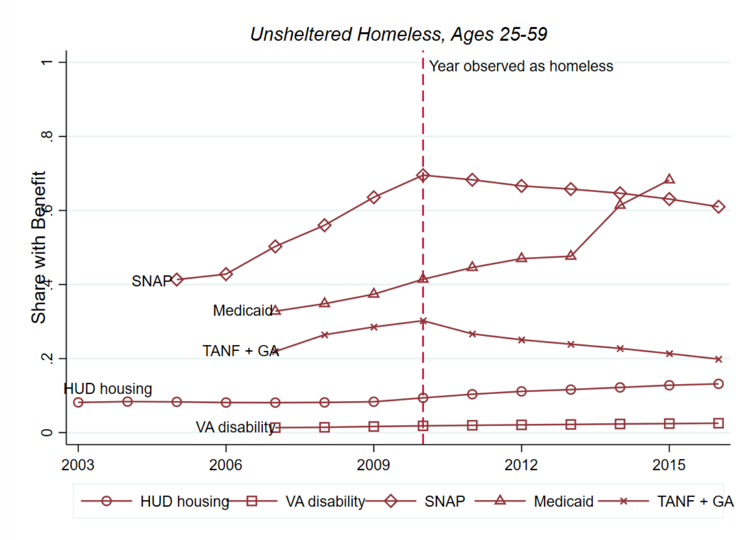
Figure 3.8: Program Receipt of Sheltered Homeless, 2003-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

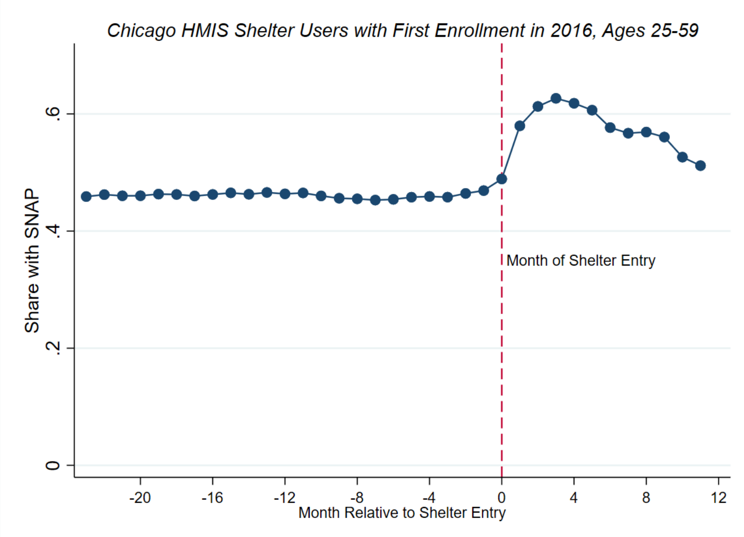
Figure 3.9: Program Receipt of Unsheltered Homeless, 2003-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 3.10: Monthy SNAP Receipt in Chicago HMIS Data



Sources: Chicago (2014-2019) HMIS dataset, Illinois SNAP dataset (2009-2016).

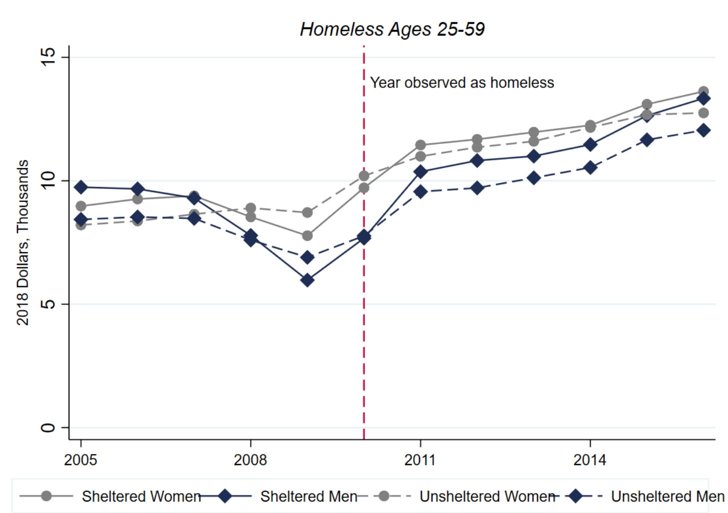
Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 3.11: Share with Earnings by Gender, 2005-2016

Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

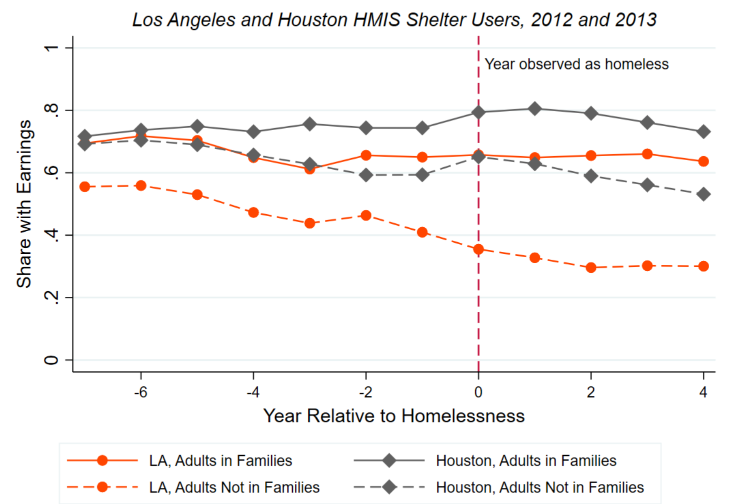
Figure 3.12: Median Earnings by Gender (Conditional on Working), 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

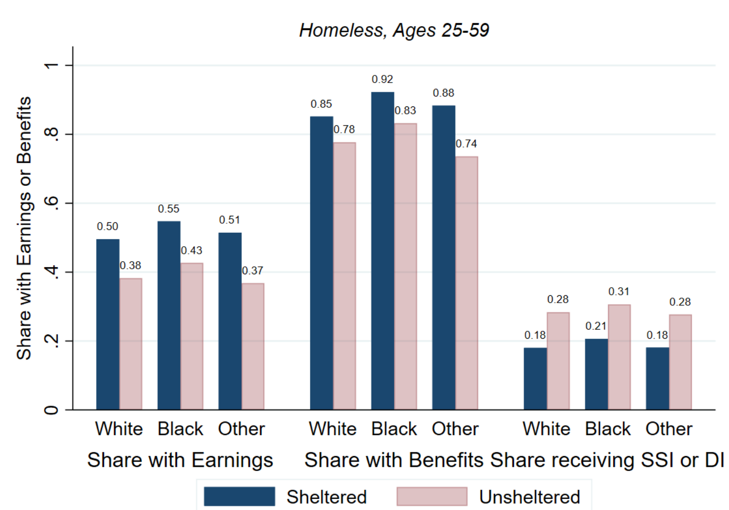
Figure 3.13: Share with Earnings by Family Status



Sources: IRS 1040s (2003-2015), W2s (2005-2016), Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

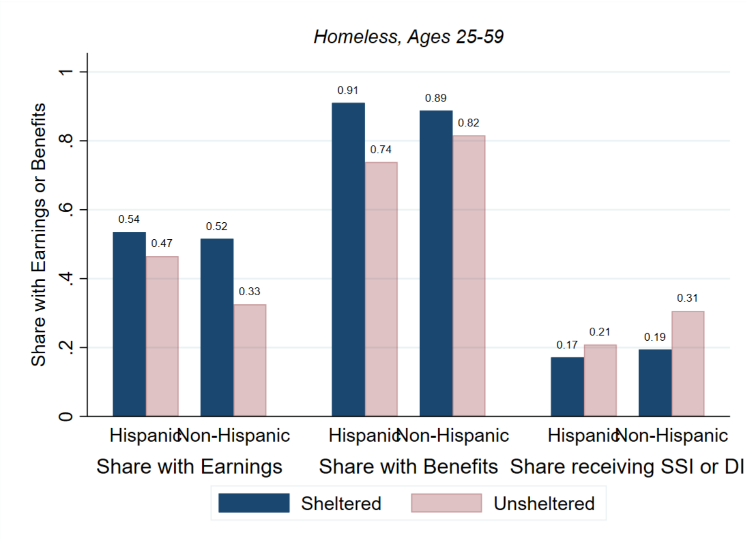
Figure 3.14: Share with Earnings, Benefits, and Disability by Race, 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

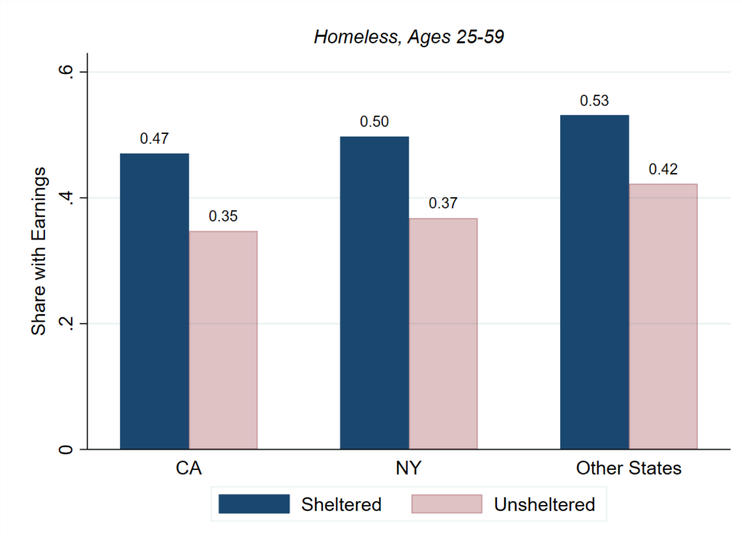
Figure 3.15: Share with Earnings, Benefits, and Disability by Ethnicity, 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (20 09-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

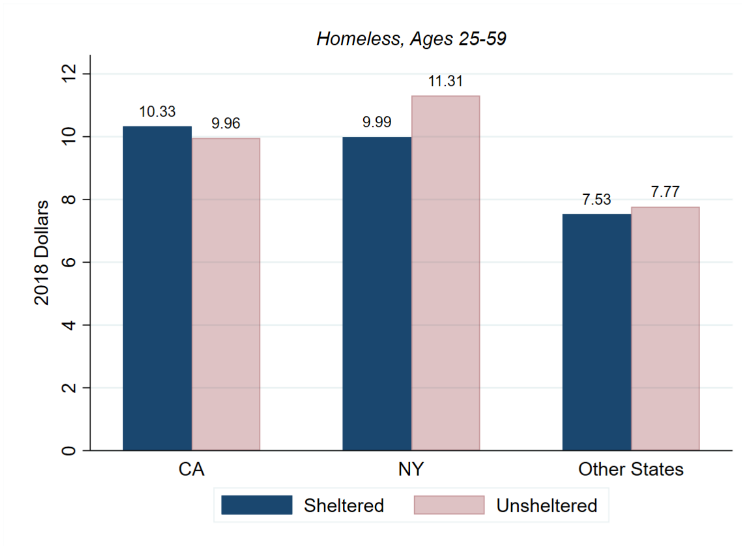
Figure 3.16: Share with Earnings by State, 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

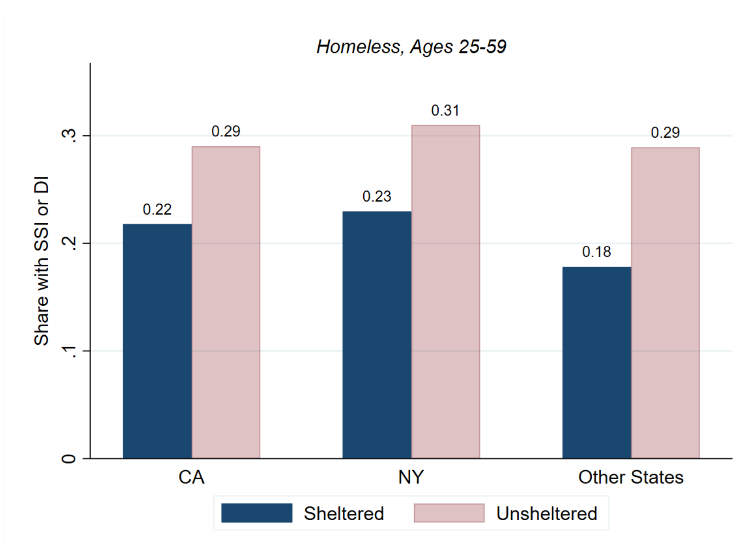
Figure 3.17: Median Earnings (Conditional on Positive) by State, 2010



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

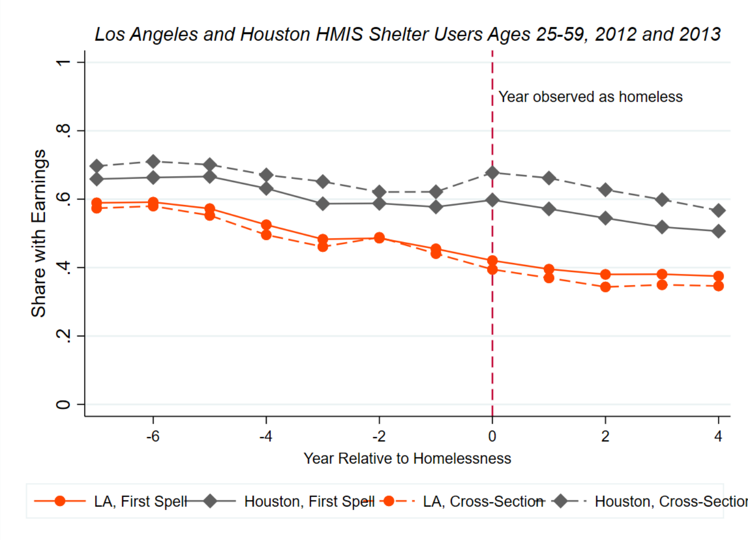
Figure 3.18: Share with SSI or DI by State, 2010



Sources: Medicare (2006-2014), Medicaid (2007-2015), SSI (2010-2014, 2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

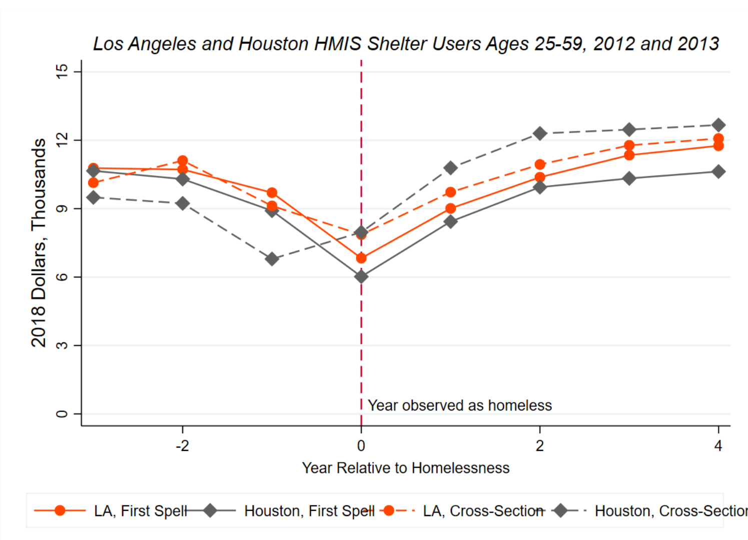
Figure 3.19: Share with Earnings in HMIS Data, Comparison of Sample Time-Frames



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, 2003-2016 IRS 1040 Datasets, 2005-2016 W2 Datasets.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

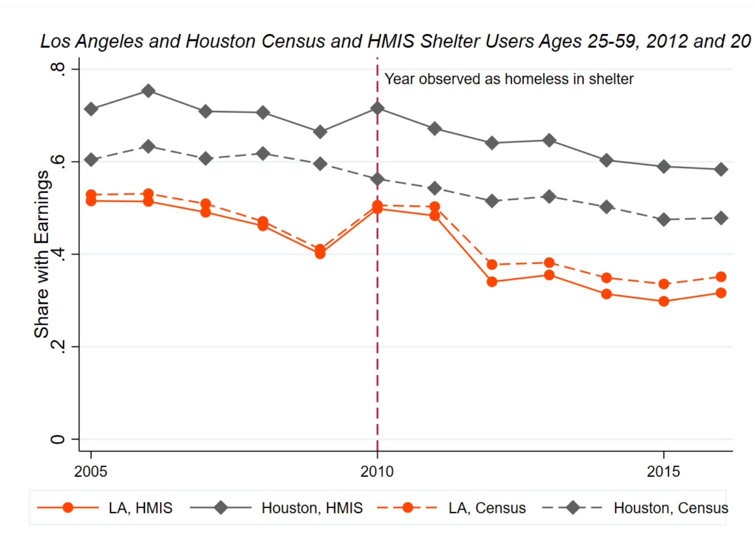
Figure 3.20: Median Earnings (Conditional on Working), Comparison of Sample Time-Frames



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, IRS 1040s (2003-2015), W2s (2005-2016).

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

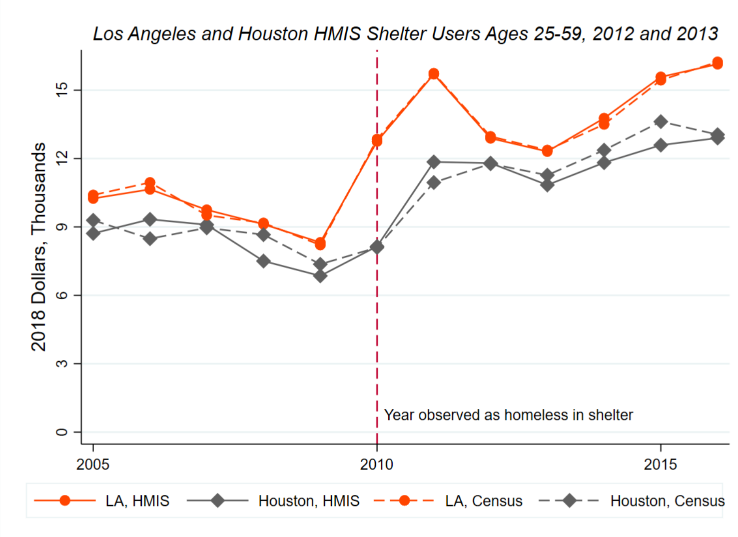
Figure 3.21: Share with Earnings, Comparison of HMIS and Census Samples



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, 2010 Census, 2003-2016 IRS 1040 Datasets, 2005-2016 W2 Datasets.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Census sample consists of sheltered homeless counted in Los Angeles or Houston. HMIS sample consists of those enrolled in HMIS shelters in Los Angeles or Houston on March 30, 2010.

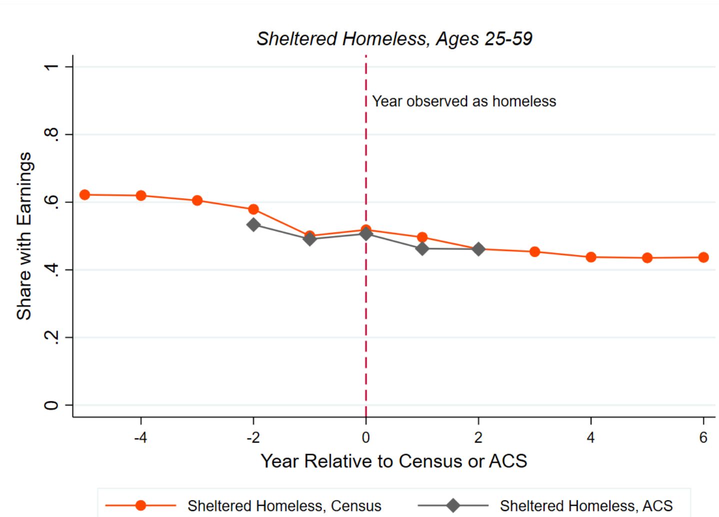
Figure 3.22: Median Earnings (Conditional on Working), Comparison of HMIS and Census Samples



Sources: 2010 Census, Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, IRS 1040s (2003-2015), W2s (2005-2016).

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Census sample consists of sheltered homeless counted in Los Angeles or Houston. HMIS sample consists of those enrolled in HMIS shelters in Los Angeles or Houston on March 30, 2010.

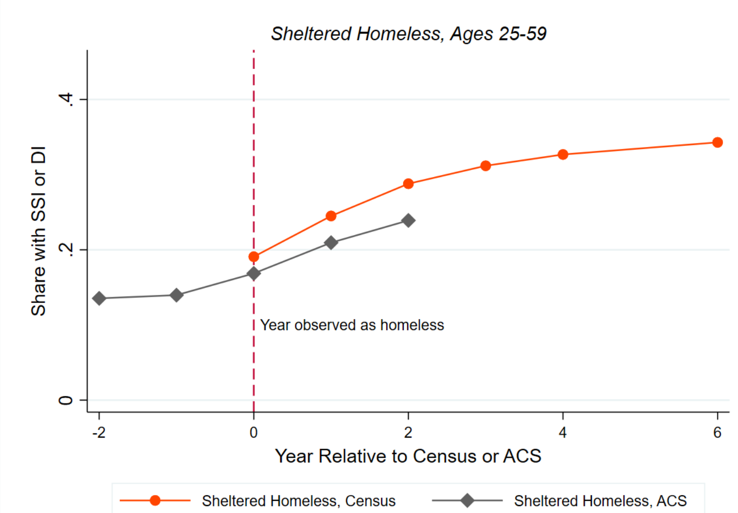
Figure 3.23: Share with Earnings, Comparison of Census and ACS Homeless



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010-2014 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 3.24: Share with SSI or DI, Comparison of Census and ACS Homeless



Sources: SSI Datasets (2010-2014, 2016), 2006-2016 Medicare Datasets, 2010 Census, 2010-2014 ACS.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Table 3.1: Characteristics of Census Homeless and Housed Comparison Groups (Ages 25-59 in 2010)

	Sheltered Homeless (1)	Unsheltered Homeless (2)	Single Housed Poor (3)	Overall Housed (4)
Age (mean)	43.48	44.43	43.85	42.35
Age 25-29	0.11	0.09	0.10	0.14
Age 30-39	0.22	0.20	0.21	0.27
Age 40-49	0.34	0.36	0.35	0.30
Age 50-59	0.33	0.35	0.34	0.29
Male	0.67	0.74	0.70	0.49
White	0.49	0.52	0.50	0.76
Black	0.40	0.38	0.39	0.13
Other race	0.10	0.10	0.10	0.11
Hispanic	0.14	0.15	0.15	0.15
Sample Size	89,500	49,500	55,000	994,000
Population	128,400	118,200	4,846,000	72,270,000
Share Assigned Linkage Key (PIK)	0.69	0.42	0.86	0.91

Sources: 2010 Census, 2010 ACS
Notes: Homeless and housed samples as defined in the text.

Sources: 2010 Census, 2010 ACS
Note: Homeless and housed samples as defined in the text.

Table 3.2: Income and Earnings (Homeless and Single Housed Poor, Ages 25-59)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
50th Percentile of Income Including the Value of In-Kind Transfers from SNAP and HUD (No SSI)												
Sheltered Homeless	$5,634	$5,029	$4,564	$3,177	$2,835	$3,948	$4,414	$3,906	$3,947	$3,527	$4,041	$4,347
Unsheltered Homeless	$2,399	$2,484	$3,619	$2,264	$2,664	$2,710	$2,630	$2,579	$2,525	$2,389	$2,439	$2,417
Single Housed Poor	$7,158	$6,786	$9,937	$7,012	$6,169	$7,026	$7,356	$7,491	$7,545	$7,411	$7,532	$8,350
50th Percentile of Income Including the Value of In-Kind Transfers from SNAP and HUD (Including SSI)												
Sheltered Homeless						$7,461	$9,149	$9,289	$9,441	$9,325		$9,518
Unsheltered Homeless						$5,479	$5,950	$6,101	$6,419	$6,303		$7,571
Single Housed Poor						$9,886	$10,140	$10,450	$10,660	$10,500		$11,030
Employment												
Sheltered Homeless	0.622	0.620	0.605	0.579	0.501	0.518	0.496	0.462	0.454	0.438	0.435	0.437
Unsheltered Homeless	0.559	0.546	0.527	0.493	0.418	0.403	0.389	0.359	0.357	0.339	0.339	0.341
Single Housed Poor	0.611	0.596	0.582	0.553	0.484	0.483	0.498	0.493	0.489	0.488	0.489	0.487
Earnings (Conditional on Employed)												
Sheltered Homeless	$9,493	$9,534	$9,327	$8,039	$6,590	$8,328	$10,870	$11,170	$11,380	$11,820	$12,860	$13,470
Unsheltered Homeless	$8,377	$8,483	$8,514	$7,847	$7,373	$8,298	$10,120	$10,310	$10,620	$11,020	$12,020	$12,320
Single Housed Poor	$14,510	$14,920	$14,230	$12,790	$10,690	$12,240	$13,890	$14,930	$15,830	$16,460	$17,650	$18,560
Sample Size												
Sheltered Homeless	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Unsheltered Homeless	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Single Housed Poor	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population												
Sheltered Homeless	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100
Unsheltered Homeless	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900
Single Housed Poor (1000s)	4,846	4,846	4,846	4,846	4,846	4,846	4,814	4,770	4,718	4,672	4,616	4,560

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)
Note: See notes in Appendix Tables for full definition of each outcome measure. Samples include PIKed adults with a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Homeless and housed samples as defined in text. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table 3.3: Benefit Receipt (Homeless and Single Housed Poor, Ages 25-59)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
SSI Receipt														
Sheltered Homeless								0.137	0.176	0.201	0.210	0.213		0.225
Unshelt. Homeless								0.210	0.234	0.255	0.260	0.260		0.270
Single Housed Poor								0.157	0.166	0.174	0.176	0.173		0.174
DI Receipt														
Sheltered Homeless				0.058	0.063	0.069	0.074	0.089	0.112	0.136	0.153	0.164	0.166	0.167
Unshelt. Homeless				0.105	0.114	0.122	0.129	0.145	0.160	0.174	0.187	0.196	0.194	0.191
Single Housed Poor				0.095	0.104	0.114	0.122	0.142	0.157	0.169	0.178	0.183	0.179	0.177
HUD Housing Assistance														
Sheltered Homeless	0.083	0.083	0.082	0.078	0.074	0.071	0.068	0.101	0.126	0.143	0.146	0.154	0.161	0.165
Unshelt. Homeless	0.082	0.084	0.083	0.081	0.081	0.082	0.083	0.094	0.104	0.111	0.116	0.122	0.128	0.132
Single Housed Poor	0.113	0.116	0.119	0.123	0.131	0.140	0.152	0.160	0.158	0.154	0.149	0.148	0.144	0.141
VA Service-Connected Disability Receipt														
Sheltered Homeless					0.015	0.017	0.023	0.026	0.029	0.031	0.033	0.034	0.035	0.036
Unshelt. Homeless					0.014	0.014	0.017	0.018	0.020	0.021	0.022	0.023	0.024	0.025
Single Housed Poor					0.011	0.013	0.014	0.015	0.016	0.017	0.018	0.019	0.020	0.021
SNAP Receipt														
Sheltered Homeless			0.358	0.382	0.538	0.600	0.738	0.826	0.786	0.737	0.707	0.681	0.652	0.628
Unshelt. Homeless			0.413	0.428	0.503	0.560	0.636	0.695	0.683	0.666	0.658	0.647	0.631	0.610
Single Housed Poor			0.374	0.408	0.437	0.473	0.548	0.595	0.594	0.575	0.558	0.549	0.528	0.507
Medicaid Receipt														
Sheltered Homeless					0.315	0.333	0.376	0.445	0.473	0.488	0.492	0.612	0.661	
Unshelt. Homeless					0.328	0.348	0.374	0.414	0.446	0.470	0.476	0.614	0.683	
Single Housed Poor					0.322	0.338	0.371	0.398	0.414	0.420	0.421	0.503	0.540	
TANF and GA Receipt (New York Only)														
Sheltered Homeless					0.333	0.361	0.469	0.584	0.486	0.396	0.343	0.303	0.289	0.275
Unshelt. Homeless					0.219	0.264	0.285	0.302	0.267	0.251	0.239	0.228	0.213	0.199
Single Housed Poor					0.183	0.182	0.186	0.191	0.162	0.145	0.122	0.113	0.109	0.103
Sample Size														
Sheltered Homeless	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Unsheltered Homeless	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Single Housed Poor	55,000	55,000	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population														
Sheltered Homeless	128,400	128,400	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100
Unsheltered Homeless	118,200	118,200	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900
Single Housed Poor (1000s)	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,846	4,814	4,770	4,718	4,672	4,616	4,560

Sources:

Note: See notes on Appendix Tables for full definition of each outcome measure. Samples include PIKed adults with a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Homeless and housed samples as defined in text. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table 3.4: Share of Individuals Misreporting Date of Birth, Place of Birth, Gender, and Citizenship Status: 2011-2018 ACS

	Homeless 2011-2018			Single Housed Poor 2011-2018			Overall Housed 2011-2018		
	Share	(SE)	Obs.	Share	(SE)	Obs.	Share	(SE)	Obs.
Date of Birth									
MM/DD/YYYY is misreported	11.7%	0.004	18,000	10.2%	0.000	2,403,000	9.2%	0.000	34,600,000
MM/YYYY is misreported	10.6%	0.004	18,000	8.0%	0.000	2,403,000	7.1%	0.000	34,600,000
YYYY is misreported	10.0%	0.004	18,000	6.8%	0.000	2,403,000	6.0%	0.000	34,600,000
YYYY is misreported by 3 or more years	3.5%	0.002	18,000	4.0%	0.000	2,403,000	3.7%	0.000	34,600,000
Age									
Age is misreported	10.6%	0.004	18,500	8.1%	0.000	2,484,000	7.3%	0.000	35,660,000
Age is misreported by 3 or more years	3.5%	0.002	18,500	4.4%	0.000	2,484,000	4.1%	0.000	35,660,000
Mean age misreport (in years)	-0.01	0.011	18,500	-0.02	0.003	2,484,000	0.00	0.001	35,660,000
Mean absolute age misreport (in years)	0.25	0.011	18,500	0.58	0.003	2,484,000	0.55	0.001	35,660,000
Place of Birth									
State or country of birth is misreported	7.4%	0.003	17,500	5.1%	0.000	2,398,000	4.9%	0.000	33,990,000
Gender									
Gender is misreported	0.5%	0.001	20,000	3.0%	0.000	2,624,000	2.7%	0.000	37,030,000
Gender is misreported [Sample: Women in Numident]	0.6%	0.001	8,000	2.4%	0.000	1,577,000	2.7%	0.000	19,130,000
Gender is misreported [Sample: Men in Numident]	0.5%	0.001	12,000	3.7%	0.000	1,047,000	2.7%	0.000	17,900,000
Citizenship									
Citizenship is misreported	3.4%	0.002	19,500	3.0%	0.000	2,505,000	3.7%	0.000	35,410,000
False positive [Sample: Non-citizens in Numident]	22.9%	0.016	1,000	25.9%	0.001	118,200	35.5%	0.000	2,021,000
False negative [Sample: Citizens in Numident]	1.6%	0.002	18,500	1.1%	0.000	2,386,000	0.9%	0.000	33,390,000

Sources: 2006-2018 ACS, 2019 Social Security Administration Numident
Note: Sample consists of PIKed individuals in the 2006-2018 ACS who link to the Social Security Administration's Numident file. Sample is further limited to observations in which the variable in question is non-blank in the Numident (e.g. for analyses of date of birth misreporting, the sample is limited to only observations for which the Numident contains date of birth data). We exclude observations in which the variable in question is hot-deck imputed in the ACS data and observations for which an alternative or edited version of the variable exists in the Numident.

Table 3.5: Share of Individuals Misreporting Income and Receipt: 2011-2018 ACS

		Wage and Salary Income			SNAP		
		Homeless	Single Housed Poor	Overall Housed	Homeless	Single Housed Poor	Overall Housed
		2011-2016**	2011-2016	2011-2016	2011-2016**	2011-2016	2011-2016
Outcome	Sample	Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate
Survey>0, Administrative=0	Full population	0.044	0.050	0.048	0.049	0.024	0.010
		(0.006)	(0.001)	(0.000)	(0.006)	(0.000)	(0.000)
Survey=0, Administrative>0	Full population	0.177	0.123	0.055	0.172	0.097	0.054
		(0.013)	(0.001)	(0.000)	(0.009)	(0.001)	(0.000)
Survey>0, Administrative>0	Full population	0.234	0.317	0.664	0.668	0.516	0.131
		(0.013)	(0.001)	(0.000)	(0.012)	(0.002)	(0.000)
Survey=0, Administrative=0	Full population	0.545	0.510	0.233	0.111	0.363	0.805
		(0.016)	(0.002)	(0.000)	(0.008)	(0.001)	(0.000)
False Negative Rate	Administrative>0	0.432	0.280	0.077	0.205	0.158	0.290
		(0.025)	(0.002)	(0.000)	(0.011)	(0.002)	(0.001)
False Positive Rate	Administrative=0	0.075	0.089	0.172	0.307	0.063	0.012
		(0.010)	(0.001)	(0.001)	(0.031)	(0.001)	(0.000)
Administrative Receipt Rate	Full population	0.411	0.440	0.719	0.840	0.613	0.185
		(0.016)	(0.002)	(0.000)	(0.010)	(0.001)	(0.000)
Survey Receipt Rate	Full population	0.278	0.367	0.712	0.717	0.541	0.141
		(0.014)	(0.002)	(0.000)	(0.011)	(0.002)	(0.000)
Mean Reported ($)	Survey>0	$9,235	$8,414	$50,250			
		($519)	($31)	($52)			
Mean True ($)	Administrative>0	$7,980	$11,120	$48,250			
		($1,059)	($105)	($108)			
Mean True ($)	Survey>0, Administrative>0	$7,929	$11,550	$50,880			
		($524)	($87)	($113)			
Mean Absolute Misreport ($)	Survey>0, Administrative>0	$5,598	$5,316	$12,190			
		($468)	($79)	($98)			
Observations		1,900	173,000	2,833,000	3,300	181,000	1,933,000

		Medicaid			Medicare		
		Homeless	Single Housed Poor	Overall Housed	Homeless	Single Housed Poor	Overall Housed
Outcome	Sample	2011-2016**	2011-2016	2011-2016	2011-2016**	2011-2016	2011-2016
		Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate	Mean or Rate
Survey>0, Administrative=0	Full population	0.096	0.072	0.033	0.022	0.018	0.007
		(0.005)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Survey=0, Administrative>0	Full population	0.087	0.085	0.032	0.033	0.034	0.015
		(0.004)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Survey>0, Administrative>0	Full population	0.440	0.372	0.084	0.045	0.072	0.031
		(0.008)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
Survey=0, Administrative=0	Full population	0.377	0.472	0.851	0.901	0.875	0.947
		(0.008)	(0.001)	(0.000)	(0.004)	(0.000)	(0.000)
False Negative Rate	Administrative>0	0.165	0.186	0.276	0.424	0.320	0.330
		(0.008)	(0.001)	(0.001)	(0.022)	(0.002)	(0.001)
False Positive Rate	Administrative=0	0.204	0.132	0.037	0.023	0.021	0.007
		(0.009)	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)
Administrative Receipt Rate	Full population	0.527	0.456	0.117	0.078	0.107	0.047
		(0.008)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
Survey Receipt Rate	Full population	0.536	0.443	0.117	0.066	0.091	0.038
		(0.008)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
Observations		8,200	708,000	10,660,000	12,500	1,015,000	15,840,000

Sources: 2006-2017 ACS, 2006-2016 IRS 1040 Datasets, 2006-2016 IRS W-2 Datasets, Illinois 2009-2016 SNAP Datasets, Indiana 2005-2016 SNAP Datasets, New Jersey 2007-2016 SNAP Datasets, New York 2007-2016 SNAP Datasets, Tennessee 2005-2016 SNAP Datasets, various states' Medicaid data, CMS Medicare 2008-2016 Datasets
Note: Sample is PIKed ACS respondents ages 18-64. Sample is limited to those who respondeded to the ACS survey in January or December, and imputed whole person observations are not included. Observations are weighted by the product of IPW weights and ACS person weights, and observations where wage and salary income are allocated are excluded. Wage and salary income is calculated from administrative datasets as the sum of wage and salary income (both taxable and deferred) across W-2s. Those with negative survey values for wage and salary income are assumed to have reported a wage and salary income of $0. Mean wage and dollar misreport amounts are reported in January 1, 2018 dollars. Standard errors are robust. * Reference period: 2005-2010. ** Reference period: 2010-2016.

Table 3.6: Comparisons to Key Prior Studies: Income, Employment, and Safety Net Participation

	(1) Present study - pooled homeless	(2) NSHAPC (Burt et al. 2001)	(3) Present study - sheltered homeless	(4) Metraux et al. (2018)	(5) Von Wachter et al. (2020)
Sample Definition					
Homeless sample	Census sheltered and unsheltered homeless (pooled)	Service users (current and recent homeless)	Census sheltered homeless	People with first HMIS enrollment in year	People with first HMIS enrollment in year
Geographic coverage	National	National	National	New York	Los Angeles
Age range	25-59	17+	25-59	18+	18+
Year(s) observed as homeless	2010	1996	2010	1990-2002	2010-2018
Resource data source	Various administrative	Self-reported	Various administrative	SSA earnings data	UI records (California)
Characteristics					
Male	0.70	0.68	0.67	0.50	0.61
White[1]	0.50	0.41	0.49	0.08	0.24
Black	0.39	0.40	0.40	0.56	0.46
Other Race	0.11	0.19	0.04	0.36	0.30
Mean Income, Share Employed, and Mean Earnings in Year Observed as Homeless (2018 Dollars)					
Pre-tax cash income (sources not specified)	-	$7,080	-	-	-
Pre-tax cash income (no SSI or TANF/GA)	$9,196	-	$8,069	-	-
Pre-tax cash income (with SSI, no TANF/GA)[2]	$10,912	-	$9,811	-	-
Pre-tax cash income (with SSI and TANF/GA; NY only)	$12,709	-	$12,175	-	-
Employment Timeframe	*Calendar year*	*Last month*	*Calendar year*	*Year of enrollment*	*Past year*
Employment in month/year (All Adults)	0.46	0.44	0.52	0.42	0.29
Employment (Adults in Families)[3]	-	0.29	0.68	0.38	0.44
Employment (Adults not in Families)	-	0.46	0.43	0.45	0.25
Earnings (conditional on working)	$14,674		$13,510	$7,700	$9,970
Program Receipt in Year Observed as Homeless					
Any benefit	0.86	0.40	0.89	-	-
SSI	0.24	0.11	0.14	-	-
Food stamps	0.77	0.37	0.83	-	-
Medicaid (All Adults)	0.46	0.30	0.45	-	-
Medicaid (Adults in Families)	-	0.60	0.69	-	-
Medicaid (Adults not in Families)	-	0.25	0.26	-	-
AFDC/TANF or GA (NY only in Census samples)	0.48	0.19	0.58	-	-
Sample Size	139,000	4,200	89,500	160,525	136,726

Sources: Burt et al. (2001), Metraux et al. (2018), Von Wachter et al. (2020), present study
Note: Notes: We inflation-adjust all dollar amounts to 2018 dollars using the Chained CPI for Urban Consumers (C-CPI-U). (1) Metraux et al. (2018) and Von Wachter et al. (2020) indicate non-Hispanic white shares, while the Census and NSHAPC indicate Hispanic and non-Hispanic whites. (2) Pre-tax cash income amounts reported in main tables do not include the value of SSI or TANF/GA from New York. We calculate pre-tax cash income with these benefits by adding the share receiving these benefits times the mean benefit amount conditional on receipt. (3) Employment for adults in families/adults not in families for the present study is calculated by pooling the Los Angeles and Houston HMIS samples. (4) We omit 2009 from the pre-period because we count people as homeless in the beginning of 2010, meaning that many individuals in our sample may have become homeless in 2009 rather than 2010. (5) Von Wachter et al. (2020) do not report the share employed in the year after shelter entry. They only report earnings in the year after shelter entry. We report the change in employment as the share employed in the year prior to shelter entry minus the share employed in the year of shelter entry.

CHAPTER 4

LIFE AND DEATH AT THE MARGINS OF SOCIETY: THE MORTALITY OF THE U.S. HOMELESS POPULATION

Abstract

This paper examines the relationship between extreme socioeconomic disadvantage and poor health by providing the first detailed and accurate picture of mortality patterns among people experiencing homelessness in the U.S. Our analyses center on 140,000 people who were sheltered or unsheltered homeless during the 2010 Census, by far the largest sample ever used to study this population and the only sample designed to be nationally representative. These individuals, along with housed comparison groups, are linked to Social Security Administration data on all-cause mortality from 2010-2022 to estimate the magnitude of health disparities associated with homelessness. We find that non-elderly people experiencing homelessness have 3.5 times the mortality risk of those who are housed, accounting for differences in demographic characteristics and geography, and that a 40-year-old homeless person faces a similar mortality risk to a housed person nearly twenty years older. Our results reveal notable patterns in relative mortality risk by age, race, gender, and Hispanic ethnicity and suggest that within the homeless population, employment, higher incomes, and more extensive observed family connections are associated with lower mortality. The mortality hazard of homeless individuals rose by 33 percent during the COVID-19 pandemic, an increase that, while similar in proportional terms to the increase for the housed population, affected a much larger share of the homeless population due to their substantially elevated baseline mortality rate. These findings elucidate the persistent hardships associated with homelessness and show that the well-documented gradient between health and poverty persists into the extreme lower tail of socioeconomic disadvantage.[1]

1. This chapter is joint work with Bruce D. Meyer and Ilina Logani.

4.1 Introduction

Of the many hardships associated with poverty, heightened mortality risk is arguably the most alarming. More than a grim outcome, mortality is a fundamental indicator of quality of life, reflecting numerous dimensions of physical and mental health and one's sense of safety and well-being. Extensive research spanning academic disciplines, countries, and time periods has established a robust correlation between heightened mortality risk and socioeconomic disadvantage (Kitigawa and Hauser 1973, Deaton and Paxson 1999, Cutler et al. 2006). This correlation holds true whether privilege is defined by income and wealth (Chetty et al. 2016, Boen et al. 2010), education (Cutler and Lleras-Muney 2006, Cutler et al. 2011), social and occupational class (Cutler et al. 2012), or geography (Currie and Schwandt 2016). Yet despite this broad literature, little is known about the mortality risk faced by people in the extreme lower tail of socioeconomic disadvantage, due in part to the difficulty of accurately identifying the most deprived individuals in existing data sources like household surveys (Meyer et al. 2021).

This paper advances our understanding of the relationship between extreme poverty and health by examining the mortality of one of the most deprived segments of the U.S. population, people experiencing homelessness. Homelessness is both a stark indicator of material deprivation and an adverse life event, one that can have detrimental effects on health and personal safety. Recent developments like the rise in unsheltered homelessness, the COVID-19 pandemic, and surging deaths from opioids and other substances have drawn renewed attention to the humanitarian toll of homelessness, while also highlighting important gaps in our present understanding of the health vulnerabilities faced by this population. Although anecdotal evidence and numerous localized studies suggest that homelessness is associated with substantially elevated mortality risk, the extent of mortality disparities between homeless and housed individuals has not been examined nationally or with representative data, and little is known about heterogeneity in mortality risk within this population.

This paper provides the first detailed and accurate picture of mortality in the U.S. homeless population. Our approach centers on 140,000 people who were experiencing sheltered or unsheltered homelessness during the 2010 Census, by far the largest sample ever used to study this population's mortality and the only sample designed to be nationally representative. We follow these individuals using linked administrative data on all-cause mortality for twelve years, including the first two years of the COVID-19 pandemic, and compare their mortality risk to representative samples of the overall housed and housed poor populations drawn from the Census and American Community Survey (ACS). Unlike prior work, we use the same, or closely comparable, datasets to calculate homeless and housed mortality risk and apply methods uniformly to both groups, an approach that facilitates direct and reliable comparisons and allows us to examine heterogeneity in mortality disparities with much greater detail than in prior work. This approach also allows us to examine the evolution of mortality disparities over time and to account for the full time-varying distribution of characteristics when comparing groups.

Our main finding is that non-elderly people who have experienced homelessness face 3.5 times the mortality risk of people who are housed, accounting for differences in demographic characteristics and geography. This disparity far exceeds the mortality gap between Black and white housed individuals, which we estimate to be 1.4, and is only slightly smaller than the mortality gap between disabled and non-disabled housed individuals, which we estimate to be 4.6. Comparing the mortality risk of people who are homeless and those who are poor but housed, we find that homelessness is associated with about a sixty percent greater mortality risk than poverty alone. Our estimates suggest that a 40-year-old homeless person has a mortality risk similar to a housed person who is nearly twenty years older and a poor housed person who is nearly ten years older.

Our analyses reveal notable patterns in mortality risk by age, race, income, family status, and type of homelessness. Homeless individuals' mortality risk relative to housed individuals differs over the life cycle and is greatest when they are in their 30s and 40s. Beginning in their 50s, however, homeless individuals' mortality hazard begins to converge with people who are housed, a pattern that may reflect both excess mortality of exceptionally vulnerable homeless individuals at younger ages and shared health vulnerabilities for elderly homeless and housed individuals. We also find that Black homeless individuals have lower mortality risk than those who are white, a pattern that may in part reflect a lower prevalence of substance abuse and behavioral health conditions among Black homeless individuals and may suggest important heterogeneity in the predominant pathways to homelessness by race. Within the homeless population, people who do not have a recent employment history, those with lower formal incomes, and those without observed family connections are especially vulnerable relative to their more advantaged and connected counterparts. Surprisingly, we find similar mortality risk for people who were initially observed in shelters and those who were unsheltered once we control for gender, a finding that illustrates the substantial health risks faced by people experiencing homelessness even when they are not sleeping on the streets.

We estimate that average annual mortality risk rose by about half a percentage point for homeless individuals during the first two years of the COVID-19 pandemic, translating to about a 33 percent increase over their average during the two years preceding the pandemic after accounting for the expected increase in mortality due to aging. While the proportional rise in mortality risk was similar for people who were housed (30 percent) and poor and housed (34 percent), the pandemic affected a much larger share of the homeless population because of their substantially elevated baseline mortality risk. Homeless men experienced a larger rise in both absolute and proportional mortality risk during the pandemic (about 0.7 percentage points and 38 percent, respectively) than homeless women (about 0.3 percentage points and 24 percent).

Our findings illustrate, for the first time, the substantial health disparities associated with homelessness using data that are designed to be representative of the U.S. homeless population, while also calling attention to subsets of this population that are especially vulnerable and helping to establish the most broadly true patterns from among the many, often conflicting findings in previous work. In doing so, this paper adds to a growing body of research establishing fundamental facts about the size, characteristics, material circumstances, and housing transition dynamics of the U.S. homeless population. More broadly, this paper contributes to an expansive literature in economics on the association between socioeconomic disadvantage and poor health, suggesting that this gradient persists even into the extreme lower tail of socioeconomic disadvantage.

This paper proceeds as follows. Section 4.2 reviews available literature on homeless individuals' mortality and health and the broader literature on the relationship between socioeconomic status and health. Section 4.3 describes the decennial Census and American Community Survey (ACS) datasets from which we draw our homeless and comparison samples, as well as the administrative data on mortality, disability status, income, and family connections to which we link these samples. Section 4.4 describes our methods for linking datasets and estimating mortality hazards and relative risks. Section 4.5 presents our findings, including results from comparisons of homeless and housed individuals, comparisons of subsets of the homeless population, and changes in mortality risk during the COVID-19 pandemic. Section 4.6 discusses and analyzes key findings and Section 4.7 concludes.

4.2 Background and related literature

4.2.1 Prior work on homelessness and mortality

Challenges in studying homeless individuals' mortality Researchers often turn to mortality as an indicator of health and wellbeing for vulnerable populations because it is straightforward to measure and reflects unambiguous hardship. To this end, a small body of research examines the mortality patterns of people experiencing homelessness and estimates mortality disparities between housed and homeless individuals. These efforts are complicated, however, by the lack of representative data and the difficulty of obtaining longitudinal information. As a result, many prior studies are based on small, non-random samples of homeless individuals in major cities, primarily Boston, New York, or Philadelphia. Other studies focus on narrow subsets of the homeless population for whom data are more readily available, such as male veterans (Schinka et al. 2018), youth (Auerswald, Lin, and Parriott 2016), or people with post-traumatic stress disorder (Kasprow and Rosenheck 2000).

Table 4.1 summarizes the data, methods, and findings from prior studies with relatively large samples and sound methodologies. Even these analyses, however, face limitations that make it difficult to assess the generality of their findings. Barrow et al. (1999) and Metraux et al. (2011) draw large samples from New York City's administrative shelter databases, an approach that offers reliable mortality estimates for the city's sheltered homeless population but does not illuminate mortality patterns nationally or among people who are unsheltered. The remaining studies draw their samples from users of homeless health services, an approach that could bias findings to people who are either unwell or health-conscious enough to use these services (Baggett et al. 2013, Hibbs et al. 1994, Hwang 1997, Roncarati et al. 2018, Roncarati et al. 2020). Another limitation of these studies lies in their ability to obtain comparable mortality estimates for the housed population. For instance, Baggett et al. (2013) and Barrow et al. (1999) measure homeless individuals' mortality using linked microdata from the Massachusetts Department of Health and the National Death Index, but they obtain housed individuals' mortality rates using aggregated data from the Center for Disease Control. These and other data and methodological discrepancies between housed and homeless mortality estimates complicate the interpretation of comparisons and limit the authors' ability to account for demographic differences between groups.

4.2.2 Key findings from prior work

Despite these data challenges, prior studies agree on several qualitative observations about homeless individuals' mortality risk relative to people who are housed. While point estimates of relative mortality risks differ widely across studies, most find that non-elderly people experiencing homelessness face a substantially elevated mortality risk relative to housed individuals of the same age group and gender. Relative mortality risks tends to be higher in early adulthood (Baggett et al. 2013, Barrow et al. 1999, Hwang et al. 1997, Hibbs et al. 1994), and compared to housed people of their gender, homeless women appear to have a greater risk than men (Baggett et al. 2013, Barrow et al. 1999, Hwang et al. 1997, Henwood et al. 2015, Hibbs et. Al. 1994).

Many of these studies also examine heterogeneity in mortality risks within the homeless population. Prior work suggests that white homeless adults face a heightened mortality risk relative to those who are Black or other races, a pattern that contrasts with mortality disparities by race in the housed population (Baggett et al. 2013, Hibbs et al. 1994, Roncarati 2018, Metraux et. al. 2011, Hibbs et. al. 1994, Roncarati et al. 2022). Prior work also broadly agrees that homeless men face higher mortality risk than homeless women, especially homeless women in families (Roncarati 2018, Hwang et al. 1997, Barrow et al. 1999, and Metraux et al. 2011). Studies that center on the unsheltered find that they face higher mortality risk relative to sheltered homeless populations (Roncarati 2018, Roncarati et al. 2020), and, unsurprisingly, that substance abusers face a particularly high mortality risk (Hibbs at al. 1994, Barrow et. al. 1999). These studies find no apparent seasonal pattern in mortality risks (Hibbs et al. 1994, Hwang et al. 1997), and there is little consensus on relationship between length of time spent homeless and Bmortality risks (Barrow et al. 1999, Metraux et al. 2011, Kasprow and Rosenheck 2000).

4.2.3 Causes of death and health risks

Prior work has suggested that the leading causes of death among people experiencing homelessness have changed over time and differed by age. Drug overdose appears to be the leading cause of death for homeless individuals under 45 in recent years, having superseded HIV/AIDS in the mid-2000s. While substance abuse disorders have long been prevalent in this population, the most frequently abused substances have changed over time from alcohol, to cocaine, to methamphetamine, fentanyl, and other opioids in more recent years (Fischer and Breakey 1991, North et al. 2004, Cawley et al. 2022, Baggett et al. 2013, Roncarati et al. 2018, Roncarati et al. 2020). Traumatic injuries, including traffic accidents and homicides, appear to constitute the second leading cause of death for younger homeless individuals (Hwang et al. 1997, Roncarati et al. 2018, Roncarati et al. 2020, Schinka et al. 2018, Cawley et al. 2022, Hwang et al. 1997). For homeless individuals aged 45-64, heart disease and cancer appear to be the leading causes of death, followed by drug overdose and traumatic injury. Few studies have examined mortality among elderly homeless adults because this group is a small share of the homeless population.

Aside from cause of death, many studies also examine health conditions and health risks that disproportionately affect people experiencing homelessness. In the most recent survey designed to be nationally representative, Burt et al. (1999) found high rates of victimization and assault, difficulties in accessing medical attention, and alcohol, drug, and mental health conditions among people experiencing homelessness. More recent evidence suggests that homeless individuals experience accelerated aging, as evidenced by the early onset of chronic medical conditions and functional and cognitive impairments typically seen in housed adults aged 75 and older (Brown et al. 2022, Baggett et al. 2013, Hwang et al. 1997, Schinka et al. 2016, Garibaldi et al. 2005, Gelberg et al. 1990). For instance, older homeless adults are more likely than older housed individuals to have functional and mobility impairment, frailty, visual impairment, and urinary incontinence, and the prevalence of these and other "geriatric" conditions is equal to or higher than that seen in housed and housed poor adults twenty years older (Brown et al. 2012, Brown et al. 2017). Trick et al. (2021) also reported that the most frequently cited reasons for homeless individuals' emergency room (ER) visits are schizophrenia or auditory hallucinations, foot pain, and suicidal ideation. In a recent study designed to be representative of California's homeless population, two-thirds of respondents indicated symptoms of mental health conditions, but much smaller shares had received counseling or medication (Kushel and Moore 2023). These findings speak to a broad array of physical and behavioral health conditions and vulnerabilities that are likely linked to elevated mortality risk.

4.2.4 Relationship to literature on the health-socioeconomic status gradient

The study of homeless individuals' mortality relates to an expansive body of economic literature on the association between socioeconomic disadvantage and poor health more broadly (e.g. Kitigawa and Hauser 1973, Deaton and Paxson 1999). This association, often called the health-socioeconomic status gradient, arises whether disadvantage is defined or proxied by income and wealth (e.g. Chetty et al. 2016, Boen et al. 2010), education (e.g. Cutler and Lleras-Muney 2006, Cutler et al. 2011), social and occupational class (Cutler et al. 2012), or geography (Currie and Schwandt 2016). Unlike prior studies, the present work examines health disparities using one of the most extreme indicators of economic hardship available, homelessness.

A key question in this literature is whether a causal relationship exists between socioeconomic advantage and health, and if so in which direction and through which channels. On the one hand, human capital models suggest that poor health impedes the ability to work productively, limits the ability to invest in human capital, and reduces returns to such investments (Schultz 1962, Becker 1962, Grossman 1972, Becker 2007). Conversely, because health is a normal good, economic theory predicts that higher-income individuals should spend more money on health, which could produce a causal relationship in the other direction. At the same time, this theoretical literature emphasizes the dynamic nature of human capital processes and likely interactions between causal mechanisms over the life course, meaning that it may be difficult to identify a predominant causal direction or channel (e.g. Currie and Moretti 2003, Case et al. 2005, Almond and Currie 2011).

Empirical work offers support for numerous causal channels. For example, studies have found that poor health in childhood limits educational attainment and reduces earnings and labor force participation in adulthood (Brown et al. 2020, Case et al. 2005, Case and Paxson 2011) and that health shocks depress wages and reduce labor force participation (Smith 1999). Mental health conditions, which are prevalent among people experiencing homelessness, may be particularly important, with Currie and Madrian (1999) finding that this facet of health is one of the most important determinants of adult working days lost. Other studies have found that socioeconomic status, typically as proxied by income, wealth, and education, causally affects health by reducing health expenditures and investments or by affecting health behaviors (Boen and Yang 2016, De Walque 2007, Gramard and Parent 2007, Lleras-Muney 2005).

While little causal evidence exists on the relationship between poor health and homelessness specifically, this broader literature suggests channels through which the two may be related. Behavioral health conditions, substance use, and physical or mental health shocks could be important drivers of homelessness, while at the same time the experience of homelessness likely causes health to deteriorate through direct effects on physical and mental health and indirect effects on access to and continuity of medical care. Early life disadvantage in the form of parental resources and behaviors, health endowments (including behavioral health and vulnerability to addiction), and adverse childhood experiences may elevate the risk of both homelessness and mortality later in life. As with health and socioeconomic status more broadly, homelessness and poor health are likely causally related in both directions, with the importance of various channels differing substantially within this population.

4.3 Data

4.3.1 Census data on the U.S. homeless population

Our homeless sample is comprised of individuals counted during the 2010 Census's Service-Based Enumeration (SBE), an operation that took place March 29-31, 2010. The SBE included in the Census people sleeping in homeless shelters, people using soup kitchens or food vans who said they lacked a residence, and people sleeping outdoors at sites called Targeted Non-Sheltered Outdoor Locations (TNSOLs). We include all individuals with sufficient personal information to be linked to death records in our analysis. The linked subset consists of 140,000 individuals who are weighted to account for the probability of linkage.[2] The SBE's enumeration frame was based on the address list of homeless service locations from the 2000 Census and augmented using internet research, queries to local officials and service providers, and a series of validation and advance visit operations. Prior work has shown that the coverage of the sheltered homeless population in the Census was surprisingly good, with about 90-95 percent of shelter users being included in its count, although it is worth noting that the Census's shelter definition excludes some facilities classified by HUD as homeless shelters (Meyer, Wyse, and Corinth 2023). The SBE also arrived at an unsheltered homeless population estimate similar in magnitude to the Department of Housing and Urban Development (HUD)'s point-in-time (PIT) estimate of the unsheltered homeless population.

Our homeless sample therefore consists of people who were literally homeless at a point

2. While our sample is drawn from the tail-end of the Great Recession, prior work suggests that our findings likely generalize to people who experienced homelessness in the surrounding years. For example, Meyer et al. (2023) compare income and safety net participation for homeless individuals from the 2010 Census to people who were surveyed in homeless shelters by the American Community Survey (ACS) in surrounding years and find similar levels and longitudinal patterns of these outcomes.

in time in late March 2010. Because the study period continues through 2022, and because people frequently transition between homeless and housed statuses, it is likely that many or most of those in our sample were housed for some of the study period. HUD estimates that about one-quarter of people experiencing homelessness at a point in time are chronically homeless, i.e. experiencing frequent or extended homeless spells, while the rest are experiencing shorter or less frequent homeless spells (HUD 2022). Even when housed, however, prior work has shown that this population faces markedly worse material deprivation than the average housed poor individual, with extremely low incomes and high reliance on the safety net persisting for at least the decade surrounding the 2010 Census enumeration date (Meyer et al. 2023). Moreover, we find no evidence of heightened mortality risk for this population in 2010 and 2011, the years closest to when we observe them as homeless, relative to later years, a finding that suggests our results are applicable to people contemporaneously experiencing homelessness.

4.3.2 Administrative data on mortality, income, and family and disability status

We obtain death dates from the Census Bureau's Numerical Identification File (Numident), which is derived from Social Security Administration (SSA) records and frequently updated. The Numident has been shown to be a "high-quality and timely source of data to study all-cause mortality" (Finlay and Genadek 2021). A limitation of our study is that the Numident does not indicate cause of death.

We draw on several additional sources of administrative data to examine heterogeneity in mortality risk by income and employment, family status, and disability status. Specifically, we use Internal Revenue Service (IRS) 1040 extract files and W-2s (2005-2009) to determine income, employment status, and identify the presence of co-filing spouses and dependents prior to our study period. We also draw on administrative data from the Centers for Medicare and Medicaid Services (CMS) to identify 2009 recipients of Disability Insurance (DI) in Medicare records and Supplemental Security Income (SSI) in Medicaid records.

4.3.3 Census and ACS data on housed comparison groups

We compare homeless individuals' mortality risk to people who are housed and to a subset of the housed population that is also poor. The overall housed comparison group consists of a one percent random sample of housed adults from the 2010 Census. The housed poor comparison group is drawn from the 2009-2010 American Community Survey (ACS), which indicates household income relative to the poverty line. To obtain a large sample of poor individuals while keeping the selection date as close to the Census as possible, we keep individuals surveyed in the last three months of the 2009 ACS or the first three months of the 2010 ACS who were alive on April 1, 2010, the beginning of our study period.

4.4 Methods

4.4.1 Linking datasets

Our approach requires us to link birth and death dates from social security records to the homeless and comparison samples from the Census and ACS. We also link administrative data on transfer programs and tax records to determine disability status, connections to others, and income. We link these datasets using unique anonymized linkage keys known as Protected Identification Keys (PIKs), which are assigned by a Census Bureau program that searches for matches based on name, date of birth, gender, and address (or, in the case of homeless individuals, enumeration site address) in a reference file based on social security records.[3] PVS assigned a linkage key to 69 percent of those counted in homeless shelters, 42

3. The system, known as the Person Identification Verification System (PVS), uses addresses to narrow the number of potential matches for a Census record in the reference file, but if this approach does not yield a linkage key, PVS proceeds to search for matches using name, date of birth, and gender only (Layne and

percent of those counted at food vans and soup kitchens, and 17 percent of those counted at outdoor locations (TNSOLs) (Meyer et al. 2021).**??** Linkage rates are close to 90 percent for the housed comparison groups. Most homeless individuals who were not assigned a linkage key did not provide sufficient personal information to enumerators, in many cases because they were sleeping during the count or were enumerated by sight at a bustling service location (Meyer et al. 2022). We adjust for non-linkage using inverse probability weights where the probability of linkage is estimated as a probit function of age, race, gender, Hispanic origin, state, and homeless location type.

4.4.2 Homeless individual and comparison sample restrictions

In our main results, we estimate mortality hazard rates and survival rates for three groups of non-elderly adults (individuals who are homeless, housed, housed and poor), defined as those ages 18-54 in 2010.[4] We focus on this age cohort in our main results because homelessness is rare among the elderly; in 2010, only 6.6 percent of the adult homeless population was 65 or older, compared to 17.3 percent of the overall housed adult population and 12.2 percent of the housed poor population. We do, however, produce results for some key outcomes with a sample that includes elderly people in all three groups to document differences in the mortality hazard by age.

Tables 4.2 and 4.3 display summary statistics for the non-elderly sample of homeless individuals and comparison groups. The non-elderly homeless sample consists of about 140,000 linked individuals and the housed comparison group includes about 1.3 million linked individuals. The housed poor sample consists of 110,000 linked individuals. Among the non-elderly, homeless individuals are older and are disproportionately likely to be between 45-49 and 50-54 years old. The homeless are also more likely to be male, especially compared to

Wagner 2014). In this way, PVS can assign linkage keys to homeless individuals in the Census even if its reference file does not include the address where they were found during the SBE.

4. Surviving individuals' ages ranged from 30-66 at the end of the study period in 2022.

the housed poor, are more likely to be Black, and are more concentrated in the Northeast and West, reflecting the substantial homeless populations in New York and California.

4.4.3 Mortality hazard model

We specify the mortality hazard $\lambda_i(t)$ using a discrete time proportional hazard model with a non-parametric baseline hazard:

$$\lambda_i(t) = \lambda_0(t) \exp z_i(t)'^{\beta} \tag{4.1}$$

In this equation, $\lambda_0(t)$ is the baseline hazard at time t (which is unknown, but estimated non-parametrically), where t indexes six-month periods between April 2010 and March 2022. $z_i(t)$ is a vector of time-dependent explanatory variables and covariates for individual i, and β is a vector of unknown parameters. The covariates included differ across specifications. We also include group interactions with the baseline hazard parameters in some specifications.

This model is a natural choice in our setting for several reasons. Proportional hazard survival models are frequently employed to study time-to-event data, particularly mortality. Moreover, while the underlying data-generating process is continuous, our data are discrete, with ties in the form of same-day deaths occurring not infrequently. The discrete model allows us to estimate the model without relying on approximations that would be required if using the Cox partial likelihood estimation method. Nevertheless, the estimates from our model are parameters of a continuous time hazard and thus retain an easy interpretation. We employ a non-parametric baseline because approaches that assume a parametric form for the baseline hazard provide inconsistent estimates when the assumed baseline hazard is incorrect, which likely leads to bias when events like the COVID-19 pandemic or other period effects give the hazard an unusual shape (Meyer 1990).

4.4.4 Mortality accounting for demographic differences between groups

We compare groups accounting for differences in their demographic characteristics in two ways. Our first approach is to estimate a hazard model with controls for covariates with key covariates being indicators for groups and a common baseline hazard. We estimate several different specifications with different sets of controls. We then interpret the coefficient on a group dummy as the proportional difference in the hazard between that group and a base group, accounting for covariate differences. The advantage of this approach is that it provides a simple summary measure of the relative hazard rate. The drawback is that it assumes a common baseline mortality hazard across all groups, which may not be correct.

Our second approach allows the baseline hazard to vary more flexibly between groups. Under this approach, we estimate a hazard model including the covariates but also interacting group indicators with the baseline hazard parameters. We then use these estimates and the distribution of covariates for the homeless population to simulate a hazard and survivor function for the homeless and our comparison groups. This approach provides us with predicted hazard rates and survivor functions for each group under the counterfactual scenario where they had the same covariates as the homeless group. In addition to allowing the baseline hazard function to vary between groups, this approach has the advantage of allowing us to estimate differences in twelve-year survival accounting for demographic differences, not just semi-annual hazards, and to see the evolution of differences in mortality hazard rates over time.

Both approaches constrain the effect of a covariate to be the same for homeless and housed groups. This assumption may not be plausible in all cases. For example, comparisons of means for several outcomes suggest that among the homeless, groups that are more disadvantaged in the overall population fare better in certain respects than those who are more advantaged in the overall population. Meyer et al. (2023) find that homeless individuals who are Black have higher incomes and are more likely to be employed than those who are white. In this case, the assumption that race has the same effect on mortality for the homeless and the housed may be incorrect, suggesting that controlling for race may not make the homeless and our comparison groups more comparable. For this reason, we estimate specifications without controls and then with the progressive addition of age, gender, race and ethnicity, and geographic controls.

4.5 Results

4.5.1 Mortality disparities between homeless and housed populations

In this section, we consider differences in mortality risk between people who are homeless and people who are housed and compare our findings to the previous literature. We estimate the magnitude of disparities between groups with and without accounting for demographic and geographic differences. We also estimate relative mortality risk for subsets of the population defined by gender, race, Hispanic ethnicity, disability status, and age.

Empirical mortality hazard and survivor functions

Figure 4.1 displays the empirical mortality hazard, defined as the probability of death in a six-month period conditional on being alive at the beginning of that period, for the non-elderly homeless population and for the housed and housed poor comparison groups. The shaded portion of the figure indicates periods during the COVID-19 pandemic. The mortality hazard increases over time as people in each cohort age, rising from 0.38 percent in the first period to about 1.19 percent in the final period for the homeless, 0.09 to 0.30 percent for the housed, and 0.18 to 0.47 percent for the housed poor. Homeless individuals' mortality hazard ranges from 3.9 to 4.9 times that of the housed population over the study's twelve-year period.

Unlike previous studies, we also compare the mortality of homeless individuals to people who are poor but housed. Our homeless sample's mortality hazard is 2.1 to 3.2 times that of the housed poor over the twelve years. We also find that housed poor individuals' mortality hazard is 1.4 to 2.1 times that of the housed population more broadly, but as we show in the next section, this disparity increases when we account for age and gender.

Figure 4.2 displays the empirical survivor function for the three groups, defined as the share of those alive at the beginning of our study who are alive at end of each six-month period. After 12 years, 96.1 percent of the housed population is still alive, compared to 93.8 percent of the housed poor and just 84.2 percent of the homeless population.

Mortality hazard accounting for differences between groups

Figure 4.3 summarizes the mortality hazard rate of the homeless and housed poor groups relative to the overall housed population and shows how the relative hazard changes after accounting for demographic and geographic differences between groups. Specifically, the figure displays the estimated coefficient on group indicators from the first estimation approach described in Section 4.4, where we regress mortality on group indicators for the homeless and housed poor samples and a common set of duration indicators for the three groups, as well as various sets of controls.

Without controls, the mortality hazard of homeless individuals is about 4.4 times that of the housed, but when we account for age and gender differences the relative hazard falls to 3.4. This estimate, which is higher than some estimates of relative mortality risk from previous literature and lower than others, is much more precise than prior work, with a 95 percent confidence interval with age and gender controls ranging from about 3.5 to 4.1 (Hwang et al. 1997, Hibbs et al. 1994, Baggett et al. 2013, Barrow et al. 2011).[5] Adding race, ethnicity, and geographic controls has little effect on the relative mortality rate, suggesting that age

5. The mortality ratios calculated by Baggett et al. (2013) and Hwang et al. (1997) adjust for age, race, and gender, while Barrow et al. (2011) adjusts for both age and gender and Hibbs et al. (1994) only adjusts for age.

and gender are the key demographic differences between samples affecting relative mortality rates. Without controls, the housed poor are 1.6 times as likely to die as the broader housed population, but after accounting for age and gender their relative mortality risk rises to 2.1. Accounting for age and gender, we estimate that people who have experienced homelessness are about 60 percent more likely to die than those who are poor but housed, suggesting that homelessness is an important risk factor for mortality that is distinct from poverty alone.

Figure 4.3 also indicates the mortality risk of sheltered and unsheltered homeless individuals relative to the housed population. Without controls, the mortality hazard is slightly higher for the unsheltered than the sheltered, but after accounting for the larger male share among the unsheltered homeless, we find that these two subsets of the homeless population face similar mortality risk.

In Figure 4.4, we display the age- and gender-adjusted mortality hazard for the homeless and comparison groups. These results correspond to the second approach described in Section 4.4, where we estimate a model with group-specific baseline hazard parameters and simulate the mortality hazard for housed and housed poor groups using the distribution of characteristics of the homeless sample.[6] The main difference between the empirical and covariate-adjusted hazards is that the housed poor have a higher mortality hazard when we account for age and gender, as we saw in Figure 4.3, reflecting the fact that when we align their characteristics with the older, more male homeless population, their mortality hazard increases. Table 4.4 reports cumulative mortality over the twelve-year study period using the empirical and covariate-adjusted hazards. When considering cumulative rather than period-specific mortality, we find people in our homeless sample were 3.2 times as likely to die during the study period as the housed and about 1.6 times as likely to die as those who are housed but poor, accounting for age and gender.

6. Figure 4.4 includes confidence intervals for the covariate-adjusted mortality hazard since these are predicted according to the methodology described in the text rather than observed in our data, as was the case for the empirical mortality hazard.

Figure 4.4 illustrates in stark terms the considerable health disparities associated with poverty and homelessness. People who are poor but housed are about twice as likely to die as the average housed person, and people who have experienced homelessness face a mortality risk that is about 60 percent higher than those who are poor but housed.

Gender and mortality

Figure 4.5 displays the mortality risk of homeless and poor housed individuals relative to the housed by gender, controlling for age. The first set of points in this figure indicates the hazard by gender and housing status relative to housed men. This set allows us to see how the mortality hazard differs by gender for a given housing status and across housing statuses for a given gender. To make it easier to see how the mortality hazard differs by housing status among women, the second set of points indicates the hazard of homeless and housed poor women relative to housed women.

We find that men have higher mortality risk than women with a given housing status. For example, housed men have mortality hazard that is 35 percent higher than housed women, and homeless men have mortality hazard that is 29 percent higher than homeless women. At the same time, homeless women face mortality risk that is four times that of their housed counterparts, whereas homeless men are only about 3.3 times as likely to die as housed males, estimates that reflect the higher mortality risk of housed men compared to housed women. These findings are consistent with prior literature suggesting that homeless women face especially elevated mortality risk relative to their housed counterparts, although the magnitude of homeless-to-housed mortality disparities for women in our study is smaller than in previous work (Baggett et al. 2013, Barrow et al. 1999, Hwang et al. 1997, Henwood et al. 2015, Hibbs et al. 1994). These findings suggest that gender differences in mortality risk found in some past studies may not generalize to the U.S. homeless population more broadly. Race and mortality

Figure 4.6 displays the mortality risk of homeless and poor housed individuals relative to the housed by race, controlling for age. The first set of points in this figure indicates the hazard by race and housing status relative to housed people who are white, while the second and third sets of points indicate the relative hazard of homeless and housed poor people who are Black and of other races, respectively, relative to housed people of the same race.

For housed and poor housed individuals, mortality risk is highest for people who are Black, followed by those who are white, and then then those of other races. Among the homeless population, however, white individuals have the highest mortality risk, followed by people who are neither white nor Black. In a reversal of the pattern observed in the housed population, Black individuals have the lowest relative mortality risk among the homeless population. This pattern in mortality risk by race is consistent with previous work, which also found lower mortality risk for Black individuals experiencing homelessness (Hibbs et al. 1994, Metraux et al. 2011, Baggett et al. 2013).

Comparing homeless individuals' mortality risk to housed individuals of the same race, we find that white homeless individuals and those of other races have the most elevated mortality risk relative to their housed counterparts, at 4.7 and 4.6 times, respectively. Black homeless individuals are 2.3 times as likely to die as their housed counterparts, a fact that reflects both the relatively low mortality hazard of Black individuals within the homeless population and the elevated mortality risk of Black housed individuals compared to those who are white and of other races. This finding, too, is consistent with previous work (Hibbs et al. 1994, Metraux et al. 2011, Baggett et al. 2013).

Hispanic ethnicity and mortality

Figure 4.7 displays relative mortality risk by housing status and Hispanic ethnicity. Hispanic individuals have lower mortality risk than non-Hispanics in each of the three housing statuses.[7] For example, a homeless Hispanic person has, on average, 23 percent lower mortality risk than a non-Hispanic person, controlling for age. Non-Hispanics who are homeless have slightly higher mortality risk relative to their housed counterparts (3.8 times) than do homeless Hispanics (3.5 times). No previous study, to our knowledge, has looked at differences in mortality risk by Hispanic ethnicity in the homeless population.

Disability status

Figure 4.8 displays relative mortality risk by housing status and disability. We define a person to be disabled if Medicare records indicate that they received Disability Insurance (DI) in 2009 or if Medicaid records indicate that they received Supplemental Security Income (SSI) in 2009. As Table 4.4 indicates, a much larger share of the homeless population was disabled before the beginning of our study (20.6 percent) than of the housed poor (10.7 percent) or of the broader housed population (3.9 percent). We note, however, that Meyer et al. (2023) find that DI and SSI receipt increase at a faster rate for the Census homeless population after 2010 than for the housed and housed poor populations, meaning that a larger share of homeless individuals indicated as non-disabled in our study became disabled or enrolled in DI or SSI during the study period.

People who are disabled face substantially higher mortality risk than non-disabled individuals with the same housing status, controlling for age. A housed disabled person is 4.5 times as likely to die in a six-month period as a non-disabled housed person, while a housed poor disabled person is 2.8 times as likely to die as a non-disabled housed poor person, accounting for age. A homeless disabled person is 1.6 times as likely to die as a non-disabled homeless person. Notably, disabled housed and housed poor individuals have even a higher mortality risk than non-disabled homeless individuals.

7. Hispanics' lower mortality risk is not a novel finding. Hispanic individuals are frequently found to experience similar or better health outcomes than non-Hispanic individuals in the United States despite socioeconomic disadvantage, a pattern that is sometimes called the "Hispanic mortality paradox" (Ruiz, Steffen, and Smith 2013).

The mortality risk is very similar for all three groups of disabled individuals. In contrast, a non-disabled homeless person is about 4 times as likely to die as a non-disabled housed person. In other words, mortality disparities between housed and homeless individuals are much smaller among people with disabilities than people without disabilities. This latter fact may reflect in part the prevalence of disabilities in the homeless population not captured by our measure, as suggested by the steep increase in disability program receipt after 2010 found in Meyer et al. (2023). Nevertheless, it appears that mortality disparities by housing status are concentrated almost exclusively among people who were not enrolled in disability assistance programs at the beginning of our study period. Our study is the first, to our knowledge, to look at mortality hazard by disability status in the U.S. homeless population.

Age and mortality

Figure 4.9 displays relative mortality risk by housing status and age, where we have selected age bins to facilitate comparisons to prior literature. Homeless individuals in the youngest age category, 18-24, have the lowest mortality risk relative to their housed counterparts; they are slightly less than twice as likely to die in a six-month period. Relative mortality risk is highest for homeless individuals ages 45-54, who are about 4.2 times as likely to die as their housed counterparts.

These findings are largely consistent with prior work, which finds a peak in the homeless-to-housed mortality ratio between the ages of 25 and 49 (Hibbs et al. 1994, Barrow et al. 1999, Baggett et al. 2013). Our estimate of homeless-to-housed mortality risk for those ages 18 to 24, however, is smaller than prior studies' estimates, which range from 2.7 to 11.8 times that of the housed young population (Hibbs et al. 1994, Hwang et al. 1997, Barrow et al. 1999, Baggett et al. 2013).[8] Hwang et al. (1997), in particular, find that homeless adults aged 18 to 24 had the highest mortality risk relative to the housed in their sample.

8. This range includes relative mortality risks estimated separately for men and women of this age range.

Figure 4.10 presents estimates of mortality hazard by housing status in two-year age bins relative to housed 30- to 31-year-olds. While all three groups' mortality risk increases as they age, the three groups' relative mortality risk begins to converge after the age of 50, a fact that is more readily apparent in Figure 4.11, which displays the ratio of estimated homeless and housed poor coefficients relative to the housed coefficient in the mortality hazard model. In their late 70s, homeless individuals face the same mortality risk as housed poor individuals and are only about 1.4 times as likely to die as their housed counterparts.

The convergence in relative mortality risk between groups may reflect the declining relative frailty of the surviving homeless population as the highest-risk individuals die. This pattern could also reflect the fact that risks such as cardiovascular disease that rise with age that affect housed and unhoused individuals similarly. We also note that safety net eligibility is changing over time and as people age, and that such shifts in eligibility may affect relative mortality risk between groups. We do not account for the safety net here, but Wyse and Meyer (2023) find that the effect on mortality of safety net programs like Medicaid and social security does not appear to be large, at least as indicated by changes around eligibility ages and policy implementation dates.

Figure 4.10 also illustrates the age at which each group will face a given level of mortality risk relative to the baseline group (30- to 31-year-old housed individuals). The dashed line on this figure indicates the mortality risk of a 40-year-old homeless person. Its intersection with the comparison groups' lines indicates the age at which people in those groups will face the same mortality risk as a 40-year-old homeless person. We see that a 40-year-old homeless individual faces a mortality risk that is similar to that of a 58-year-old housed person and a 48-year-old housed poor person. In other words, homelessness is associated with a health detriment equivalent to nearly twenty years of aging relative to the typical housed person.

4.5.2 Identifying the most vulnerable subsets of the homeless population

In this section, we consider differences in the mortality risk among subsets of the homeless population with the goal of identifying the most vulnerable groups and factors which may be protective against mortality risk. We also consider differences by type of homelessness during the 2010 Census (i.e. sheltered or unsheltered), state of residence, income and employment status, and the extent of observed family connections.

Mortality risk by type of homelessness

Figure 4.12 shows the mortality hazard in each period for sheltered and unsheltered men and sheltered and unsheltered women, controlling for age.[9] Both sheltered and unsheltered men are about half a percentage point more likely to die in a six-month period than sheltered and unsheltered women. As in Figure 4.3, conditional on gender and age, sheltered and unsheltered people have very similar mortality hazard rates, conflicting with prior work finding that unsheltered individuals have higher mortality risk than sheltered individuals (Roncarati et al. 2018, Roncarati et al. 2020). This result may reflect the fact that our sample is designed to be representative of the overall homeless population, not just of health services users as in Roncarati et. al (2018, 2020). We caution, however, that our study indicates sheltered or unsheltered status in the year 2010, and we are unable to ascertain people's living situations at other points in time. It is likely that many people in our sample transitioned between sheltered and unsheltered homelessness and other housing statuses throughout our study period.

This finding is surprising, too, because we know based on prior work that people who were sheltered homeless during the 2010 Census had greater incomes, employment, and connections to the safety net than unsheltered people of the same gender. For example,

9. We use the age distribution of sheltered males to simulate the covariate-adjusted hazard for the other three groups.

Meyer et al. (2023) found that about 55 percent of sheltered women had formal employment in 2010, compared to 42 percent of unsheltered women. About 50 percent of sheltered males and 40 percent of unsheltered males were formally employed that year. Yet despite important apparent differences in these populations' material well-being, mortality appears to be similar between sheltered and unsheltered homeless individuals.

Figure 4.13 indicates mortality risk relative to the sheltered white group by sheltered status, race, and gender. Black homeless individuals have lower mortality risk than those who are white even conditional on gender and type of homelessness. White women who are unsheltered have slightly lower mortality risk than sheltered homeless white women, while sheltered and unsheltered white men have nearly the same mortality hazard.

Figure 4.14 displays mortality risk by age relative to the youngest sheltered homeless cohort (ages 18-24), controlling for gender. Once again, sheltered and unsheltered individuals have similar mortality risk by age group. Mortality risk in New York, California, and other states

Figure 4.15 displays the relative mortality hazard rate by state of residence (New York, California, or other states), controlling for demographic characteristics, type of homelessness, and income according to 2005-2009 tax records. People who are homeless in New York have a mortality risk that is about 13.4 percent lower than those in other states, while the mortality risk for California's homeless population is not statistically significantly different from the risk for homeless individuals in states besides New York.

New York residents' lower mortality does not reflect differences in demographic characteristics, income, or type of homelessness, because we have controlled for these variables in our estimation. Their lower mortality risk also does not appear to reflect differences in disability status or safety net engagement. Meyer et al. (2023) find that homeless individuals in New York and in the rest of the country have similar rates of disability program receipt (23 percent and 19 percent, respectively) and similar rates of receipt of other major safety net programs (93 and 89 percent).[10] One possible explanation lies in the generosity of homelessness services in New York, where a court-mandated "right to shelter" policy has increased the availability and quality of shelter beds, especially for families (O'Flaherty 2019). Better services could improve the health of people experiencing homelessness. Higher shelter quality could also affect the relative affluence of the average shelter resident by making shelters preferable to some extremely undesirable housed situations, resulting in a sheltered homeless population that is drawn from a slightly less disadvantaged population.[11]

Mortality risk by employment and income status

Figure 4.15 also shows how mortality differs by employment status and income among people experiencing homelessness. We define someone as employed if they had formal earnings in 2009 according to IRS 1040 and W2 datasets.[12] We define someone as being in the top half of the income distribution by taking the average of their inflation-adjusted pre-tax cash income according to tax records over 2005-2009 and comparing this to the median for people with the same sheltered status.[13]

10. These shares reflect receipt of benefits through the Supplemental Nutrition Assistance Program (SNAP), housing benefits through the Department of Housing and Urban Development (HUD), Medicare or Medicaid, or service-connected disability through the Veterans Benefit Administration. A key exception in New York's safety net generosity concerns Medicaid, which was available to all poor adults at the beginning of our study period in the state but only became available to poor adults in most other states after 2014, under provisions of the Affordable Care Act (ACA). However, Wyse and Meyer (2023) do not find evidence that Medicaid enrollment reduces homeless individuals' mortality risk, suggesting that a causal relationship between Medicaid availability and lower mortality risk in New York is weak, if present.

11. Families in New York must be vetted before being admitted to the shelter system and O'Flaherty (2019) notes that most families who apply are rejected, meaning they were determined to have access to other housing options and may hence be less disadvantaged than the typical homeless person in other states.

12. For people who link to a 1040, we define earnings as the sum of 1040 wage and salary income, estimated non-negative 1040 self-employment income (when a self-employment schedule was filed), and W2 deferred compensation, minus any W2 wages and tips associated with a co-filer. For people who do not link to a 1040 but do link to a W2, earnings are equal to wages and tips across W2s. For people who link to neither, earnings are zero.

13. For people who link to a 1040, pre-tax income is equal to the sum of total money income and VA service-connected disability compensation. For people who do not link to a 1040, pre-tax income is equal to the sum of wages and tips and deferred compensation in W2s, VA service-connected disability compensation, and IRA and employer-sponsored retirement distributions across 1099-Rs.

We find that people with a recent history of employment and people in the top half of the income distribution are about 34.6 and 32.7 percent less likely to die in a six-month period than those who were not employed and those in the bottom half of the income distribution. These findings show that even among people who have experienced homelessness, those who are more economically disadvantaged and more disconnected from the formal labor market have worse health outcomes.

Mortality risk by extent of observed family connections

The third set of results on Figure 4.15 show how mortality differs by the extent of observed family connections. We classify individuals as having or having once had a spouse if they ever had a co-filer on a 1040 in 2005-2009, and we classify them as having a child if they ever included a dependent on a 1040 in those years. We also attribute family connections to individuals who were recorded in the Census as being housed in addition to homeless. Meyer et al. (2022) document widespread double-counting of people experiencing homelessness in the Census and find that duplicate records often reflect those individuals' inclusion on the Census form of a housed family member, oftentimes their parent. In addition to demographic characteristics, we control for income to ensure that our estimates are not confounded by the fact of tax filing, which is in turn associated with higher income.

Having at least one observed family connection is associated with 17.3 percent lower mortality risk for people experiencing homelessness. Homeless individuals who have a current or former spouse face a mortality risk that is 21.3 percent lower than those who do not, and people who have children are 21.6 percent less lower mortality risk than those who do not. Homeless individuals who were recorded on a housed family member's Census form are 13.6 percent less likely to die than those who were not. Family connections appear to be an important protective factor against mortality for people who have experienced homelessness, albeit one that is not as potent as our measures of income and employment.

4.5.3 Mortality during the COVID-19 pandemic

The empirical hazard in Figure 4.1 suggests a steep rise in mortality hazard during the COVID-19 pandemic. In this section, we examine the pandemic-era rise in mortality and compare its magnitude across groups. Specifically, we consider the absolute and proportional change in average annual mortality risk in the two years prior to the pandemic (April 2018-March 2020) and the first two years of the pandemic (April 2020-March 2022). We calculate these changes using both the empirical mortality hazard and the covariate-adjusted mortality hazard, which uses the distribution of age and gender among the homeless to provide a comparable hazard for the three groups.

In describing the COVID-era rise in mortality hazard, we wish to account for the fact that aging would have caused our cohorts' mortality hazards to rise over these four years regardless of the COVID-19 pandemic. To do so, we regress the mortality hazard in six-month periods indexed by $j = 1, \ldots, 20$ on a constant and a time trend. We then take the estimated coefficient on this time trend and multiply it by eight to obtain the estimated effect of aging on the average annual mortality hazard, which we subtract from the observed rise in the mortality hazard to obtain an aging-adjusted estimate of the hazard increase.[14]

Table 4.6 displays the results from applying this methodology. We find that all three groups experienced an approximately 30-35 percent increase in their average annual mortality hazard in the two years of the pandemic relative to the two preceding years exceeding the change we would have expected due to aging. At the same time, the absolute increase in mortality was much larger for the homeless population than other housing status groups given their substantially elevated baseline mortality risk. Figure 4.1 displays the observed mortality hazard alongside the predicted hazard accounting for aging, which is indicated by a dashed line. The gap between predicted and observed hazard illustrates the magnitude of

14. Multiplying this estimate by four gives us the effect of aging on average biannual hazard between the midpoint of our pre-pandemic period and the midpoint of our post-pandemic period. We then multiply the estimate by two to convert the estimate's effect on the biannual hazard to its effect on an annual one.

excess mortality.

We also calculate differences in the pandemic-era mortality rise by gender and type of homelessness and display these findings in Table ??. Sheltered and unsheltered males saw a much larger absolute and proportional rise in their mortality risk (35 and 28 percent, respectively) during the pandemic beyond what we would have expected due to aging. Sheltered and unsheltered females saw a 24 and 21 percent increase in their mortality risk. Again, the distinction between genders is much more pronounced than the distinction between sheltered and unsheltered homelessness. An important caveat is that type of homelessness reflects status in 2010 and may not reflect people's living situations during the pandemic.

Because we lack information on cause of death, however, we caution against attributing excess mortality to COVID-19 directly. Previous research has indicated that excess mortality during the pandemic could be attributed to rising fentanyl, other opioid, or methamphetamine use over the last two decades, or, possibly relatedly, to difficulties in obtaining medical services for life-threatening situations like overdoses and traumatic injuries due to hospital overcrowding (Cawley et al. 2022, Baggett et al. 2011). Cawley et al. (2022) found that the substantial rise in homeless individuals' mortality in San Francisco during the pandemic was driven by difficulties in obtaining care for emergencies from an overburdened medical system. COVID-19 itself was not a leading cause of death for homeless individuals in their sample. The pandemic-era rise in mortality should therefore be interpreted as the combined effect of the pandemic and any associated changes in all-cause mortality risk.

4.6 Discussion

The findings in this paper, which are based on the largest and most representative sample used to study homeless mortality to date, establish the most broadly true patterns among the mixed findings in prior work. For example, we find, as do many prior studies, that homeless individuals' mortality risk relative to the housed population is greatest when they are in their 30s and 40s and that homelessness is associated with more elevated mortality risk for women than for men when compared to housed people of the same gender. We also find that Black homeless individuals have lower mortality than white homeless individuals, a pattern that is consistent not only with others' results on mortality but also with work on race group differences for other indicators of wellbeing for this population, such as income and connections to the formal labor market (Hibbs et al. 1994, Baggett et al. 2013, Metraux et al. 2011, Meyer et al. 2023).

Mortality differences by race in the homeless population are especially noteworthy because they diverge from those observed in the housed population and may provide insight into the relative importance of different pathways to homelessness between racial groups. For example, a key question in homelessness research is the extent to which homelessness is driven by personal vulnerabilities like addiction and poor mental health versus poverty and economic shocks (Lee, Tyler, and Wright 2010). Prior work suggests that a proximate explanation for white homeless individuals' elevated mortality risk lies in the higher prevalence of substance abuse and behavioral health conditions in this group, which could in turn suggest that personal vulnerabilities are more important drivers of homelessness among white individuals while economic circumstances are relatively more important for Black individuals (Hibbs et al. 1994, Baggett et al. 2013). Such a pattern could arise because white individuals, on average, have access to better-resourced social and family networks to protect against homelessness, meaning that only those with especially difficult personal circumstances become homeless. This pattern could also arise because Black individuals face greater housing discrimination, meaning that even relatively better-off individuals find themselves homeless because no affordable housing options are available to them. These hypotheses merit further study in future work.

Another advantage of our data lies in the richness of demographic, economic, and social information available, which in turn allows us to examine in great detail the association between these factors and mortality and to highlight especially vulnerable segments of an already extremely deprived population. For example, we find that people with lower incomes and those who are less connected to family and to the labor market have especially poor health outcomes. Moreover, while disabled homeless individuals have a higher mortality rate than those who are not disabled, even non-disabled homeless individuals have a substantially elevated mortality rate relative to their housed counterparts. Somewhat surprisingly, we find no major difference in mortality rates between unsheltered and sheltered homeless individuals after controlling for gender, and we find that both of these groups experienced substantial increases in mortality during the COVID-19 pandemic. These findings may prove useful to policymakers and service providers looking to target resources to the neediest individuals. They also highlight the significant health risks associated with homelessness even among people sleeping in shelters, a group that figures less prominently in policy debates than their more visible unsheltered counterparts.

While our analyses indicate strong associations between homelessness, individual characteristics, and mortality, we caution that our study does not allow us to identify a causal or directional relationship between homelessness and elevated mortality risk. As with socioeconomic status and health in the housed population, homelessness and mortality are likely causally related in both directions, with the importance of various channels differing across sub-groups. Behavioral health disorders, addiction, and substance abuse, for instance, could drive both homelessness and heightened mortality risk for some. For others, particularly those who are chronically homeless, heightened mortality risk could be a consequence of the exceedingly severe long-term material deprivation the homeless population experiences. We also caution that, in relating our findings to the literature on the health-socioeconomic status gradient, it is probably incorrect to view homelessness purely as a proxy for extreme poverty. Mortality patterns within the homeless population point to a complicated selection procedure into homelessness that differs across racial groups and genders appears to be determined only in part by economic circumstances.

4.7 Conclusions

This study examines health disparities in the United States using one of most fundamental indicators of well-being, mortality, for one of the most disadvantaged segments of the population, people experiencing homelessness. We base our analyses on by far the largest and most representative data ever used to compare the mortality risk of homeless and housed populations, data that include a rich set of demographic characteristics that facilitate detailed comparisons by age, gender, race, Hispanic ethnicity, and disability status. Within the homeless population, we examine mortality differences by sheltered status, income, employment, and the extent of observed family connections to identify factors associated with heightened mortality risk, analyses which may serve to help researchers, service providers, and policymakers identify the most vulnerable subsets of this already exceptionally vulnerable population.

In addition to the size, national scope, and representativeness of these data, this approach benefits from important advantages. Unlike prior studies, we compare housed and homeless mortality using data from the same sources and applying a common methodology to both groups, allowing for more nuanced and reliable comparisons. We also link the individuals in our study to administrative tax and program data to access rich longitudinal information on income, employment, disability status, and safety net participation, which in turn allows us to compare mortality risk between subsets of the homeless population and to characterize the patterns of long-term material deprivation that accompany elevated mortality risk. We supplement our analyses using a nationally representative sample of poor housed individuals from a closely comparable data source to learn about homelessness as a risk factor for mortality that is distinct from poverty in general. We view this work as complementary to an extensive and growing body of clinical and public health research into the relationship between homelessness and health, adding a nationally representative perspective to prior findings and helping to establish the most broadly true patterns from the wide array of results in prior work.

Our findings reveal severe disparities in health and wellbeing between people who are homeless and those who are housed. People who have experienced homelessness face 3.5 times the mortality risk of people who are housed, accounting for differences in demographic characteristics and geography. Put differently, a 40-year-old homeless person faces a mortality risk similar to a housed person nearly twenty years older. These disparities reflect more than economic disadvantage: homeless individuals' mortality risk is about 60 percent greater than poor housed individuals of the same age and gender. Mortality disparities change over the course of the life cycle, however, with homeless individuals' relative mortality risk peaking between the ages of 30 and 50 before falling to converge with the poor housed population's mortality risk by the age of 70.

Many of the groups that face higher mortality risk in the housed population – men, non-Hispanics, people with lower incomes, people who are disabled – also face higher risk in the homeless population, but race is a notable exception. Among people who are housed, someone who is Black has 40 percent greater mortality risk than someone who is white, but among people who have experienced homelessness, someone who is Black has 27 percent lower mortality risk than someone who is white. This finding mirrors prior work showing that Black homeless individuals have higher incomes and are more connected to the formal labor market and safety net than those who are white (Meyer et al. 2023). These patterns merit further examination, as they may suggest that the predominant pathways to homelessness differ by race, with individual conditions like addiction and behavioral health issues perhaps playing a greater role for white individuals, while structural issues like discrimination and poverty being more important drivers for Black individuals.

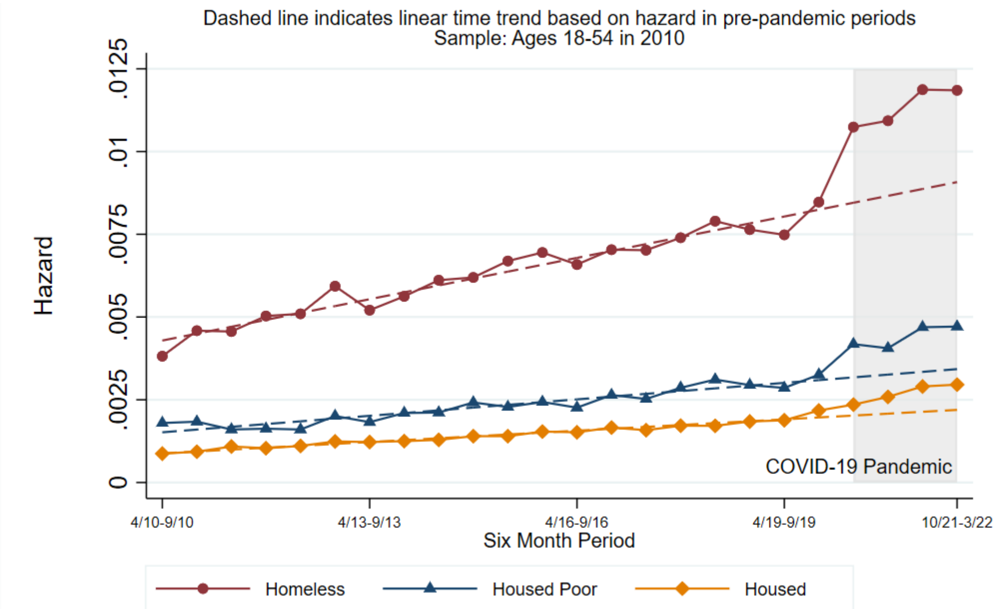
Our findings also speak to the exceptionally severe toll of the COVID-19 pandemic on people experiencing homelessness. The pandemic coincided with a 33 percent increase in mortality for people experiencing homelessness beyond what we would have expected due to the aging of our cohort. While housed and poor housed people saw similar proportional rises in their mortality risk, the pandemic affected a much larger share of the homeless population because of their already elevated baseline mortality rate. Homeless men seem to have been hit especially hard, with their mortality risk rising by 35-38 percent during the pandemic, compared to 22-24 percent for homeless women. The causes of excess mortality during the pandemic are not apparent from our data, however, and could include both the direct effects of virus itself, as well as indirect effects from strain on healthcare systems and reduced access to emergency services, with these latter issues potentially interacting with surging fentanyl use to exacerbate the pandemic's harm on people experiencing homelessness.

Within the homeless population, connection to the formal labor force and to family are associated with lower mortality risk; having been observed in a shelter in the 2010 Census, as opposed to an unsheltered location, is not. People who have or had spouses, have children, or who were included on a family member's housed Census form all have mortality risk that is about 20 percent lower than their counterparts. People who are homeless in New York have a lower mortality risk, but those who are homeless in California face a similar mortality risk as people in other states. Perhaps surprisingly, we find very little difference in mortality between people we initially observe in homeless shelters and those who are unsheltered, conditional on gender. This last finding highlights the substantial health risks faced even by people experiencing homelessness in shelters, a group that is less visible and receives less attention than those who sleep on the streets, but who nevertheless experience substantial health disparities. Our findings on mortality differences between sub-groups of the homeless population point to dimensions linking health and socioeconomic status that may be especially important among extremely disadvantaged individuals more broadly, such as housing quality and stability, social connections and family resources, and disability status.

This paper joins a growing body of work through the Comprehensive Income Dataset (CID) project that aims to establish fundamental facts about homelessness in the United States by linking Census and administrative data to unlock new insights. Recent work has improved our understanding of the size of the U.S. homeless population, established the surprisingly good coverage of people experiencing homelessness in the Census, and revealed persistent extremely low incomes and high reliance on the safety net. Ongoing and planned work aims to understand the effects of safety net programs on homeless individuals' mortality and material well-being and to learn about the dynamics of transitions between housing, institutional settings, and homelessness. In providing the first national estimates of homeless mortality in the U.S., this paper not only adds to the emerging picture of the persistent hardships and stark health disparities associated with homelessness, but also sheds light on some of the most vulnerable subsets of an already exceptionally vulnerable population and contributes to efforts to more effectively mitigate the mortality risks faced by people experiencing homelessness.

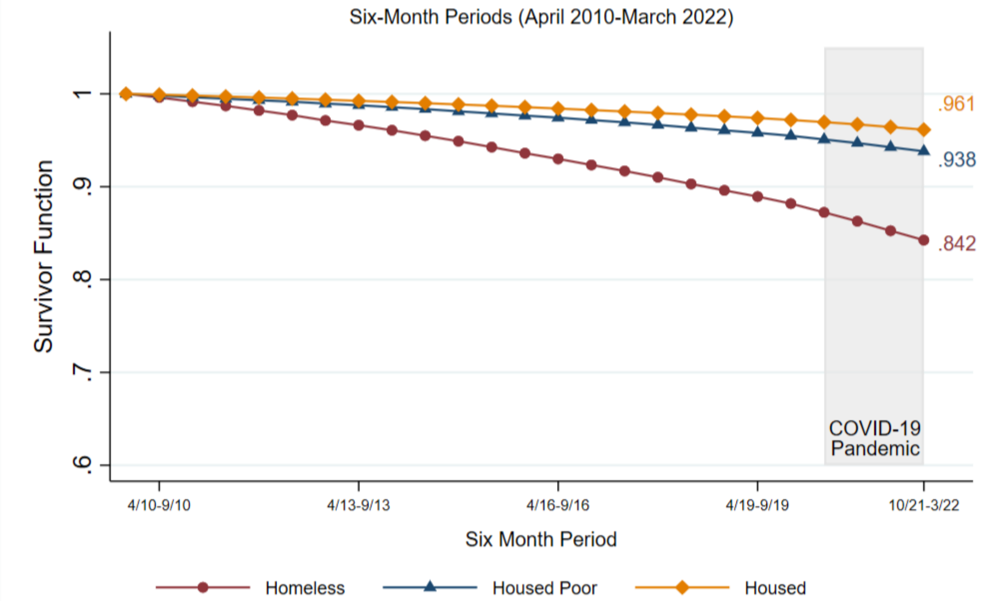
4.8 Exhibits

Figure 4.1: Mortality Hazard (Probability of Death in Six-Month Period)



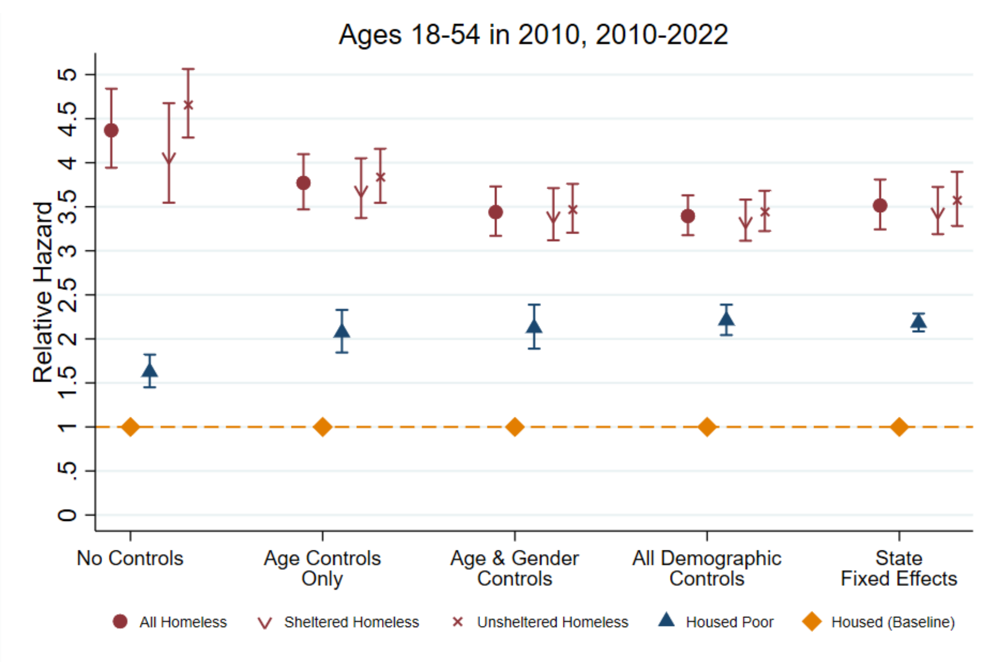
Sources: 2010 Decennial Census, 2022 SSA Numident

Figure 4.2: Share Survived to End of Period, Ages 18-54 in 2010



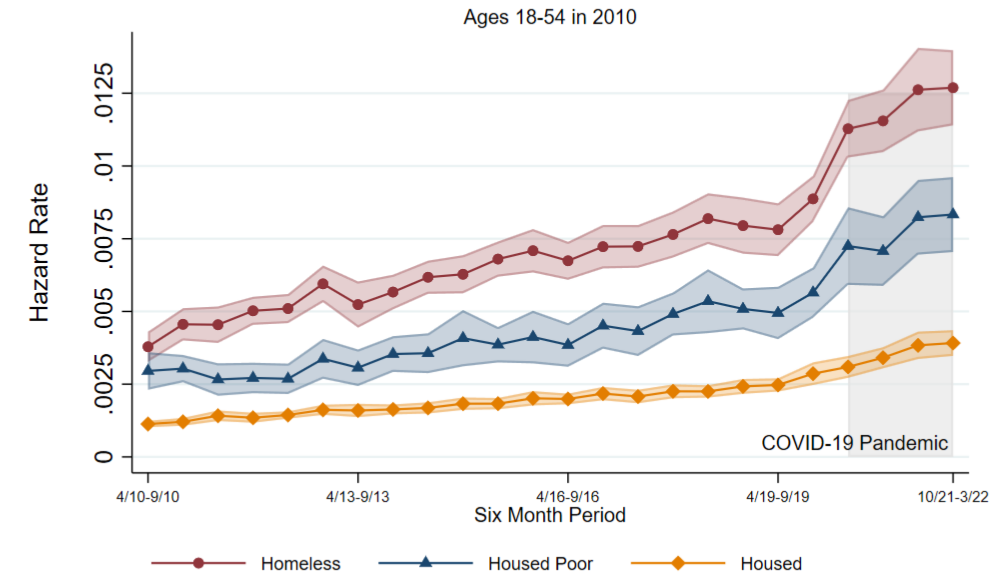
Sources: 2010 Decennial Census, 2022 SSA Numident

Figure 4.3: Mortality Hazard Relative to Housed Group



Sources: 2010 Decennial Census, 2022 SSA Numident

Figure 4.4: Covariate-Adjusted Mortality Hazard (Probability of Death in Six-Month Period Using Age and Gender Distribution of Homeless



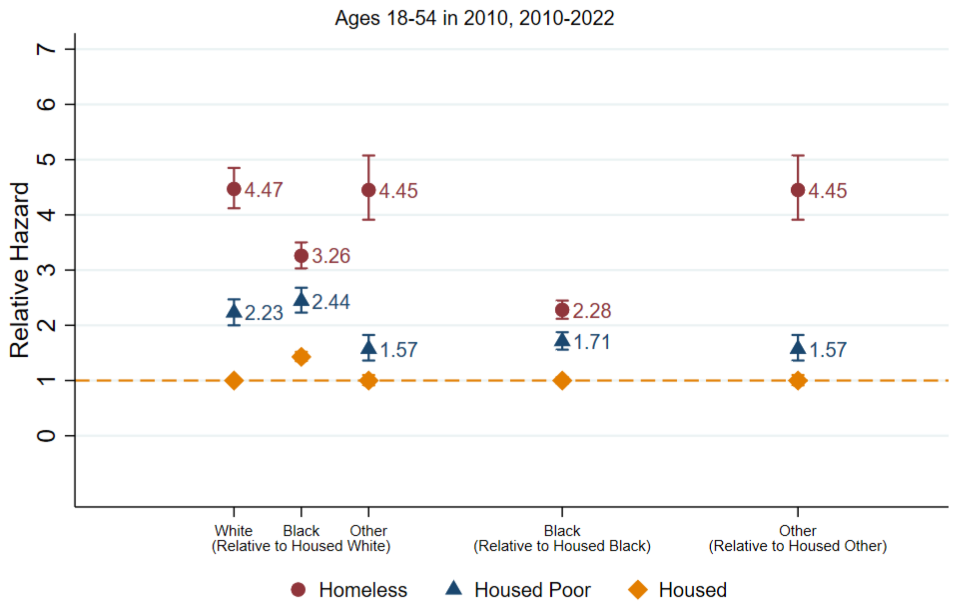
Sources: 2010 Decennial Census, 2022 SSA Numident

Figure 4.5: Mortality Hazard Rate by Housing Status and Gender

Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Plot displays coefficient from hazard model including age controls.

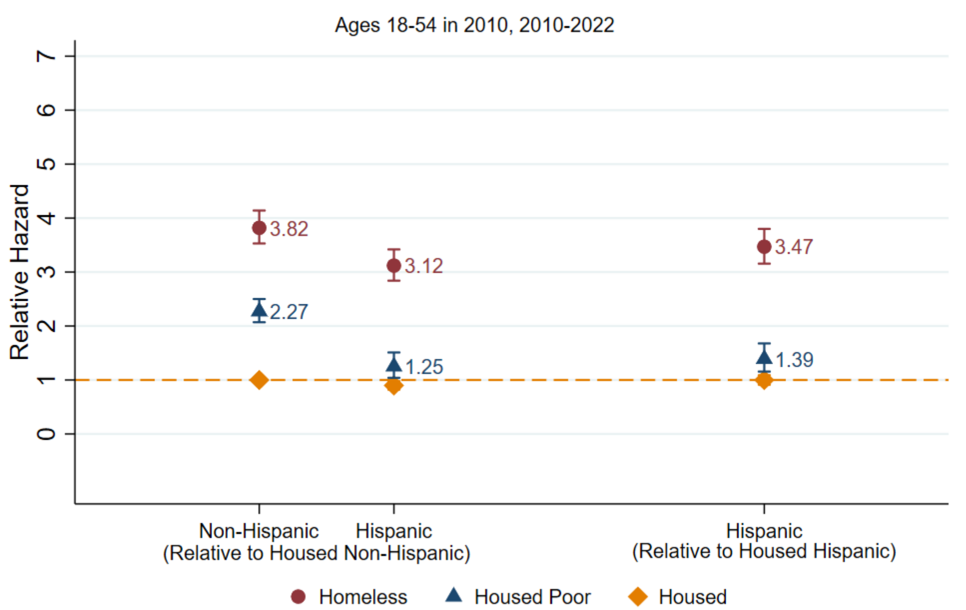
Figure 4.6: Mortality Hazard Rate by Housing Status and Race



Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Plot displays coefficient from hazard model including age controls.

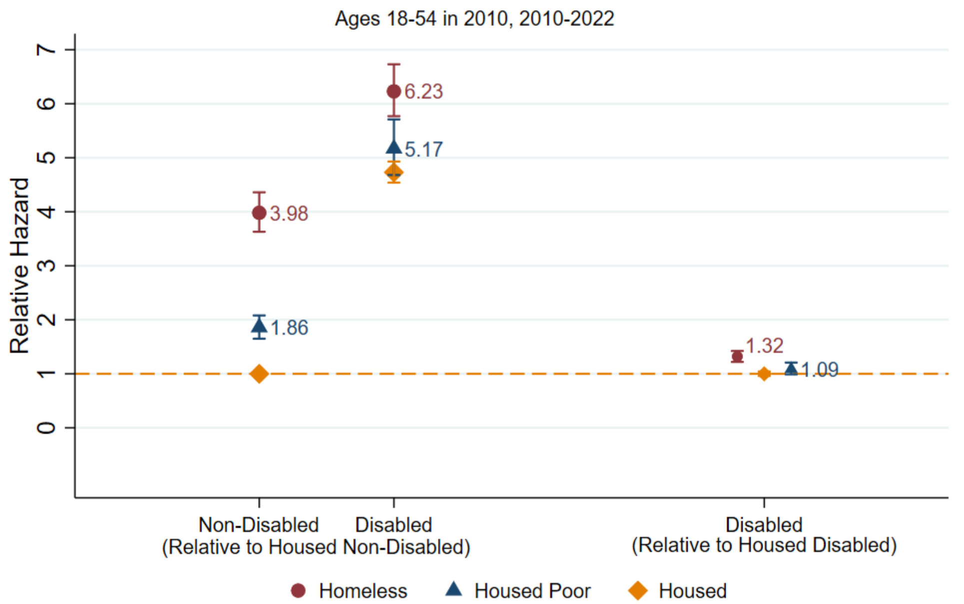
Figure 4.7: Mortality Hazard Rate by Housing Status and Hispanic Ethnicity



Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Plot displays coefficient from hazard model including age controls.

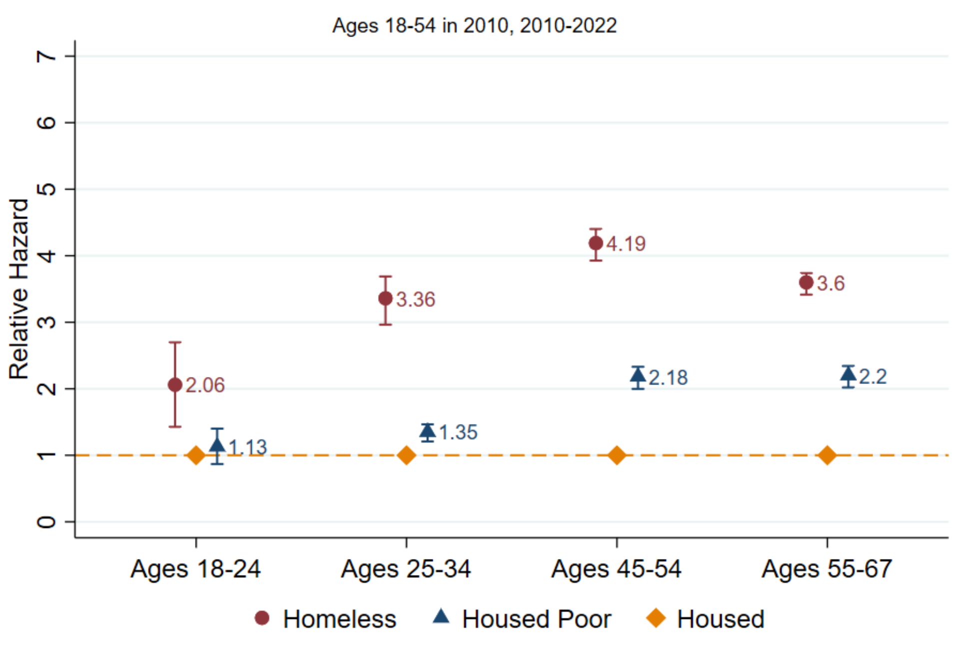
Figure 4.8: Mortality Hazard Rate by Housing Status and Disability Status



Sources: 2010 Decennial Census, 2022 SSA Numident

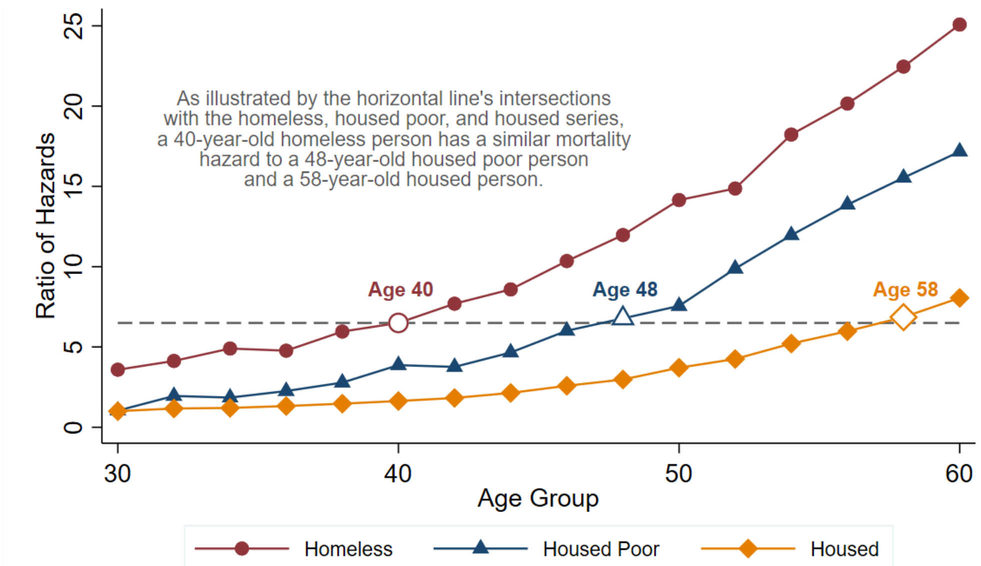
Note: Plot displays coefficient from hazard model including age controls.

Figure 4.9: Mortality Hazard Relative to Housed in Same Group



Sources: 2010 Decennial Census, 2022 SSA Numident

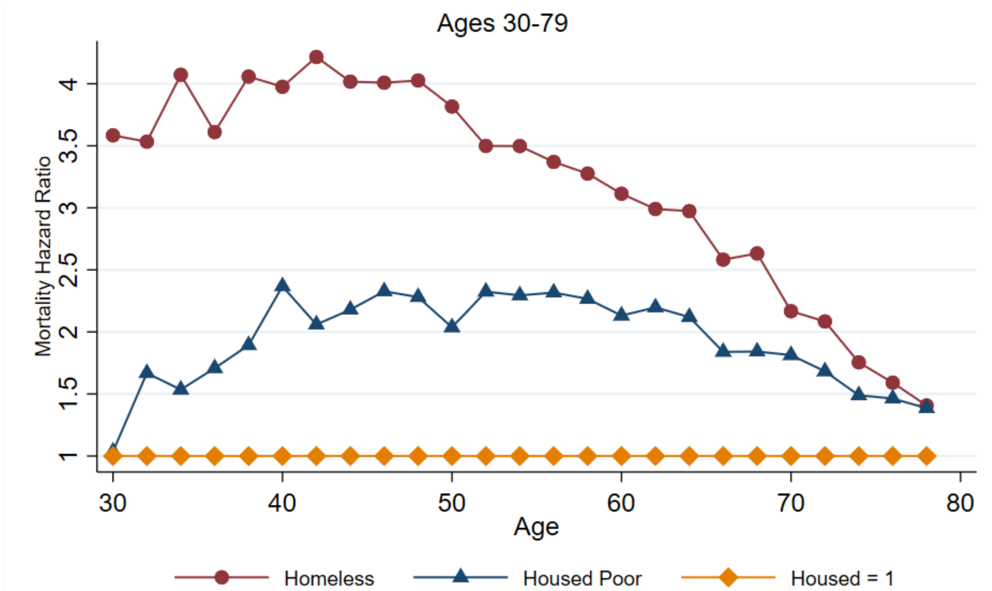
Figure 4.10: Proportional Mortality Hazard by Age, 30-79



Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Figure displays coefficient on two-year age dummy with group interaction in model assuming common baseline hazard and controlling for gender. Sample includes people ages 30-79 in 2010-2022.

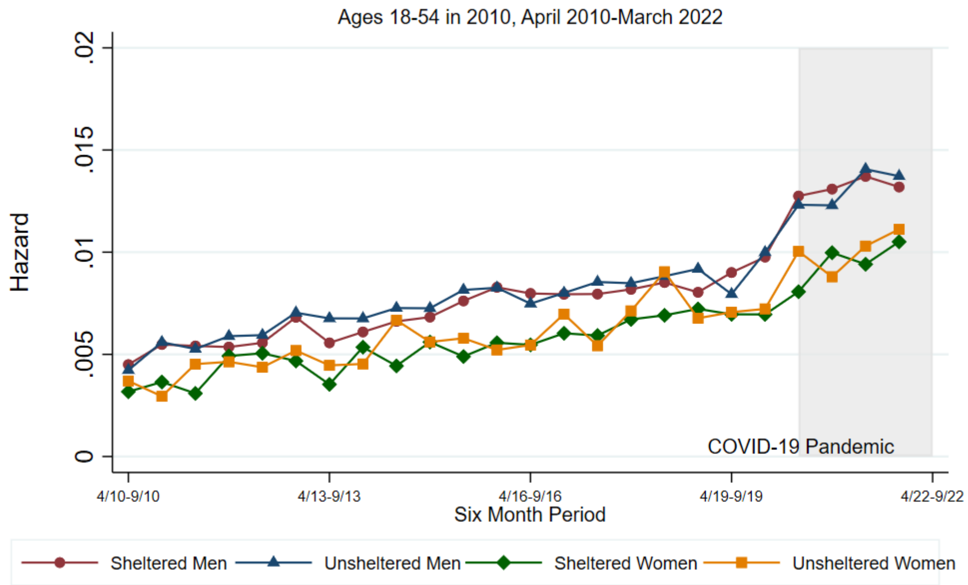
Figure 4.11: Ratio of Homeless and Poor Housed Mortality Hazard to Housed Mortality Hazard



Sources: 2010 Decennial Census, 2022 SSA Numident

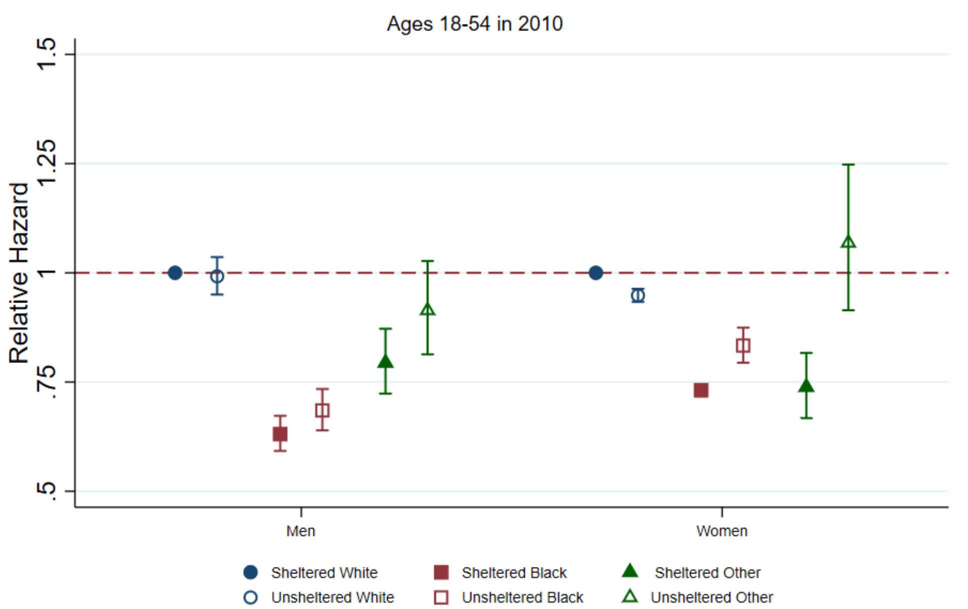
Note: Figure displays coefficient on two-year age dummy with group interaction in model assuming common baseline hazard and controlling for gender. Sample includes people ages 30-79 in 2010-2022.

Figure 4.12: Covariate-Adjusted Mortality Hazard (Probability of Death in Six-Month Period) Using Age Distribution of Sheltered Men



Sources: 2010 Decennial Census, 2022 SSA Numident

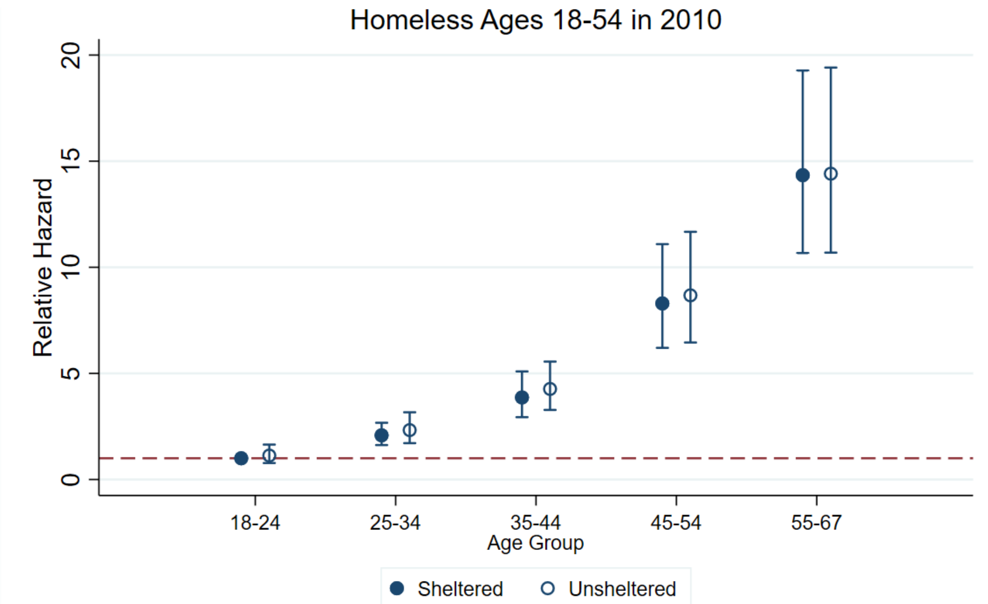
Figure 4.13: Mortality Hazard Relative to Sheltered White Homeless



Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Plot displays coefficient from hazard model including age controls.

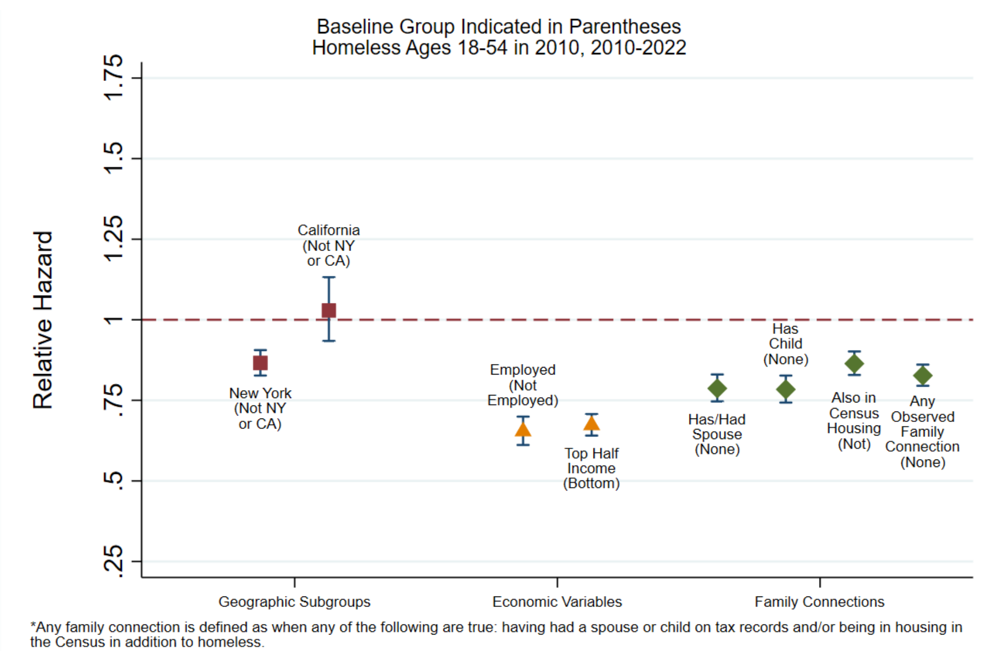
Figure 4.14: Mortality Hazard Relative to Sheltered Ages 18-24



Sources: 2010 Decennial Census, 2022 SSA Numident

Note: Plot displays coefficient from hazard model controlling for gender.

Figure 4.15: Relative Mortality Hazard by Geography, Employment, and Family Connections



Sources: 2010 Decennial Census, 2022 SSA Numident

Table 4.1: Prior Estimates of Homeless Individuals' Relative Mortality Risk

Author(s) and Year	Location and Collection Period	Mortality Period	Sample Demographics and Mortality Data	Comparison Group, Mortality Data	Estimates (Standardized Mortality Rates)
Baggett et al. (2013)	Boston, 2003-2008	2003-2008	28,033 sheltered and unsheltered, ages 18-64, the universe served by Boston Health Care for the Homeless Program (BHCHP) between 2003-2008. Mortality data from Massachusetts Department of Public Health death occurrence files.	2003-2008 Massachusetts population. Mortality rates obtained from CDC WONDER.	Race-adjusted totals: Ages 25-44: 8.6 (men), 9.6 (women) Ages 45-64: 4.5 (both genders) Ages 65-84: 1.1 (both genders)
Barrow et al. (1999)	NYC, 1987	1987-1994	1,260 sheltered in 1987, ages 18+, randomly selected from bed rosters in 22 municipally run congregate shelters in NYC and systemically selected from food and clothing lines in 4 shelters. Mortality data from the National Death Index.	1987-1994 U.S. and NYC populations. Mortality rates obtained from the CDC's mortality files.	Total age-adjusted totals in NYC: 2.2 (men), 3.7 (women)
Metraux et. al. (2011)	NYC, 1990-2002	1990-2007	160,525 sheltered adults, ages 18-74, with a record of first entering a homeless shelter run by NYC DHS from 1990-2002 and who had SSNs (universe); among families, one adult selected who was designated by DHS as head of household. Mortality data from Social Security Death Index.	None to housed population; only compares those who are homeless in families to those who are homeless as single adults.	Age- and sex-adjusted totals (no comparisons to general population): Males (family/single): 0.56 Females (family/single): 0.28
Roncarati (2018)	Boston, 2000	2000-2009	445 unsheltered adults in Boston, ages 18-81, seen face-to-face by BHCHP street team in 2000 (universe). Mortality data from Massachusetts Department of Public Health death occurrence files and, at times, the National Death Index.	Massachusetts housed population; sheltered adult homeless cohort. Mortality rates obtained from CDC WONDER.	Age-standardized totals: Relative to MA general population: 9.8 Relative to sheltered homeless: 2.7
Hibbs et. al. (1994)	Philadelphia, 1985-1988	1985-1988	6,308 sheltered and unsheltered, ages 15-74, all served by one or both of two agencies for the homeless (mental health program and Philadelphia Office of Services for Homeless Adults) between 1985 and 1988 (universe). Mortality data from Pennsylvania Department of Health.	Philadelphia housed population. Mortality rates obtained from census data from Pennsylvania Department of Health.	Age-weighted (but not race-weighted) totals: Relative to general Philadelphia Population: 3.5
Hwang et al. (1997)	Boston, 1988-1993	1988-1993	17,292 sheltered and unsheltered, ages 18-64, all served by BHCHP between July 1988 and December 1993. Mortality data from Massachusetts death registry.	Boston housed population. Mortality rate data source for housed population unclear.	Non-adjusted totals: 18-24: 5.9 (men), 11.8 (women) 25-44: 3.0 (men), 3.9 (women) 45-64: 1.6 (men), 1.5 (women)

Table 4.2: Summary Statistics: Demographic Characteristics and Region

	Homeless (Census)		Housed Poor (ACS)		Housed (Census)	
Age in 2010	Ages 18+	Ages 18-54	Ages 18+	Ages 18-54	Ages 18+	Ages 18-54
Mean	45.1	39.6	41.9	33.6	47.3	37.1
Ages 18-24	0.101	0.132	0.236	0.310	0.121	0.181
25-29	0.078	0.103	0.108	0.142	0.088	0.132
30-34	0.078	0.102	0.091	0.120	0.084	0.126
35-39	0.086	0.112	0.084	0.111	0.086	0.129
40-44	0.119	0.155	0.082	0.108	0.091	0.136
45-49	0.151	0.197	0.082	0.108	0.099	0.149
50-54	0.153	0.200	0.077	0.102	0.098	0.148
55-59	0.110		0.063		0.087	
60-64	0.059		0.054		0.074	
65-69	0.029		0.033		0.055	
70 and older	0.037		0.089		0.118	
Gender, Race, and Ethnicity						
Female	0.312	0.327	0.586	0.574	0.519	0.508
White	0.523	0.511	0.655	0.641	0.768	0.735
Black	0.379	0.388	0.212	0.218	0.124	0.137
Other Race	0.098	0.102	0.133	0.141	0.108	0.128
Hispanic	0.153	0.161	0.216	0.230	0.129	0.155
Region						
Northeast	0.230	0.231	0.159	0.153	0.185	0.182
Midwest	0.174	0.176	0.216	0.222	0.221	0.219
South	0.279	0.282	0.408	0.404	0.366	0.367
West	0.318	0.312	0.217	0.221	0.228	0.233
Weighted Count	341,800	261,500	14,110,000	10,740,000	2,182,000	1,454,000
N	181,000	140,000	158,000	110,000	2,000,000	1,313,000

Note: Weighted counts reflect inverse probability weighting adjustment to account for non-linkage for all three groups. For housed poor, weighted count also reflects survey weights, and for overall housed, weighted count is adjusted to reflect one percent random sampling from the 2010 Census housed population. All reported ages reflect age in 2010.

Table 4.3: Summary Statistics: Disability, Economic Status, Family Connections, and State

	Homeless (Census)		Housed Poor (ACS)		Housed (Census)	
Age in 2010	Ages 18+	Ages 18-54	Ages 18+	Ages 18-54	Ages 18+	Ages 18-54
SSI receipt (2009)	0.205	0.189	0.113	0.093	0.030	0.028
DI receipt (2009)	0.092	0.081	0.066	0.052	0.032	0.023
SSI or DI	0.229	0.206	0.135	0.107	0.049	0.039
Employed in 2009	0.443	0.489				
Top Half of Prior Income	0.494	0.491				
Has Spouse or Former Spouse	0.149	0.143				
Also Recorded in Housing	0.306	0.286				
Has Child	0.266	0.307				
Any Indicator of Family Connection	0.501	0.507				
New York	0.115	0.117	0.066	0.063	0.065	0.065
California	0.185	0.180	0.117	0.118	0.119	0.123
Other State	0.700	0.704	0.817	0.818	0.816	0.812
Sheltered Homeless	0.469	0.492				
Weighted Count	341,800	261,500	14,110,000	10,740,000	2,182,000	1,454,000
N	181,000	140,000	158,000	110,000	2,000,000	1,313,000

Note: Weighted counts reflect inverse probability weighting adjustment to account for non-linkage for all three groups. For housed poor, weighted count also reflects survey weights, and for overall housed, weighted count is adjusted to reflect one percent random sampling from the 2010 Census housed population. All reported ages reflect age in 2010.

Table 4.4: Cumulative Mortality April 2010-March 2022 (Ages 18-54 in 2010)

Based on Empirical Survivor Function (No Controls)

	Homeless	Housed Poor	Housed
Share died	0.1575	0.0619	0.0385
Probability of dying relative to housed	4.09	1.60	1.00
Probability of dying relative to housed poor	2.55	1.00	0.62

Based on Covariate-Adjusted Survivor Function (Age and Gender Controls)

	Homeless	Housed Poor	Housed
Share died	0.1620	0.1037	0.0503
Probability of dying relative to housed	3.22	2.06	1.00
Probability of dying relative to housed poor	1.56	1.00	0.48

Table 4.5: Average Annual Mortality Hazard by Group in Two Years Before and During COVID-19 Pandemic (Ages 18-54 in 2010)

Empirical Mortality Hazard (No Controls)			
	Homeless	Housed Poor	Housed
April 2018-March 2020	0.0157	0.0061	0.0038
April 2020-March 2022	0.0226	0.0088	0.0054
Change without accounting for aging of population			
Absolute increase	0.0069	0.0027	0.0016
Proportional increase	43.87%	44.84%	41.77%
Change accounting for aging of population			
Absolute increase	0.0052	0.0021	0.0011
Proportional increase	33.25%	33.91%	29.76%
Covariate-Adjusted Mortality Hazard			
	Homeless	Housed Poor	Housed
April 2018-March 2020	0.0163	0.0105	0.0050
April 2020-March 2022	0.0239	0.0154	0.0071
Change without accounting for aging of population			
Absolute increase	0.0076	0.0049	0.0021
Proportional increase	46.39%	46.68%	42.32%
Change accounting for aging of population			
Absolute increase	0.0057	0.0037	0.0015
Proportional increase	35.12%	35.17%	30.13%

Note: Covariate-adjusted mortality hazard controls for difference in age and gender distribution between groups. Increase accounting for aging of population is equal to the increase without accounting for aging minus eight times the estimated coefficient from a regression of the hazard in the first 20 periods on a time trend, which yields an estimate of the change in the average annual hazard between these two time periods attributable to the aging of our cohort.

Table 4.6: Average Annual Mortality Hazard by Homeless Sub-Group in Two Years Before and During COVID-19 Pandemic (Ages 18-54 in 2010)

Empirical Mortality Hazard (No Controls)			
	Homeless	Housed Poor	Housed
April 2018-March 2020	0.0157	0.0061	0.0038
April 2020-March 2022	0.0226	0.0088	0.0054
Change without accounting for aging of population			
Absolute increase	0.0069	0.0027	0.0016
Proportional increase	43.87%	44.84%	41.77%
Change accounting for aging of population			
Absolute increase	0.0052	0.0021	0.0011
Proportional increase	33.25%	33.91%	29.76%
Covariate-Adjusted Mortality Hazard			
	Homeless	Housed Poor	Housed
April 2018-March 2020	0.0163	0.0105	0.0050
April 2020-March 2022	0.0239	0.0154	0.0071
Change without accounting for aging of population			
Absolute increase	0.0076	0.0049	0.0021
Proportional increase	46.39%	46.68%	42.32%
Change accounting for aging of population			
Absolute increase	0.0057	0.0037	0.0015
Proportional increase	35.12%	35.17%	30.13%

Note: Covariate-adjusted mortality hazard controls for difference in age and gender distribution between groups. Increase accounting for time trend is equal to the increase without accounting for time trend minus eight times the estimated coefficient from a regression of the hazard in the first 20 periods on a time trend, which yields an estimate of the change in the average annual hazard between these two time periods attributable to the aging of our cohort.

APPENDIX A

APPENDIX

A.1 Chapter 2 Appendix

A.1.1 Text

Comparison of sheltered homeless characteristics across sources

We also compare the characteristics of sheltered homeless individuals in the PIT, Census, and ACS to assess the extent to which they represent the same population. Table A.1 reports the share under 18, gender/sex, race, and Hispanic ethnicity of sheltered individuals in the 2016 ACS and PIT. The share belonging to various race categories and the share Hispanic are similar across the two data sources. The share female, however, is about 5 percentage points higher in the PIT (44.4 percent, compared to 39.4 percent in the ACS) and the share under age 18 is about 17 percentage points higher in the PIT (29.1 percent, compared to 12.2 percent in the ACS). A back-of-the-envelope analysis suggests that the PIT's inclusion of domestic violence shelter residents could explain much of the gender discrepancy but little of the age discrepancy. For 2016, we estimate that about 9.2 percent of the sheltered PIT population consisted of people in domestic violence shelters. If we assume that all adults in domestic violence shelters were female and accompanied by one child on average, who was equally likely to be male or female, then removing domestic violence shelter occupants from the PIT would decrease the share female to 41.3 percent and decrease the share under 18 to 27.0 percent. Such an adjustment would therefore close most of the gap in the share female, but only a small portion of the gap in the share under 18.

Table A.2 compares the share female and the share under 18 in the 2010 ACS to that in the Census. We observe that the share female is similar in these two sources, while the share under 18 is about 5 percentage points lower in the ACS than in the Census. This comparison once again suggests that the ACS may have missed some of those under 18. This finding suggests the need for caution in analyses studying the child homeless population using the ACS, but is reassuring for analyses that are limited to adults, such as studies of income and safety net program participation. We revisit this puzzle about differences in share of children across sources in the Appendix.

Characteristics of recent HMIS shelter occupants missed by the Census

Los Angeles HMIS shelter users dropped by refinements 1 and 2 were disproportionately likely to have unknown status. The weighted count of people with unknown status fell from about 2,500 prior to refinements to fewer than 1,000 after refinements 1 and 2, where this weighted count is taken as the share of shelter users under a given refinement that fall into the residual category. In this section, we describe the characteristics of those individuals and discuss implications for the Census's coverage of the homeless and recently homeless population.

We know from HMIS shelter names that most of the people dropped in refinements 1 and 2 were participants in Los Angeles's Winter Shelter Program, which runs from December 1 to March 15 of each year. Unfortunately, because "status unknown" is a residual category, we do not know precisely which of the individuals dropped from the HMIS data fell into this category. We can, however, compare the overall characteristics of those who were kept and those who were dropped, as seen in Table A.5. We observe that dropped individuals – those who were disproportionately likely to have unknown status – were older, more white, more Hispanic, and more male. They also had more frequent but shorter HMIS spells between 2004 and 2014.

One hypothesis is that these individuals were missed by the Census because they migrated to Mexico. We do indeed find that dropped individuals are more likely to be Hispanic (39 percent) than kept individuals (30 percent), but not overwhelmingly so. Another hypothesis is that these individuals may have transitioned to marginal living situations like couch-surfing, where they might have been left off the housing unit questionnaire submitted to Census. A third hypothesis that that these individuals transitioned to unsheltered status. This hypothesis aligns with the Winter Shelter Program's primary purpose of shielding homeless individuals who would otherwise be unsheltered from the elements during the winter. Prior work has shown that unsheltered individuals tend to be older, more white, and more male that sheltered individuals, so these individuals' characteristics align with that profile (Meyer et al. 2021).

Taken together, the available evidence does not provide satisfactory resolution to the puzzle of why recent participants in Los Angeles's Winter Shelter Program were disproportionately likely to be missed by the Census. This group does, however, offer concrete evidence of a subset of recent shelter occupants who were missed by the Census.

Coverage of homeless children in linked HMIS-Census data

We also use the linked Census-HMIS data to revisit the puzzle identified in our aggregate comparisons section on the difference in the share of homeless individuals under age 18 in the PIT versus the ACS and Census. Table A.6 displays the share of Los Angeles and Houston HMIS shelter users in various Census status disaggregated into those under 18 and those 18 and older. In contrast to our findings in Section 2.4, which suggested that children in the PIT were under-covered in the Census homeless enumeration, we see that about 48-52 percent of children in HMIS shelters were counted in homeless shelters in the Census, compared to 40-43 percent of adults. Children were also more likely to be counted as housed (30-32 percent) than adults (22-23 percent). We note that in 2010, HMIS data would likely not have included many facilities intended for unaccompanied youth because there was a separate system for tracking shelters intended for runaway and homeless youth prior to 2015. It is also possible that the Census classified some youth shelters as non-shelter facilities, as we found to be the case for some adult-oriented HMIS shelter. In Houston, we note that about 20 HMIS shelter users were counted in a single juvenile correctional facility in the Census, providing strong evidence of differential classification between sources in at least this instance.

A.1.2 Exhibits

Table A.1: Characteristics of Sheltered Homeless in PIT and ACS (2016)

Source	ACS	PIT
Includes Domestic Violence?	No	Yes
Age		
Under 18	0.122	0.291
18 and Older	0.878	0.709
Gender/Sex*		
Male	0.606	0.554
Female	0.394	0.444
Other Gender	-	0.002
Race		
White	0.430	0.439
Black	0.454	0.451
Asian	0.018	0.009
American Indian/Pac Islander	0.038	0.033
Other Race (incl multiple)	0.060	0.067
Hispanic Ethnicity		
Hispanic	0.224	0.233
Non-Hispanic	0.776	0.767

Sources: ACS 2016 one-year estimates, 2016 PIT file.
Note: ACS results approved for disclosure, CBDRB-FY20-ERD002-004. PIT and HMIS results obtained from public sources.
*ACS collects data on sex. PIT collects data on gender, including transgender and gender non-conforming.

Table A.2: Share Under 18 and Share Female of Sheltered Homeless in ACS, Census, and PIT

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Under Age 18														
ACS	0.178	0.189	0.159	0.131	0.153	0.135	0.104	0.133	0.158	0.128	0.122			
Census					0.202									
PIT										0.292	0.291	0.286	0.282	0.273
Female														
ACS	0.384	0.426	0.364	0.369	0.379	0.388	0.364	0.403	0.397	0.374	0.394			
Census					0.379									
PIT										0.445	0.444	0.445	0.447	0.441

Sources: 2006-2016 ACS one-year estimates, 2010 Census, 2015-2019 PIT.
Note: Table displays the share of sheltered homeless individuals in the 2006-2016 ACS, 2010 Census, and 2015-2019 PIT who fall into a given age or gender category. The ACS shares are weighted using survey weights prior to 2011. From 2011 onwards, we include only non-imputed ACS records, which are scaled up by a constant such that the new weighted count of non-imputed observations is equal to the old weighted sum of imputed and non-imputed records. All results were approved for release by the Census Bureau, authorization number CBDRB-FY20-ERD002-004.

Table A.3: Share of HMIS Shelter Users in a Given County/State in the Census, by Housing Status in Census

Status in Census	County in Census		State in Census	
	L.A.	Other	CA	Other
Sheltered	0.956	0.044	0.978	0.022
Unsheltered	0.928	0.072	0.962	0.038
Other GQ	0.863	0.137	0.971	0.029
Housed	0.741	0.259	0.849	0.151

Sources: 2010 PIT, 2010 Census.
Note: Table displays weighted share of HMIS shelter users who were in a given county or state in the Census, by housing status. Weight is calculated as the midpoint of the upper bound weight and the lower bound weight. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table A.4: Probability of L.A. HMIS Shelter Entry and Hazard Rate for Exit

Entry Probability												
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2009	0.34	0.28	0.20	0.18	0.16	0.16	0.14	0.14	0.16	0.15	0.16	0.49
2010	0.40	0.30	0.28	0.31	0.27	0.21	0.19	0.18	0.19	0.18	0.17	0.57
2011	0.40	0.35	0.27	0.17	0.16	0.17	0.20	0.18	0.19	0.18	0.19	0.55
2012	0.40	0.33	0.29	0.21	0.19	0.16	0.16	0.16	0.13	0.14	0.16	0.54
2013	0.43	0.27	0.20	0.14	0.14	0.12	0.14	0.12	0.12	0.14	0.09	0.41
Hazard Rate for Exit												
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2009	0.08	0.08	0.72	0.12	0.11	0.30	0.13	0.14	0.18	0.14	0.14	0.18
2010	0.12	0.11	0.67	0.19	0.15	0.23	0.15	0.15	0.18	0.18	0.19	0.20
2011	0.15	0.10	0.18	0.08	0.07	0.71	0.17	0.19	0.18	0.21	0.21	0.29
2012	0.30	0.29	0.46	0.23	0.23	0.21	0.19	0.19	0.17	0.20	0.30	0.23
2013	0.29	0.31	0.38	0.17	0.19	0.18	0.17	0.17	0.16	0.19	0.17	0.21

Sources: L.A. HMIS data (2004-2014).
Note: Table displays the probability of entering an L.A. HMIS shelter in a given month and year as a share of the 2010 Los Angeles population and the probability of exiting an HMIS shelter in a given month/year conditional on being in the shelter on the first day of the month. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table A.5: Characteristics of People Kept and Dropped in Refinements 1 and 2

	Kept	Dropped
Age at First Entry (Mean)	35.60	40.52
White (Share)	0.39	0.52
Black (Share)	0.52	0.35
Other Race (Share)	0.09	0.13
Hispanic (Share)	0.30	0.39
Female (Share)	0.41	0.27
Enrolled in Emergency Shelter (Share)	0.61	0.99
Number of Spells (2004-2014) (Mean)	3.74	4.29
Average Spell Length (Mean)	216.70	75.35

Sources: LA (CA-600, 2004-2014) HMIS administrative data.
Note: All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-006.

Table A.6: Coverage of HMIS Shelter Users in the 2010 Census by Child/Adult (L.A. and Houston Combined)

	Children (Age < 18)		Adults (Age 18+)	
Census Status	Lower	Upper	Lower	Upper
Sheltered	0.482	0.524	0.403	0.434
Unsheltered	0.001	0.001	0.086	0.094
Other GQ	0.082	0.088	0.089	0.097
Housed	0.299	0.316	0.218	0.232
Status Unknown (not in Census)	0.071	0.136	0.142	0.203
Share of HMIS users	0.175		0.825	
Weighted Total	1226		5770	

Sources: LA (2004-2014) HMIS administrative data, Houston (2004-2015) HMIS administrative data, 2010 Census.
Note: Table displays the weighted share of individuals who were present in an emergency or transitional shelter in HMIS data on March 30, 2010, according to HMIS records, who appeared in the 2010 Census in various GQ types or as housed. For L.A., sample consists of HMIS shelter users under Refinement 2. Where exit dates were missing in HMIS data, we imputed an exit date based on the median stay length for users of that shelter type. Bounds are calculated per methods described in the text. For L.A., the analysis is based on HMIS shelter users under Refinement 2. All shares and counts are rounded per Census Bureau disclosure rules. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release, authorization number CBDRB-FY2022-CES005-008.

Table A.7: Coverage of Census Sheltered and Unsheltered Homeless in HMIS in Los Angeles and Houston

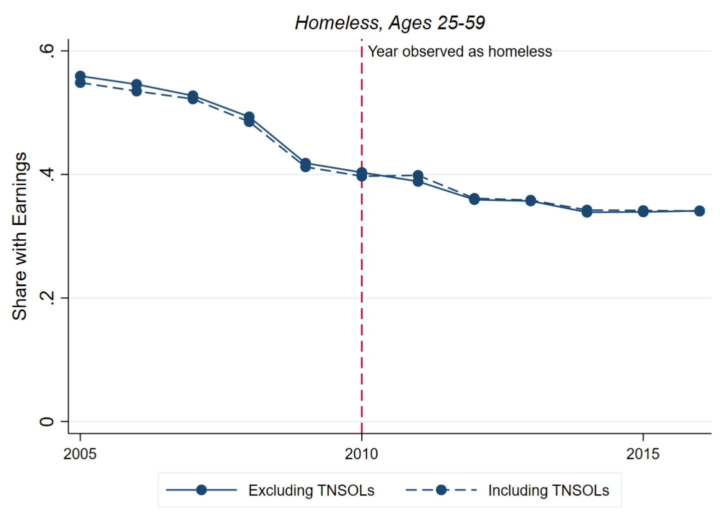
Panel A: Los Angeles				
	Sheltered		Unsheltered	
	Lower	*Upper*	*Lower*	*Upper*
In HMIS Shelter during SBE	0.361	0.393	0.085	0.095
Excluding 3/31 exits and WSP	0.331	0.359	0.042	0.046
Ever in HMIS Shelter (2004-2014)	0.681	0.743	0.336	0.376
Weighted Total	7344		10900	
Panel B: Houston				
	Sheltered		Unsheltered	
	Lower	*Upper*	*Lower*	*Upper*
In HMIS Shelter during SBE	0.207	0.218	0.021	0.022
Ever in HMIS Shelter (2004-2015)	0.720	0.765	0.623	0.663
Weighted Total	2515		2578	

Sources: LA (CA-600, 2004-2014) HMIS administrative data, Houston (TX-700, 2004-2015) HMIS administrative data, 2010 Census.
Note: Table displays the weighted share of individuals who were enumerated as sheltered and unsheltered homeless in the Los Angeles CoC who were present in HMIS shelters on March 30, 2010 ("in HMIS shelter during SBE") or ever in an HMIS shelter during the 2004-2014 period ("ever in HMIS shelter"), according to HMIS records. Where exit dates were missing in HMIS data, we imputed an exit date based on the median stay length for users of that shelter type. Lower bound assumes that the probability of being PIKed in HMIS data conditional on being PIKed in the Census is equal to one. Upper bound assumes that probability of being PIKed in HMIS data is independent of probability of being PIKed in Census data.

A.2 Chapter 3 Appendix

A.2.1 Exhibits

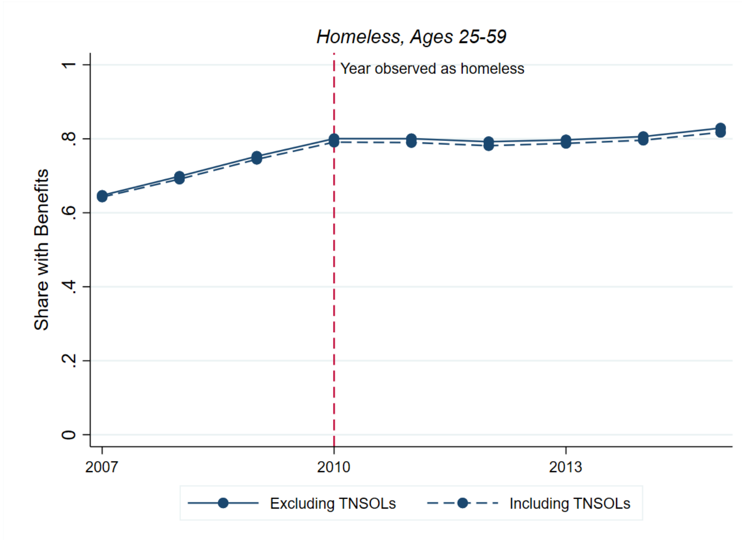
Figure A.1: Share with Earnings, Including and Excluding TNSOLs, 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

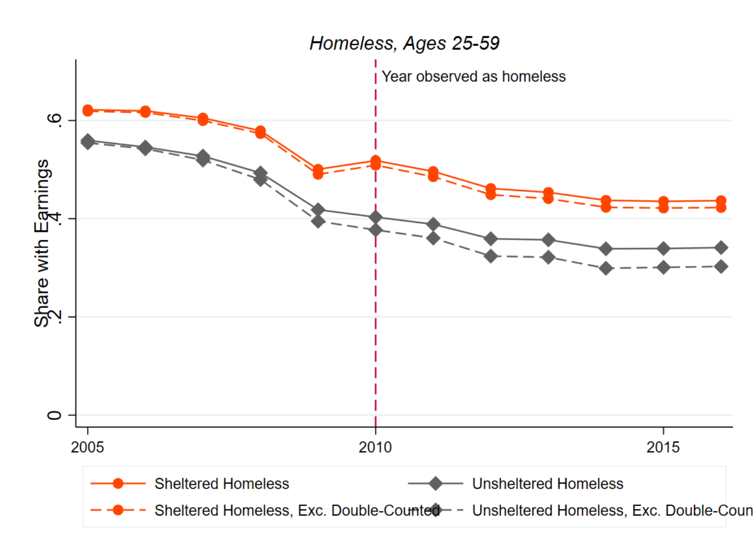
Figure A.2: Share with Benefits, Including and Excluding TNSOLs, 2005-2016



Sources: 2010 Census, 2003-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2016 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016).

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

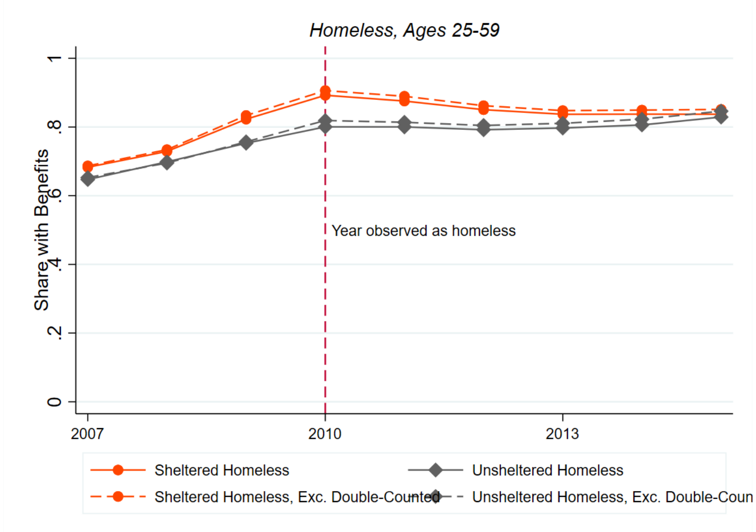
Figure A.3: Share with Earnings, Including and Excluding Double-Counted, 2005-2016



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

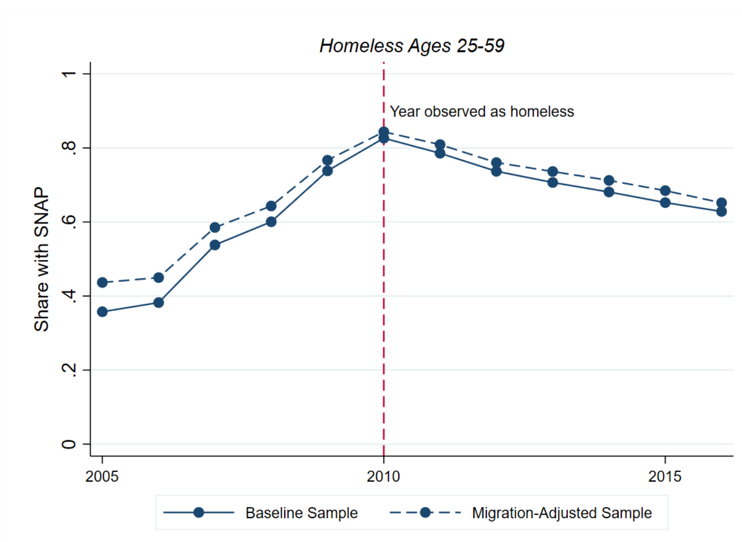
Figure A.4: Share with Benefits, Including and Excluding Double-Counted, 2005-2016



Sources: 2010 Census, 2003-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2016 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016).

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure A.5: Baseline and Migration-Adjusted SNAP Receipt, 2005-2016



Sources: SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census, 2000 Census.

Note: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Baseline sample consists of homeless residing in SNAP states in 2010. Migration-adjusted sample consists of homeless residing in SNAP states in both 2010 and 2000.

Table A.8: Summary of Connections to Formal Work, Safety Net, and Disability Programs, Ages 25-59 in 2010, 2005-2016

Sheltered and Unsheltered Homeless												
Sheltered Homeless												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share employed[1]	0.622	0.620	0.605	0.579	0.501	0.518	0.496	0.462	0.454	0.438	0.435	0.437
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share receiving any safety net benefits[2]			0.683	0.729	0.823	0.892	0.876	0.851	0.837	0.838	0.837	
			(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	
Share receiving disability benefits (SSI or DI)						0.191	0.245	0.288	0.312	0.327		0.343
						(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.002)
Share with benefits or earnings			0.888	0.899	0.929	0.966	0.960	0.951	0.947	0.947	0.945	
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	
Share with disability benefits or earnings						0.657	0.679	0.694	0.709	0.714		
						(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
Sample Size	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Population	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100
Unsheltered Homeless												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share employed[1]	0.559	0.546	0.528	0.493	0.418	0.403	0.389	0.359	0.357	0.339	0.339	0.341
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Share receiving any safety net benefits[2]			0.647	0.699	0.753	0.800	0.800	0.792	0.797	0.806	0.829	
			(0.012)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	
Share receiving disability benefits (SSI or DI)						0.291	0.327	0.359	0.376	0.385		0.396
						(0.005)	(0.005)	(0.005)	(0.005)	(0.005)		(0.005)
Share with benefits or earnings			0.881	0.892	0.899	0.926	0.928	0.921	0.927	0.930	0.936	
			(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	
Share with disability benefits or earnings						0.623	0.642	0.653	0.667	0.667		0.678
						0.004	0.004	0.004	0.004	0.004		0.005
Sample Size	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Population	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Note: Notes: Sample includes PIKed adults from the 2010 Decennial Census and 2009-2010 ACS who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars. (1) Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables A3-A6. (2) Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A.9: Summary of Connections to Formal Work, Safety Net, and Disability Programs, Ages 25-59 in 2010, 2005-2016

Single Housed Poor and Overall Housed												
Single Housed Poor												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share employed[1]	0.611	0.596	0.582	0.553	0.484	0.483	0.498	0.493	0.489	0.488	0.489	0.487
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share receiving any safety net benefits[2]			0.577	0.608	0.662	0.707	0.717	0.707	0.698	0.717	0.716	
			(0.011)	(0.010)	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.012)	
Share receiving disability benefits (SSI or DI)						0.251	0.274	0.292	0.305	0.308		0.307
						(0.005)	(0.004)	(0.005)	(0.004)	(0.005)		(0.005)
Share with benefits or earnings			0.860	0.868	0.861	0.892	0.903	0.909	0.907	0.919	0.928	
			(0.008)	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	
Share with disability benefits or earnings						0.691	0.726	0.740	0.748	0.753		0.750
						0.004	0.003	0.003	0.003	0.003		0.004
Sample Size	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population (100,000s)	48.46	48.46	48.46	48.46	48.46	48.46	48.14	47.70	47.18	46.72	46.16	45.60
Overall Housed												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share employed[1]	0.857	0.860	0.864	0.861	0.848	0.843	0.837	0.831	0.825	0.815	0.809	0.801
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share receiving any safety net benefits[2]			0.185	0.192	0.201	0.217	0.225	0.228	0.229	0.247	0.261	
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	
Share receiving disability benefits (SSI or DI)						0.059	0.064	0.068	0.073	0.077		0.078
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
Share with benefits or earnings						0.931	0.928	0.927	0.925	0.924		
						(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Share with disability benefits or earnings						0.884	0.882	0.880	0.878	0.873		0.859
						0.000	0.000	0.000	0.000	0.000		0.000
Sample Size	994,000	994,000	994,000	994,000	994,000	994,000	992,000	989,000	986,000	983,000	979,000	975,000
Population (100,000s)	722.70	722.70	722.70	722.70	722.70	722.70	722.70	722.70	721.30	719.10	716.80	714.40

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Note: Notes: Sample includes PIKed adults from the 2010 Decennial Census and 2009-2010 ACS who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars. (1) Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables A3-A6. (2) Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A.10: Income and Benefit Receipt among All Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2005-2016

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Employment and Earnings												
Share employed[1]	0.622	0.620	0.605	0.579	0.501	0.518	0.496	0.462	0.454	0.438	0.435	0.437
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50th percentile (cond. on +)	$9,493	$9,534	$9,327	$8,039	$6,590	$8,328	$10,870	$11,170	$11,380	$11,820	$12,860	$13,470
	($69)	($71)	($68)	($68)	($68)	($63)	($63)	($71)	($77)	($89)	($102)	($103)
75th percentile (cond. on +)	$20,290	$19,780	$18,700	$16,780	$14,950	$16,570	$20,060	$20,450	$20,980	$21,780	$23,850	$24,850
	($120)	($108)	($103)	($94)	($99)	($98)	($121)	($116)	($131)	($141)	($156)	($156)
Pretax Cash Income, Plus In-Kind Transfers (no SSI)[3]												
50th percentile	$5,634	$5,029	$4,564	$3,177	$2,835	$3,948	$4,414	$3,906	$3,947	$3,527	$4,041	$4,347
	($247)	($218)	($135)	($87)	($33)	($100)	($139)	($126)	($131)	($127)	($151)	($158)
75th percentile	$14,920	$14,380	$14,370	$12,930	$11,950	$13,940	$15,690	$15,490	$15,560	$15,220	$16,220	$16,670
	($423)	($382)	($153)	($152)	($126)	($118)	($145)	($145)	($144)	($154)	($168)	($170)
Safety Net Program Receipt												
Share receiving any safety net benefits[2]			0.669	0.717	0.795	0.856	0.846	0.827	0.821	0.825	0.834	
			(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	
Share receiving SNAP	0.384	0.404	0.524	0.584	0.697	0.774	0.745	0.709	0.687	0.667	0.644	0.621
	(0.007)	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Share enrolled in Medicaid			0.321	0.340	0.375	0.430	0.460	0.479	0.484	0.613	0.672	
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	
Share receiving disability benefits (SSI or DI)						0.239	0.284	0.322	0.343	0.355		0.368
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)
Sample Size	139,000	139,000	139,000	139,000	139,000	139,000	138,000	136,500	134,500	132,500	131,000	128,500
Population	246,600	246,600	246,600	246,600	246,600	246,600	244,800	241,900	238,800	235,500	232,000	228,000

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Note: Notes: Sample includes PIKed adults from the 2010 Decennial Census and 2009-2010 ACS who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars. (1) Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables A3-A6. (2) Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A.11: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2005-2016*

	Income and Earnings											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Employment and Earnings[1]												
Share with earnings	0.622	0.620	0.605	0.579	0.501	0.518	0.496	0.462	0.454	0.438	0.435	0.437
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mean (cond. on +)	$14,810	$14,620	$14,040	$12,810	$11,610	$13,510	$15,780	$15,890	$16,330	$16,620	$17,890	$18,480
	($83)	($82)	($78)	($84)	($86)	($103)	($103)	($108)	($111)	($116)	($121)	($120)
Std Deviation (cond. on +)	$19,020	$19,080	$17,940	$18,740	$17,570	$21,610	$21,090	$21,690	$21,730	$21,820	$22,580	$22,620
25th percentile (cond. on +)	$2,943	$2,958	$3,014	$2,435	$1,738	$2,452	$3,659	$3,662	$3,941	$4,061	$4,413	$4,656
	($38)	($38)	($40)	($34)	($26)	($38)	($58)	($58)	($68)	($70)	($78)	($79)
50th percentile (cond. on +)	$9,493	$9,534	$9,327	$8,039	$6,590	$8,328	$10,870	$11,170	$11,380	$11,820	$12,860	$13,470
	($69)	($71)	($68)	($68)	($68)	($63)	($63)	($71)	($77)	($89)	($102)	($103)
75th percentile (cond. on +)	$20,290	$19,780	$18,700	$16,780	$14,950	$16,570	$20,060	$20,450	$20,980	$21,780	$23,850	$24,850
	($120)	($108)	($103)	($94)	($99)	($98)	($121)	($116)	($131)	($141)	($156)	($156)
Pretax Cash Income[2]												
Mean	$9,519	$9,475	$9,432	$8,055	$6,520	$8,069	$9,050	$8,393	$8,337	$8,245	$8,835	$9,192
	($65)	($63)	($60)	($62)	($52)	($61)	($62)	($63)	($64)	($66)	($70)	($71)
Std Deviation	$18,760	$18,560	$17,600	$18,380	$15,200	$17,870	$18,110	$18,460	$18,760	$19,170	$20,200	$20,210
25th percentile	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0
	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)
50th percentile	$2,230	$2,250	$3,520	$1,450	$238	$758	$681	$12	$0	$0	$0	$0
	($50)	($50)	($60)	($39)	($17)	($35)	($43)	($13)	($6)	($0)	($0)	($0)
75th percentile	$13,430	$13,600	$13,360	$11,230	$8,346	$10,980	$13,070	$12,220	$12,020	$11,850	$12,950	$13,360
	($96)	($97)	($76)	($79)	($84)	($69)	($77)	($98)	($103)	($107)	($94)	($98)
Pretax Cash Income, Plus In-Kind Transfers (no SSI)[3]												
Mean	$10,270	$9,666	$10,120	$9,121	$8,543	$10,040	$10,970	$10,680	$10,710	$10,430	$11,120	$11,540
	($235)	($222)	($112)	($106)	($96)	($99)	($107)	($107)	($111)	($111)	($117)	($128)
Std Deviation	$13,700	$12,970	$15,400	$14,590	$14,270	$14,870	$15,870	$15,800	$16,290	$16,210	$16,960	$18,440
25th percentile	$754	$754	$902	$833	$1,277	$1,994	$1,790	$1,565	$1,469	$1,210	$1,159	$1,041
	($91)	($85)	($33)	($29)	($23)	($22)	($27)	($28)	($29)	($30)	($34)	($39)
50th percentile	$5,634	$5,029	$4,564	$3,177	$2,835	$3,948	$4,414	$3,906	$3,947	$3,527	$4,041	$4,347
	($247)	($218)	($135)	($87)	($33)	($100)	($139)	($126)	($131)	($127)	($151)	($158)
75th percentile	$14,920	$14,380	$14,370	$12,930	$11,950	$13,940	$15,690	$15,490	$15,560	$15,220	$16,220	$16,670
	($423)	($382)	($153)	($152)	($126)	($118)	($145)	($145)	($144)	($154)	($168)	($170)
Pretax Cash Income, Plus In-Kind Transfers (with SSI)												
Mean						$11,280	$12,550	$12,460	$12,600	$12,280		$13,150
						($100)	($111)	($110)	($113)	($112)		($126)
Std Deviation						$14,980	$16,450	$16,240	$16,640	$16,340		$18,140
25th percentile						$2,413	$2,411	$2,330	$2,285	$2,083		$2,132
						($16)	($25)	($29)	($33)	($33)		($44)
50th percentile						$7,461	$9,149	$9,289	$9,441	$9,325		$9,518
						($142)	($115)	($106)	($102)	($96)		($73)
75th percentile						$15,130	$17,090	$17,190	$17,310	$17,040		$18,260
						($132)	($133)	($130)	($125)	($136)		($156)
Sample Size	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Population	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100

Note: *Sources and notes in table A.23.

Table A.12: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

Connections to Employment and Formal Income														
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1040 Filing Status														
Share filing 1040	0.390	0.381	0.374	0.376	0.447	0.372	0.330	0.381	0.399	0.341	0.332	0.308	0.306	0.299
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
1040 cofiling rate (cond. on filing)	0.204	0.200	0.193	0.180	0.153	0.158	0.149	0.131	0.131	0.171	0.177	0.187	0.194	0.204
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Share with dependents (cond. on filing)	0.415	0.419	0.421	0.417	0.354	0.375	0.365	0.367	0.358	0.412	0.425	0.447	0.441	0.437
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean dependents (cond. on +)	1.753	1.756	1.742	1.736	1.726	1.756	1.770	1.790	1.805	1.821	1.846	1.857	1.875	1.890
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Income Sources on 1040s														
Share filing 1040 with positive total money income	0.388	0.378	0.359	0.360	0.430	0.356	0.315	0.367	0.376	0.330	0.321	0.298	0.296	0.290
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Median total money income (cond. on +)	$16,760	$16,400	$14,040	$14,180	$12,300	$12,150	$11,290	$12,730	$14,790	$15,020	$15,190	$15,600	$16,590	$17,440
	($108)	($103)	($94)	($92)	($65)	($78)	($64)	($80)	($79)	($80)	($77)	($77)	($92)	($110)
Share filing 1040 with self-employment income (+ or -)	0.038	0.040	0.040	0.043	0.047	0.047	0.049	0.053	0.056	0.054	0.054	0.051	0.048	0.047
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median self-employment income (cond. on +)	$7,283	$7,170	$6,953	$7,914	$7,863	$8,444	$9,897	$10,030	$10,060	$10,070	$9,755	$9,437	$9,188	$8,352
	($261)	($245)	($239)	($230)	($220)	($184)	($151)	($136)	($134)	($135)	($175)	($189)	($222)	($257)
Share filing 1040 with social security income	0.003	0.003	0.004	0.007	0.054	0.013	0.010	0.016	0.020	0.020	0.021	0.021	0.025	0.027
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Median social security income (cond. on +)	$11,360	$11,280	$10,750	$10,240	$9,945	$10,370	$11,170	$12,950	$12,830	$12,330	$11,050	$11,280	$11,390	$11,630
	($460)	($478)	($348)	($215)	($60)	($175)	($233)	($226)	($124)	($173)	($151)	($158)	($131)	($138)
Share filing 1040 with wage and salary income	0.372	0.362	0.354	0.352	0.375	0.336	0.285	0.325	0.329	0.296	0.292	0.274	0.274	0.270
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Median 1040 wage and salary income (cond. on +)	$16,000	$15,880	$13,240	$13,160	$11,820	$10,800	$9,466	$10,810	$13,140	$13,560	$13,930	$14,530	$15,730	$16,600
	($123)	($116)	($104)	($108)	($88)	($88)	($88)	($76)	($108)	($107)	($120)	($122)	($132)	($139)
IRS Information Returns (W2s and 1099Rs)														
Share receiving W2			0.602	0.597	0.583	0.548	0.454	0.448	0.423	0.406	0.402	0.403	0.406	0.411
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Median W2 wage and tips (cond. on +)			$9,073	$8,973	$8,690	$7,231	$5,021	$5,759	$8,176	$9,456	$10,260	$11,210	$12,580	$13,230
			($72)	($74)	($69)	($65)	($54)	($57)	($87)	($95)	($102)	($104)	($114)	($113)
Mean W2s received (cond. on +)			2.073	2.101	2.099	1.940	1.647	1.650	1.611	1.623	1.646	1.700	1.764	1.802
			(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Share receiving 1099R	0.040	0.041	0.039	0.041	0.042	0.042	0.039	0.030	0.028	0.033	0.034	0.038	0.041	0.044
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sample Size	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Population	128,400	128,400	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100

Note: *Sources and notes in table A.23.

Table A.13: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

	Safety Net Program Receipt													
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Housing Benefits (HUD)														
Share with housing benefits	0.083	0.083	0.082	0.078	0.074	0.071	0.068	0.101	0.126	0.143	0.146	0.154	0.161	0.165
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean housing benefit amount (equivalized) (cond. on +)[4]	$4,904	$5,043	$4,972	$4,860	$4,858	$4,790	$4,906	$4,291	$5,455	$5,684	$6,067	$5,983	$6,094	$6,267
	($41)	($41)	($41)	($42)	($42)	($43)	($46)	($35)	($33)	($33)	($33)	($32)	($32)	($32)
Mean assistance unit size (cond. on +)	2.839	2.791	2.668	2.585	2.454	2.267	2.012	1.829	1.819	1.844	1.841	1.849	1.849	1.836
	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)	(0.016)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Share with child in assistance unit (cond. on +)	0.611	0.585	0.544	0.507	0.456	0.392	0.298	0.256	0.257	0.262	0.263	0.262	0.258	0.254
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mean months of housing benefit receipt (cond. on +)	10.300	10.360	10.200	9.992	9.892	9.607	9.245	7.829	9.755	10.080	10.630	10.550	10.640	10.730
	(0.046)	(0.044)	(0.045)	(0.045)	(0.046)	(0.047)	(0.049)	(0.042)	(0.034)	(0.032)	(0.028)	(0.028)	(0.026)	(0.025)
Veterans' Benefits (VA)														
Share with VA service-connected disability					0.015	0.017	0.023	0.027	0.029	0.031	0.033	0.034	0.035	0.036
					(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Supplemental Nutrition Assistance Program (SNAP)[5]														
Share with SNAP receipt			0.358	0.382	0.538	0.601	0.738	0.826	0.786	0.737	0.707	0.681	0.652	0.628
			(0.008)	(0.008)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean SNAP benefit amount (equivalized) (cond. on +)			$1,224	$1,203	$1,278	$1,364	$1,736	$1,886	$1,812	$1,795	$1,748	$1,581	$1,589	$1,564
			($24)	($22)	($8)	($8)	($8)	($6)	($7)	($8)	($8)	($8)	($8)	($9)
Mean months of SNAP receipt (cond. on +)			7.327	7.401	8.905	9.108	9.189	10.200	10.100	10.160	10.360	10.300	10.410	10.380
			(0.110)	(0.104)	(0.036)	(0.034)	(0.028)	(0.020)	(0.023)	(0.024)	(0.024)	(0.025)	(0.025)	(0.026)
Mean assistance unit size (cond. on +)			1.965	1.918	2.029	2.000	1.938	1.941	1.947	1.939	1.941	1.930	1.926	1.922
			(0.043)	(0.041)	(0.017)	(0.016)	(0.012)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
Share with child in assistance unit (cond. on +)			0.332	0.308	0.338	0.319	0.298	0.291	0.287	0.279	0.273	0.264	0.256	0.249
			(0.013)	(0.013)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.000)
Medicaid and Medicare														
Share enrolled in Medicaid					0.315	0.333	0.376	0.445	0.473	0.488	0.492	0.612	0.662	
					(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	
Share enrolled in Medicare Part A or B				0.059	0.064	0.069	0.074	0.090	0.113	0.137	0.154	0.166	0.181	0.198
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Disability programs (DI and SSI)														
Share receiving DI as indicated by Medicare records				0.058	0.063	0.069	0.074	0.089	0.112	0.136	0.153	0.164	0.166	0.167
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share receiving SSI								0.137	0.176	0.201	0.210	0.214		0.225
								(0.001)	(0.001)	(0.002)	(0.002)	(0.002)		(0.002)
Mean SSI amount (cond. on +)								$8,885	$9,898	$9,797	$9,183	$8,691		$8,000
								($87)	($116)	($117)	($89)	($72)		($53)
Share receiving SSI or DI according to Medicare								0.191	0.245	0.288	0.312	0.327		0.343
								(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.002)
Share living in SNAP state in 2010			0.038	0.038	0.206	0.206	0.242	0.242	0.242	0.243	0.243	0.244	0.244	0.245
Share living in Medicaid state in 2010					0.946	0.946	0.946	0.946	0.946	0.947	0.946	0.806	0.368	
Sample Size	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,500	89,000	88,000	86,500	85,500	84,500	83,000
Population	128,400	128,400	128,400	128,400	128,400	128,400	128,400	128,400	127,500	126,000	124,400	122,800	121,100	119,100

Note: *Sources and notes in table A.23.

Table A.14: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

	Employment and Income											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Employment and Earnings[1]												
Share with earnings	0.559	0.546	0.528	0.493	0.418	0.403	0.389	0.359	0.357	0.339	0.339	0.341
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Mean (cond. on +)	$15,210	$15,410	$15,450	$14,800	$14,700	$16,300	$17,890	$18,310	$18,660	$19,100	$20,300	$21,010
	($173)	($179)	($215)	($169)	($186)	($203)	($231)	($257)	($263)	($255)	($268)	($296)
Std Deviation (cond. on +)	$23,320	$25,140	$24,140	$24,590	$24,740	$26,280	$27,870	$30,860	$30,610	$30,440	$31,300	$34,140
25th percentile (cond. on +)	$2,100	$2,245	$2,359	$2,014	$1,607	$2,066	$2,902	$2,642	$2,920	$3,048	$3,403	$3,479
	($62)	($70)	($83)	($56)	($59)	($66)	($125)	($102)	($121)	($99)	($116)	($120)
50th percentile (cond. on +)	$8,377	$8,483	$8,514	$7,847	$7,373	$8,298	$10,120	$10,310	$10,620	$11,020	$12,020	$12,320
	($155)	($147)	($187)	($126)	($166)	($143)	($188)	($172)	($172)	($175)	($185)	($197)
75th percentile (cond. on +)	$19,820	$19,860	$19,740	$18,510	$17,730	$19,750	$21,920	$21,810	$22,520	$23,440	$25,410	$26,370
	($281)	($257)	($333)	($224)	($302)	($307)	($385)	($303)	($343)	($324)	($359)	($337)
Pretax Cash Income[2]												
Mean	$8,931	$9,002	$9,692	$8,104	$7,070	$7,926	$8,361	$7,753	$7,788	$7,659	$8,205	$8,453
	($109)	($117)	($136)	($109)	($102)	($107)	($111)	($118)	($125)	($125)	($133)	($136)
Std Deviation	$20,910	$23,010	$21,560	$21,420	$20,040	$21,070	$21,860	$23,560	$24,580	$24,750	$26,110	$25,950
25th percentile	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0	$0
	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)
50th percentile	$610	$475	$2,205	$114	$0	$0	$0	$0	$0	$0	$0	$0
	($62)	($58)	($122)	($29)	($0)	($0)	($0)	($0)	($0)	($0)	($0)	($0)
75th percentile	$10,900	$10,800	$12,340	$9,595	$7,261	$8,174	$9,080	$7,238	$7,212	$6,489	$7,402	$7,844
	($228)	($218)	($171)	($207)	($234)	($223)	($242)	($289)	($304)	($326)	($359)	($352)
Pretax Cash Income, Plus In-Kind Transfers (no SSI)[3]												
Mean	$9,252	$9,270	$11,030	$10,070	$9,514	$10,420	$10,830	$10,400	$10,740	$10,070	$11,120	$11,110
	($364)	($385)	($296)	($282)	($248)	($259)	($276)	($261)	($307)	($267)	($302)	($319)
Std Deviation	$15,960	$16,870	$19,530	$19,580	$20,120	$20,720	$21,580	$20,620	$23,440	$21,010	$23,570	$24,200
25th percentile	$170	$162	$420	$453	$817	$1,350	$1,161	$992	$880	$703	$616	$507
	($54)	($51)	($72)	($72)	($79)	($68)	($67)	($77)	($80)	($76)	($93)	($86)
50th percentile	$2,399	$2,484	$3,619	$2,264	$2,664	$2,710	$2,630	$2,579	$2,525	$2,389	$2,439	$2,417
	($184)	($175)	($353)	($112)	($22)	($32)	($37)	($20)	($42)	($1)	($17)	($36)
75th percentile	$11,940	$11,500	$14,300	$12,790	$11,350	$12,530	$13,070	$12,650	$12,580	$11,970	$13,130	$13,280
	($704)	($569)	($492)	($543)	($459)	($482)	($502)	($501)	($470)	($499)	($519)	($521)
Pretax Cash Income, Plus In-Kind Transfers (with SSI)												
Mean						$11,920	$12,480	$12,210	$12,640	$11,960		$12,900
						($268)	($288)	($273)	($316)	($277)		($329)
Std Deviation						$20,610	$21,600	$20,570	$23,360	$20,830		$23,940
25th percentile						$1,870	$1,534	$1,594	$1,653	$1,461		$1,407
						($67)	($71)	($102)	($107)	($114)		($100)
50th percentile						$5,479	$5,950	$6,101	$6,419	$6,303		$7,571
						($384)	($418)	($434)	($431)	($436)		($402)
75th percentile						$14,280	$15,230	$15,030	$14,990	$14,640		$15,520
						($373)	($506)	($458)	($471)	($458)		($511)
Sample Size	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Population	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900

Note: *Sources and notes in table A.23.

Table A.15: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

	Connections to Employment and Formal Income													
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1040 Filing Status														
Share filing 1040	0.348	0.338	0.327	0.327	0.432	0.326	0.291	0.311	0.325	0.270	0.262	0.244	0.241	0.239
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
1040 cofiling rate (cond. on filing)	0.257	0.267	0.255	0.243	0.202	0.229	0.236	0.218	0.208	0.276	0.278	0.293	0.303	0.308
	(0.004)	(0.007)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Share with dependents (cond. on filing)	0.407	0.405	0.407	0.394	0.306	0.362	0.362	0.345	0.327	0.382	0.392	0.405	0.398	0.383
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean dependents (cond. on +)	1.801	1.793	1.779	1.779	1.756	1.775	1.832	1.822	1.804	1.811	1.811	1.830	1.834	1.844
	(0.012)	(0.012)	(0.010)	(0.011)	(0.011)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)
Income Sources on 1040s														
Share filing 1040 with positive total money income	0.346	0.335	0.313	0.311	0.415	0.309	0.275	0.297	0.303	0.259	0.252	0.234	0.231	0.231
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Median total money income (cond. on +)	$17,100	$17,450	$14,520	$14,750	$12,150	$13,640	$13,890	$14,810	$15,510	$15,790	$15,920	$16,810	$18,110	$18,570
	($204)	($273)	($181)	($170)	($137)	($172)	($228)	($160)	($211)	($187)	($171)	($181)	($180)	($202)
Share filing 1040 with self-employment income (+ or -)	0.033	0.034	0.035	0.035	0.039	0.040	0.045	0.044	0.044	0.042	0.042	0.040	0.038	0.036
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median self-employment income (cond. on +)	$5,637	$5,854	$6,071	$6,373	$6,153	$6,701	$8,296	$8,188	$7,285	$6,651	$6,830	$6,783	$6,063	$5,792
	($340)	($315)	($351)	($356)	($314)	($319)	($1046)	($317)	($344)	($353)	($395)	($373)	($389)	($426)
Share filing 1040 with social security income	0.006	0.006	0.007	0.013	0.098	0.024	0.020	0.023	0.027	0.026	0.027	0.027	0.029	0.032
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median social security income (cond. on +)	$10,850	$11,300	$10,610	$10,790	$9,808	$10,580	$11,540	$13,090	$12,840	$12,520	$11,740	$12,200	$12,330	$12,370
	($448)	($423)	($331)	($220)	($66)	($157)	($195)	($212)	($154)	($216)	($220)	($208)	($254)	($205)
Share filing 1040 with wage and salary income	0.332	0.322	0.311	0.305	0.327	0.291	0.248	0.260	0.264	0.233	0.229	0.216	0.213	0.212
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Median 1040 wage and salary income (cond. on +)	$16,320	$16,700	$13,600	$13,710	$12,550	$11,830	$11,500	$12,200	$13,490	$14,000	$14,320	$15,210	$16,570	$17,110
	($223)	($287)	($197)	($206)	($249)	($198)	($187)	($206)	($295)	($243)	($237)	($222)	($223)	($237)
IRS Information Returns (W2s and 1099Rs)														
Share receiving W2			0.538	0.526	0.507	0.464	0.371	0.331	0.312	0.310	0.310	0.309	0.315	0.319
			(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Median W2 wage and tips (cond. on +)			$8,371	$8,419	$7,939	$7,170	$5,533	$5,290	$7,407	$8,625	$9,808	$10,720	$11,760	$12,330
			($155)	($169)	($163)	($130)	($130)	($135)	($173)	($203)	($240)	($218)	($209)	($218)
Mean W2s received (cond. on +)			1.993	2.019	1.989	1.841	1.575	1.536	1.532	1.539	1.572	1.619	1.668	1.685
			(0.012)	(0.015)	(0.015)	(0.012)	(0.024)	(0.009)	(0.011)	(0.009)	(0.010)	(0.012)	(0.012)	(0.011)
Share receiving 1099R	0.034	0.035	0.031	0.032	0.034	0.035	0.036	0.031	0.030	0.032	0.032	0.036	0.039	0.041
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sample Size	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Population	118,200	118,200	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900

Note: *Sources and notes in table A.23.

Table A.16: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

	Safety Net Program Receipt													
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Housing Benefits (HUD)														
Share with housing benefits	0.082	0.084	0.083	0.081	0.081	0.082	0.083	0.094	0.104	0.111	0.116	0.122	0.128	0.132
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mean housing benefit amount (equivalized) (cond. on +)[4]	$4,875	$4,926	$4,905	$4,835	$4,927	$4,957	$5,161	$5,138	$5,463	$5,510	$5,628	$5,676	$5,850	$6,002
	($60)	($64)	($63)	($84)	($56)	($55)	($76)	($60)	($52)	($63)	($57)	($63)	($56)	($62)
Mean assistance unit size (cond. on +)	2.404	2.405	2.361	2.282	2.182	2.113	2.052	1.913	1.821	1.755	1.710	1.651	1.623	1.616
	(0.027)	(0.055)	(0.056)	(0.058)	(0.060)	(0.060)	(0.079)	(0.072)	(0.053)	(0.050)	(0.049)	(0.048)	(0.047)	(0.046)
Share with child in assistance unit (cond. on +)	0.445	0.425	0.405	0.385	0.349	0.321	0.283	0.243	0.219	0.201	0.186	0.168	0.160	0.155
	(0.010)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Mean months of housing benefit receipt (cond. on +)	10.450	10.550	10.580	10.370	10.380	10.430	10.360	9.969	10.410	10.490	10.570	10.550	10.660	10.780
	(0.064)	(0.068)	(0.066)	(0.115)	(0.066)	(0.063)	(0.091)	(0.068)	(0.056)	(0.049)	(0.050)	(0.075)	(0.045)	(0.041)
Veterans' Benefits (VA)														
Share with VA service-connected disability					0.014	0.014	0.017	0.018	0.020	0.021	0.022	0.023	0.024	0.025
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Supplemental Nutrition Assistance Program (SNAP)[5]														
Share with SNAP receipt			0.413	0.428	0.503	0.560	0.636	0.695	0.683	0.666	0.658	0.647	0.631	0.610
			(0.011)	(0.011)	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Mean SNAP benefit amount (equivalized) (cond. on +)			$1,136	$1,101	$1,141	$1,197	$1,644	$1,790	$1,713	$1,687	$1,681	$1,515	$1,513	$1,445
			($28)	($27)	($14)	($15)	($16)	($14)	($14)	($18)	($40)	($23)	($25)	($16)
Mean months of SNAP receipt (cond. on +)			8.127	8.081	9.222	9.301	9.712	10.190	10.260	10.450	10.650	10.700	10.750	10.620
			(0.141)	(0.135)	(0.063)	(0.138)	(0.049)	(0.045)	(0.077)	(0.041)	(0.051)	(0.048)	(0.048)	(0.057)
Mean assistance unit size (cond. on +)			1.910	1.816	1.809	1.793	1.707	1.658	1.662	1.653	1.659	1.662	1.657	1.647
			(0.052)	(0.048)	(0.037)	(0.040)	(0.030)	(0.027)	(0.025)	(0.025)	(0.029)	(0.030)	(0.031)	(0.032)
Share with child in assistance unit (cond. on +)			0.278	0.238	0.195	0.170	0.149	0.134	0.134	0.132	0.127	0.124	0.118	0.111
			(0.016)	(0.015)	(0.007)	(0.008)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.000)
Medicaid and Medicare														
Share enrolled in Medicaid					0.328	0.348	0.374	0.414	0.446	0.470	0.476	0.614	0.683	
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	
Share enrolled in Medicare Part A or B				0.106	0.114	0.123	0.130	0.146	0.161	0.175	0.188	0.197	0.209	0.227
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Disability programs (DI and SSI)														
Share receiving DI as indicated by Medicare records				0.106	0.114	0.122	0.129	0.145	0.160	0.174	0.187	0.196	0.194	0.191
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share receiving SSI								0.210	0.234	0.255	0.260	0.260		0.270
								(0.004)	(0.004)	(0.004)	(0.004)	(0.003)		(0.004)
Mean SSI amount (cond. on +)								$8,018	$8,525	$8,511	$8,513	$8,388		$7,834
								($79)	($100)	($104)	($101)	($193)		($79)
Share receiving SSI or DI according to Medicare								0.291	0.327	0.359	0.376	0.385		0.396
								(0.005)	(0.005)	(0.005)	(0.005)	(0.005)		(0.005)
Share living in SNAP state in 2010			0.036	0.036	0.148	0.148	0.175	0.175	0.175	0.175	0.175	0.176	0.176	0.176
Share living in Medicaid state in 2010					0.953	0.953	0.953	0.953	0.953	0.953	0.953	0.839	0.415	
Sample Size	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,500	49,000	48,500	48,000	47,000	46,500	45,500
Population	118,200	118,200	118,200	118,200	118,200	118,200	118,200	118,200	117,300	115,900	114,400	112,700	110,900	108,900

Note: *Sources and notes in table A.23.

Table A.17: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

A: Employment and Income												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Employment and Earnings[1]												
Share with earnings	0.611	0.596	0.582	0.553	0.484	0.483	0.498	0.493	0.489	0.488	0.489	0.487
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
50th percentile (cond. on +)	$14,510	$14,920	$14,230	$12,790	$10,690	$12,240	$13,890	$14,930	$15,830	$16,460	$17,650	$18,560
	($180)	($168)	($155)	($153)	($122)	($147)	($157)	($158)	($156)	($171)	($213)	($235)
75th percentile (cond. on +)	$28,010	$28,090	$26,420	$23,500	$18,510	$21,160	$23,930	$26,120	$27,810	$29,910	$31,830	$33,460
	($288)	($308)	($301)	($263)	($206)	($243)	($260)	($290)	($315)	($332)	($360)	($365)
Pretax Cash Income, Plus In-Kind Transfers (no SSI)[3]												
50th percentile	$7,158	$6,786	$9,937	$7,012	$6,169	$7,026	$7,356	$7,491	$7,545	$7,411	$7,532	$8,350
	($642)	($588)	($344)	($375)	($334)	($314)	($328)	($358)	($357)	($380)	($426)	($434)
75th percentile	$20,890	$19,640	$20,480	$18,630	$16,160	$17,560	$18,930	$19,200	$19,710	$20,160	$21,890	$23,200
	($899)	($1018)	($554)	($560)	($400)	($406)	($465)	($496)	($537)	($577)	($574)	($627)
Pretax Cash Income, Plus In-Kind Transfers (with SSI)												
50th percentile						$9,886	$10,140	$10,450	$10,660	$10,500		$11,030
						($249)	($253)	($245)	($240)	($259)		($254)
75th percentile						$19,090	$20,070	$20,460	$21,100	$21,600		$23,890
						($396)	($411)	($428)	($436)	($527)		($551)
Sample Size	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population (100,000s)	48.46	48.46	48.46	48.46	48.46	48.46	48.14	47.70	47.18	46.72	46.16	45.60

Note: *Sources and notes in table A.23.

Table A.18: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

B: Connections to Employment and Formal Income														
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share filing 1040	0.518	0.515	0.509	0.512	0.612	0.499	0.466	0.468	0.480	0.457	0.451	0.446	0.442	0.433
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
1040 cofiling rate (cond. on filing)	0.225	0.215	0.201	0.185	0.147	0.152	0.138	0.138	0.147	0.179	0.193	0.204	0.218	0.233
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share filing 1040 with dependents (cond. on filing)	0.510	0.514	0.517	0.512	0.436	0.501	0.497	0.511	0.497	0.518	0.522	0.524	0.514	0.505
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Mean number of dependents (cond. on filing with dependents)	1.816	1.802	1.801	1.793	1.780	1.798	1.835	1.846	1.844	1.874	1.870	1.865	1.852	1.852
	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.013)
Share filing 1040 with positive total money income	0.511	0.508	0.488	0.485	0.587	0.475	0.439	0.447	0.456	0.437	0.431	0.426	0.424	0.416
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Share filing 1040 with self-employment income, positive or negative	0.085	0.089	0.090	0.095	0.101	0.101	0.104	0.105	0.105	0.101	0.101	0.101	0.101	0.097
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share filing 1040 with positive social security income	0.007	0.007	0.006	0.014	0.106	0.027	0.025	0.025	0.030	0.030	0.032	0.037	0.041	0.044
	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share filing 1040 with positive wage and salary income	0.471	0.464	0.455	0.448	0.456	0.416	0.359	0.359	0.375	0.372	0.372	0.368	0.366	0.361
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Share receiving W2			0.557	0.539	0.521	0.485	0.407	0.394	0.411	0.415	0.415	0.421	0.425	0.427
			(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mean number of W2s received (cond. on +)			1.679	1.690	1.684	1.588	1.442	1.485	1.483	1.480	1.502	1.541	1.562	1.565
			(0.011)	(0.010)	(0.011)	(0.009)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Share receiving 1099R	0.050	0.049	0.047	0.053	0.063	0.067	0.073	0.064	0.058	0.059	0.061	0.068	0.070	0.074
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Sample Size	55,000	55,000	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population (100,000s)	48.46	48.46	48.46	48.46	48.46	48.46	48.46	48.46	48.14	47.70	47.18	46.72	46.16	45.60

Note: *Sources and notes in table A.23.

Table A.19: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

C: Safety Net Program Receipt														
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Housing Benefits (HUD)														
Share with housing benefits	0.113	0.117	0.120	0.123	0.131	0.140	0.152	0.160	0.158	0.155	0.149	0.148	0.144	0.141
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Mean housing benefit amount (equivalized) (cond. on +)[4]	$5,045	$5,211	$5,237	$5,228	$5,186	$5,281	$5,680	$5,833	$5,719	$5,672	$5,773	$5,704	$5,867	$5,975
	($73)	($79)	($73)	($72)	($67)	($73)	($69)	($66)	($65)	($68)	($74)	($76)	($81)	($85)
Mean assistance unit size (cond. on +)	2.736	2.707	2.672	2.589	2.553	2.445	2.359	2.346	2.355	2.298	2.236	2.193	2.155	2.109
	(0.033)	(0.035)	(0.035)	(0.036)	(0.034)	(0.030)	(0.027)	(0.029)	(0.029)	(0.030)	(0.030)	(0.029)	(0.028)	(0.030)
Share with child in assistance unit (cond. on +)	0.570	0.545	0.535	0.514	0.498	0.469	0.438	0.421	0.413	0.397	0.381	0.359	0.339	0.320
	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Mean months of housing benefit receipt (cond. on +)	11.140	11.190	11.210	11.170	11.100	11.070	11.240	11.390	11.320	11.240	11.340	11.230	11.280	11.250
	(0.071)	(0.066)	(0.063)	(0.066)	(0.061)	(0.056)	(0.051)	(0.053)	(0.040)	(0.048)	(0.048)	(0.063)	(0.060)	(0.043)
Veterans' Benefits (VA)														
Share with VA service-connected disability					0.011	0.013	0.014	0.015	0.016	0.017	0.018	0.019	0.020	0.021
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Supplemental Nutrition Assistance Program (SNAP)[5]														
Share with SNAP receipt			0.374	0.408	0.437	0.473	0.548	0.595	0.594	0.575	0.558	0.549	0.528	0.507
			(0.016)	(0.018)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
Mean SNAP benefit amount (equivalized) (cond. on +)			$1,377	$1,403	$1,385	$1,479	$1,911	$1,992	$1,890	$1,810	$1,759	$1,582	$1,570	$1,505
			($43)	($46)	($25)	($25)	($29)	($26)	($23)	($23)	($24)	($21)	($23)	($22)
Mean months of SNAP receipt (cond. on +)			8.604	8.884	9.611	9.938	9.999	10.380	10.360	10.450	10.700	10.510	10.550	10.450
			(0.175)	(0.196)	(0.103)	(0.089)	(0.093)	(0.085)	(0.069)	(0.074)	(0.065)	(0.070)	(0.073)	(0.074)
Mean assistance unit size (cond. on +)			2.516	2.396	2.333	2.302	2.192	2.194	2.166	2.145	2.091	2.039	2.029	2.003
			(0.075)	(0.078)	(0.053)	(0.049)	(0.039)	(0.035)	(0.035)	(0.035)	(0.037)	(0.035)	(0.037)	(0.031)
Share with child in assistance unit (cond. on +)			0.510	0.484	0.426	0.408	0.373	0.367	0.346	0.331	0.308	0.289	0.279	0.269
			(0.023)	(0.026)	(0.016)	(0.014)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)	(0.000)
Medicaid and Medicare														
Share enrolled in Medicaid					0.322	0.338	0.371	0.398	0.414	0.420	0.421	0.503	0.540	
					(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	
Share enrolled in Medicare Part A or B				0.097	0.105	0.115	0.123	0.143	0.158	0.170	0.179	0.185	0.197	0.216
				(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Disability programs (DI and SSI)														
Share receiving DI as indicated by Medicare records				0.095	0.104	0.114	0.122	0.142	0.157	0.169	0.178	0.183	0.179	0.177
				(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Share receiving SSI								0.157	0.166	0.174	0.177	0.173		0.174
								(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)
Mean SSI amount (cond. on +)								$7,540	$8,050	$7,785	$7,800	$7,608		$7,410
								($101)	($171)	($155)	($95)	($94)		($147)
Share receiving SSI or DI according to Medicare								0.251	0.274	0.292	0.305	0.308		0.307
								(0.005)	(0.004)	(0.005)	(0.004)	(0.005)		(0.005)
Share living in SNAP state in 2010			0.048	0.048	0.131	0.131	0.174	0.174	0.174	0.174	0.174	0.173	0.174	0.173
Share living in Medicaid state in 2010					0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.786	0.391	
Sample Size	55,000	55,000	55,000	55,000	55,000	55,000	55,000	55,000	54,500	54,000	54,000	53,500	53,000	52,500
Population (100,000s)	48.46	48.46	48.46	48.46	48.46	48.46	48.46	48.46	48.14	47.70	47.18	46.72	46.16	45.60

Note: *Sources and notes in table A.23.

Table A.20: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

	Employment and Income											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Earnings												
Share with earnings	0.857	0.860	0.864	0.861	0.848	0.843	0.837	0.831	0.825	0.815	0.809	0.801
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
50th percentile (cond. on +)	$34,400	$35,750	$36,930	$37,090	$36,930	$37,730	$37,950	$38,790	$39,540	$39,930	$41,550	$42,130
	($53)	($53)	($53)	($54)	($56)	($58)	($58)	($59)	($61)	($61)	($64)	($64)
75th percentile (cond. on +)	$60,360	$62,080	$63,830	$64,140	$64,610	$66,480	$67,160	$68,560	$70,080	$70,390	$73,510	$74,490
	($84)	($87)	($90)	($89)	($91)	($96)	($99)	($103)	($109)	($109)	($114)	($117)
Pretax Cash Income, Plus In-Kind Transfers (no SSI)												
50th percentile	$28,490	$29,510	$34,650	$34,920	$35,280	$36,210	$35,960	$36,560	$37,200	$37,510	$39,000	$39,740
	($217)	($228)	($162)	($159)	($140)	($143)	($149)	($152)	($153)	($153)	($159)	($160)
75th percentile	$52,370	$53,680	$66,390	$66,660	$67,240	$69,620	$70,290	$71,760	$73,320	$74,080	$77,380	$78,790
	($346)	($350)	($274)	($275)	($235)	($248)	($254)	($263)	($275)	($272)	($287)	($299)
Pretax Cash Income, Plus In-Kind Transfers (with SSI)												
50th percentile						$36,230	$36,000	$36,590	$37,220	$37,550		$39,770
						($142)	($149)	($151)	($152)	($152)		($161)
75th percentile						$69,650	$70,320	$71,800	$73,350	$74,100		$78,840
						($249)	($254)	($264)	($274)	($271)		($300)
Sample Size	994,000	994,000	994,000	994,000	994,000	994,000	992,000	989,000	986,000	983,000	979,000	975,000
Population (100,000s)	722.70	722.70	722.70	722.70	722.70	722.70	722.70	722.70	721.30	719.10	716.80	714.40

Note: *Sources and notes in table A.23.

Table A.21: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

Connections to Employment and Formal Income														
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share filing 1040	0.827	0.835	0.840	0.848	0.886	0.866	0.863	0.860	0.857	0.847	0.841	0.835	0.831	0.821
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1040 cofiling rate (cond. on filing)	0.545	0.554	0.565	0.572	0.569	0.588	0.598	0.603	0.606	0.616	0.622	0.626	0.632	0.637
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share filing 1040 with dependents (cond. on +)	0.538	0.542	0.545	0.545	0.531	0.543	0.546	0.533	0.525	0.521	0.513	0.524	0.513	0.501
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean number of dependents (cond. on +)	1.876	1.869	1.864	1.859	1.855	1.868	1.882	1.875	1.876	1.876	1.873	1.871	1.868	1.864
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share receiving W2			0.781	0.783	0.783	0.778	0.758	0.747	0.741	0.736	0.729	0.723	0.717	0.709
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean number of W2s received (cond. on +)			1.478	1.469	1.445	1.397	1.322	1.322	1.322	1.325	1.327	1.339	1.346	1.339
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sample Size	994,000	994,000	994,000	994,000	994,000	994,000	994,000	994,000	992,000	989,000	986,000	983,000	979,000	975,000
Population (100,000s)	722.70	722.70	722.70	722.70	722.70	722.70	722.70	722.70	721.30	719.10	716.80	714.40	711.70	708.80

Note: *Sources and notes in table A.23.

Table A.22: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

	Safety Net Program Receipt													
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Housing Benefits (HUD)														
Share with housing benefits	0.027	0.027	0.026	0.025	0.025	0.025	0.026	0.026	0.026	0.026	0.025	0.025	0.024	0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean housing benefit amount (equiv'd) (cond. on +)	10.890	10.940	10.900	10.910	10.920	11.020	11.150	11.220	11.230	11.190	11.190	11.130	11.110	11.120
	(0.029)	(0.030)	(0.030)	(0.030)	(0.026)	(0.028)	(0.027)	(0.026)	(0.024)	(0.024)	(0.025)	(0.024)	(0.025)	(0.023)
Veterans' Benefits (VA)														
Share with VA service-connected disability					0.009	0.010	0.011	0.012	0.012	0.013	0.014	0.015	0.016	0.017
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food Assistance (SNAP)														
Share with SNAP receipt			0.124	0.122	0.098	0.108	0.123	0.137	0.144	0.144	0.144	0.142	0.138	0.132
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean SNAP benefit amount (equiv'd) (cond. on +)			8.017	8.280	9.176	9.175	9.220	9.467	9.468	9.810	10.090	10.030	10.130	10.060
			(0.085)	(0.074)	(0.051)	(0.047)	(0.035)	(0.035)	(0.030)	(0.035)	(0.030)	(0.028)	(0.031)	(0.032)
Medicaid and Medicare														
Share enrolled in Medicaid					0.095	0.095	0.103	0.109	0.114	0.115	0.116	0.153	0.174	
					(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	
Share enrolled in Medicare Part A or B				0.027	0.030	0.033	0.036	0.042	0.046	0.050	0.055	0.060	0.076	0.100
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disability programs (DI and SSI)														
Share receiving DI as indicated by Medicare records				0.027	0.030	0.033	0.036	0.042	0.046	0.050	0.055	0.059	0.059	0.060
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share receiving SSI								0.026	0.027	0.028	0.028	0.027		0.027
								(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
Share receiving SSI or DI according to Medicare								0.059	0.064	0.068	0.073	0.077		0.078
								(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
Share living in SNAP state in 2010			0.042	0.042	0.134	0.134	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177
Share living in Medicaid state in 2010					0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.786	0.402	
Sample Size	994,000	994,000	994,000	994,000	994,000	994,000	994,000	994,000	992,000	989,000	986,000	983,000	979,000	975,000
Population (100,000s)	722.70	722.70	722.70	722.70	722.70	722.70	722.70	722.70	721.30	719.10	716.80	714.40	711.70	708.80

Note: *Sources and notes in table A.23.

Table A.23: Sources and Notes for Income and Benefit Tables

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC & TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Notes: Samples include PIKed adults with a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Homeless and housed samples as defined in text. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

[1] Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets. Earnings is the sum of 1040 wage and salary income, estimated non-negative 1040 self-employment income (when a self employment schedule was filed), and W2 deferred compensation less any W2 wages and tips associated with a cofiler for individuals filing a 1040. Self-employment income is equal to total money income less wage and salary income, dividend income, rental income, social security, and interest income. For individuals without a 1040, earnings is equal to wages and tips across W2s.

[2] For individuals with a 1040, pre-tax cash income is equal to the sum of total money income and VA SCD compensation, measured as ¾ of the annual SCD amount for the fiscal year corresponding to the calendar year and ¼ of the annual SCD amount of the fiscal year corresponding to the year after the calendar year specified. Total money income income includes wage and salary, total interest (taxable and tax-exempt), taxable dividends, alimony received, business income (+/-), total pensions and annuities, net rents royalties, estates and trusts (+/-), farm income (+/-), unemployment compensation, and total social security benefits. For individuals without a 1040, pre-tax income is equal to the sum of wages and tips and deferred compensation in W2s, VA SCD compensation, and IRA and employer sponsored retirement distributions across 1099-Rs. We drop a few observations with implausibly high pre-tax income.

[3] Pre-tax cash income is measured as above. In-kind transfers include benefits from HUD and SNAP benefits, as well as SSI when indicated. SNAP benefit amounts are estimated by multiplying the months of SNAP receipt in a year by the average monthly SNAP benefit received in that year.

[4] Benefits are equivalized using the two-factor NAS (Ctiro and Michael 1995) equivalence scale of the form $(A+PK)^F$, where A and K are the number of adults and children in the assistance unit, respectively. Following Meyer and Sullivan (2012), we set P=F=0.7 to allow for diminishing marginal costs with each additional individual and a large cost of adults relative to children.

[5] Because our SNAP data cover only certain states and years, the sample underlying year Y of SNAP receipt (or the two outcomes that use SNAP receipt as an input, namely "share receiving any benefits" and "share receiving any earnings") is composed only of individuals who in 2010 resided in a state for which we have SNAP data in year Y. For example, because we lack 2007 SNAP data from Illinois, 2007 SNAP receipt is calculated as a share of individuals who lived in Indiana, New York, New Jersey, or Tennessee - but not Illinois - at the time of the 2010 Census.

Table A.24: TANF and General Assistance Receipt among Homeless and Comparison Groups, Ages 25-59 in 2010 Decennial Census, New York, 2003-2016

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share receiving TANF - Sheltered	0.333	0.361	0.469	0.584	0.486	0.396	0.343	0.303	0.290	0.275
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mean TANF amount (cond on +)	$4,330	$4,602	$3,725	$4,047	$5,411	$4,871	$5,382	$5,476	$5,625	$5,771
	($92)	($98)	($77)	($71)	($87)	($82)	($98)	($103)	($102)	($104)
Share receiving TANF - Unsheltered	0.219	0.264	0.286	0.302	0.267	0.251	0.239	0.228	0.214	0.199
	(0.010)	(0.023)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)	(0.025)	(0.025)	(0.026)
Mean TANF amount (cond on +)	$3,550	$3,582	$3,696	$3,912	$4,077	$4,022	$4,601	$4,278	$4,504	$4,540
	($188)	($387)	($284)	($215)	($436)	($376)	($226)	($416)	($401)	($403)
Share receiving TANF - Single Housed Poor	0.183	0.182	0.186	0.191	0.162	0.145	0.122	0.113	0.109	0.103
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
Mean TANF amount (cond on +)	$4,226	$4,569	$4,872	$4,742	$5,162	$5,014	$5,605	$5,471	$5,311	$5,287
	($497)	($447)	($488)	($506)	($491)	($510)	($575)	($477)	($481)	($532)
Share receiving TANF - Overall Housed	0.028	0.027	0.028	0.028	0.027	0.025	0.023	0.022	0.020	0.019
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean TANF amount (cond on +)	$3,913	$4,140	$4,397	$4,453	$4,646	$4,531	$4,809	$4,623	$4,906	$4,883
	($235)	($212)	($225)	($222)	($210)	($185)	($192)	($176)	($191)	($196)
Sample Size - Sheltered	13,000	13,000	13,000	13,000	13,000	12,500	12,500	12,500	12,500	12,000
Population - Sheltered	17,820	17,820	17,820	17,820	17,690	17,550	17,370	17,200	17,030	16,810
Sample Size - Unsheltered	3,500	3,500	3,500	3,500	3,400	3,400	3,400	3,300	3,300	3,200
Population - Unsheltered	9,694	9,694	9,694	9,694	9,635	9,544	9,437	9,341	9,195	9,037
Sample - Single Housed Poor	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,100	3,100
Population - Single Housed Poor	304,600	304,600	304,600	304,600	303,300	299,100	295,300	291,000	288,800	285,200
Sample Size - Overall Housed	60,500	60,500	60,500	60,500	60,500	60,500	60,000	60,000	60,000	59,500
Population - Overall Housed	4,563,000	4,563,000	4,563,000	4,563,000	4,556,000	4,545,000	4,533,000	4,519,000	4,507,000	4,494,000

Sources: 2010 Decennial Census, 2019 Numident, 2007-2016 New York TANF dataset
Note: Sample includes PIKed homeless adults from the 2010 Decennial Census, PIKed single adults in poverty, and PIKed housed adults who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010 and lived in New York stat in that year. Table displays the weighted means and shares. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.25: Monthly SNAP receipt among Chicago HMIS Shelter Users Ages 25-59

Month relative to shelter enrollment:	1	2	3	4	5	6	7	8	9	10	11	12
24-13 months prior	0.459	0.462	0.460	0.460	0.463	0.463	0.460	0.463	0.465	0.463	0.466	0.464
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Sample Size	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737
12-0 months prior	0.465	0.460	0.456	0.455	0.453	0.454	0.458	0.459	0.458	0.464	0.469	0.489
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Sample Size	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737	5737
1-12 months after	0.580	0.613	0.627	0.618	0.606	0.577	0.567	0.569	0.561	0.526	0.512	
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)	(0.013)	(0.016)	(0.022)	
Sample Size	5300	4900	4400	3900	3400	3000	2500	2100	1500	1000	550	

Sources: Chicago (2014-2019) HMIS dataset, various states' SNAP datasets
Note: Sample consists of people with first observed homeless spell in 2016.

Table A.26: Share of Sheltered Homeless with Income and Benefit Receipt by Gender, Ages 25-59 in 2010 Census

Panel A: Income and Benefit Receipt among Sheltered Homeless Women Ages 25-59 in 2010 Decennial Census, 2003-2016	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.613	0.618	0.612	0.593	0.523	0.552	0.532	0.503	0.497	0.483	0.487	0.490
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
50th percentile earnings (cond. on +)	$8,975	$9,262	$9,388	$8,536	$7,777	$9,715	$11,450	$11,680	$11,970	$12,250	$13,100	$13,620
	($108)	($115)	($108)	($110)	($119)	($106)	($92)	($103)	($117)	($130)	($135)	($135)
75th percentile earnings (cond. on +)	$18,140	$18,280	$17,620	$16,160	$15,380	$16,390	$18,770	$18,970	$19,450	$19,840	$21,650	$22,910
	($172)	($149)	($159)	($131)	($129)	($119)	($138)	($147)	($163)	($186)	($215)	($214)
50th percentile pre-tax income + in-kind transfers	$5,983	$5,454	$6,666	$5,376	$4,252	$6,906	$8,072	$7,569	$7,769	$7,250	$8,012	$8,284
	($366)	($360)	($209)	($196)	($152)	($237)	($271)	($275)	($267)	($273)	($271)	($260)
75th percentile pre-tax income + in-kind transfers	$13,680	$13,760	$15,360	$14,700	$13,900	$15,920	$17,170	$17,040	$17,250	$16,910	$18,070	$18,420
	($652)	($587)	($224)	($212)	($173)	($175)	($177)	($192)	($192)	($202)	($194)	($216)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.791	0.821	0.890	0.930	0.919	0.903	0.891	0.893	0.874	
			(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	
Share receiving SNAP	0.491	0.506	0.628	0.683	0.806	0.869	0.840	0.797	0.767	0.741	0.709	0.681
	(0.015)	(0.015)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Share with child in assistance unit (cond on +)	0.584	0.559	0.562	0.545	0.538	0.532	0.521	0.504	0.492	0.473	0.457	0.445
	(0.019)	(0.018)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Share enrolled in Medicaid			0.502	0.514	0.561	0.619	0.636	0.640	0.637	0.732	0.757	
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	
Share receiving SSI or DI (according to Medicare records)						0.200	0.253	0.293	0.315	0.331		0.344
						(0.003)	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)
Panel B: Income and Benefit Receipt among Sheltered Homeless Men Ages 25-59 in 2010 Decennial Census, 2003-2016												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.627	0.621	0.602	0.572	0.490	0.502	0.479	0.441	0.432	0.415	0.410	0.410
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50th percentile earnings (cond. on +)	$9,741	$9,672	$9,300	$7,786	$5,977	$7,674	$10,370	$10,820	$11,000	$11,470	$12,640	$13,340
	($90)	($92)	($86)	($84)	($77)	($70)	($99)	($106)	($111)	($130)	($150)	($148)
75th percentile earnings (cond. on +)	$21,260	$20,610	$19,280	$17,110	$14,660	$16,720	$20,900	$21,450	$22,040	$22,990	$25,180	$26,120
	($148)	($145)	($135)	($128)	($139)	($150)	($161)	($163)	($173)	($188)	($211)	($205)
50th percentile pre-tax income + in-kind transfers	$5,446	$4,816	$3,268	$2,264	$2,666	$2,896	$3,103	$2,794	$2,618	$2,389	$2,452	$2,635
	($318)	($264)	($139)	($46)	($11)	($56)	($89)	($65)	($63)	($53)	($72)	($89)
75th percentile pre-tax income + in-kind transfers	$15,700	$14,700	$13,530	$11,400	$10,140	$12,370	$14,220	$14,070	$14,150	$13,770	$14,460	$14,990
	($555)	($537)	($211)	($193)	($191)	($153)	($189)	($190)	($199)	($201)	($222)	($229)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.611	0.667	0.780	0.869	0.848	0.817	0.803	0.802	0.821	
			(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	
Share receiving SNAP	0.300	0.329	0.478	0.545	0.695	0.799	0.751	0.698	0.668	0.642	0.615	0.594
	(0.010)	(0.010)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share with child in assistance unit (cond on +)	0.158	0.140	0.141	0.125	0.120	0.119	0.117	0.109	0.106	0.099	0.095	0.091
	(0.014)	(0.010)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Share enrolled in Medicaid			0.223	0.242	0.284	0.359	0.392	0.411	0.419	0.551	0.616	
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	
Share receiving SSI or DI (according to Medicare records)						0.186	0.241	0.286	0.310	0.325		0.342
						(0.002)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Note: Sample includes PIKed adults enumerated in emergency and transitional shelters in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.27: Share of Unsheltered Homeless with Income and Benefit Receipt by Gender, Ages 25-59 in 2010 Census

Panel A: Income and Benefit Receipt among Sheltered Homeless Women Ages 25-59 in 2010 Decennial Census, 2003-2016												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.613	0.618	0.612	0.593	0.523	0.552	0.532	0.503	0.497	0.483	0.487	0.490
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
50th percentile earnings (cond. on +)	$8,975	$9,262	$9,388	$8,536	$7,777	$9,715	$11,450	$11,680	$11,970	$12,250	$13,100	$13,620
	($108)	($115)	($108)	($110)	($119)	($106)	($92)	($103)	($117)	($130)	($135)	($135)
75th percentile earnings (cond. on +)	$18,140	$18,280	$17,620	$16,160	$15,380	$16,390	$18,770	$18,970	$19,450	$19,840	$21,650	$22,910
	($172)	($149)	($159)	($131)	($129)	($119)	($138)	($147)	($163)	($186)	($215)	($214)
50th percentile pre-tax income + in-kind transfers	$5,983	$5,454	$6,666	$5,376	$4,252	$6,906	$8,072	$7,569	$7,769	$7,250	$8,012	$8,284
	($366)	($360)	($209)	($196)	($152)	($237)	($271)	($275)	($267)	($273)	($271)	($260)
75th percentile pre-tax income + in-kind transfers	$13,680	$13,760	$15,360	$14,700	$13,900	$15,920	$17,170	$17,040	$17,250	$16,910	$18,070	$18,420
	($652)	($587)	($224)	($212)	($173)	($175)	($177)	($192)	($192)	($202)	($194)	($216)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.791	0.821	0.890	0.930	0.919	0.903	0.891	0.893	0.874	
			(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	
Share receiving SNAP	0.491	0.506	0.628	0.683	0.806	0.869	0.840	0.797	0.767	0.741	0.709	0.681
	(0.015)	(0.015)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Share with child in assistance unit (cond on +)	0.584	0.559	0.562	0.545	0.538	0.532	0.521	0.504	0.492	0.473	0.457	0.445
	(0.019)	(0.018)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Share enrolled in Medicaid			0.502	0.514	0.561	0.619	0.636	0.640	0.637	0.732	0.757	
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	
Share receiving SSI or DI (according to Medicare records)						0.200	0.253	0.293	0.315	0.331		0.344
						(0.003)	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)
Panel B: Income and Benefit Receipt among Sheltered Homeless Men Ages 25-59 in 2010 Decennial Census, 2003-2016												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.627	0.621	0.602	0.572	0.490	0.502	0.479	0.441	0.432	0.415	0.410	0.410
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50th percentile earnings (cond. on +)	$9,741	$9,672	$9,300	$7,786	$5,977	$7,674	$10,370	$10,820	$11,000	$11,470	$12,640	$13,340
	($90)	($92)	($86)	($84)	($77)	($70)	($99)	($106)	($111)	($130)	($150)	($148)
75th percentile earnings (cond. on +)	$21,260	$20,610	$19,280	$17,110	$14,660	$16,720	$20,900	$21,450	$22,040	$22,990	$25,180	$26,120
	($148)	($145)	($135)	($128)	($139)	($150)	($161)	($163)	($173)	($188)	($211)	($205)
50th percentile pre-tax income + in-kind transfers	$5,446	$4,816	$3,268	$2,264	$2,666	$2,896	$3,103	$2,794	$2,618	$2,389	$2,452	$2,635
	($318)	($264)	($139)	($46)	($11)	($56)	($89)	($65)	($63)	($53)	($72)	($89)
75th percentile pre-tax income + in-kind transfers	$15,700	$14,700	$13,530	$11,400	$10,140	$12,370	$14,220	$14,070	$14,150	$13,770	$14,460	$14,990
	($555)	($537)	($211)	($193)	($191)	($153)	($189)	($190)	($199)	($201)	($222)	($229)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.611	0.667	0.780	0.869	0.848	0.817	0.803	0.802	0.821	
			(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	
Share receiving SNAP	0.300	0.329	0.478	0.545	0.695	0.799	0.751	0.698	0.668	0.642	0.615	0.594
	(0.010)	(0.010)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share with child in assistance unit (cond on +)	0.158	0.140	0.141	0.125	0.120	0.119	0.117	0.109	0.106	0.099	0.095	0.091
	(0.014)	(0.010)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Share enrolled in Medicaid			0.223	0.242	0.284	0.359	0.392	0.411	0.419	0.551	0.616	
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	
Share receiving SSI or DI (according to Medicare records)						0.186	0.241	0.286	0.310	0.325		0.342
						(0.002)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)
Note: Sample includes PIKed adults enumerated in unsheltered locations in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.28: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 by Family Status (Point-in-Time Samples, 2012-2013)

Panel A1: Los Angeles - Adults in Families												
	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Share with earnings	0.695	0.718	0.704	0.649	0.612	0.656	0.650	0.657	0.649	0.655	0.660	0.636
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.022)
50th percentile earnings (cond. on +)	$10,490	$11,230	$11,700	$11,790	$12,290	$12,270	$11,270	$11,760	$14,290	$15,150	$15,630	$15,560
	($651)	($650)	($592)	($595)	($588)	($482)	($482)	($456)	($436)	($408)	($491)	($779)
Share enrolled in Medicaid			0.560	0.587	0.639	0.698	0.779	0.853	0.853	0.838		
			(0.016)	(0.016)	(0.016)	(0.015)	(0.014)	(0.012)	(0.012)	(0.012)		
Share receiving SSI or DI (according to Medicare records)						0.051	0.056	0.069	0.081	0.098	0.083	0.103
						(0.006)	(0.006)	(0.006)	(0.008)	(0.012)	(0.008)	(0.008)
Sample Size	950	950	950	950	950	950	950	950	950	950	900	500
Panel A2: Los Angeles - Adults Not in Families												
	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Share with earnings	0.555	0.559	0.530	0.473	0.438	0.463	0.410	0.355	0.328	0.296	0.302	0.301
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
50th percentile earnings (cond. on +)	$10,120	$10,170	$9,461	$9,309	$9,280	$10,740	$8,242	$6,737	$7,590	$8,921	$10,180	$10,740
	($303)	($306)	($320)	($315)	($293)	($370)	($298)	($247)	($286)	($394)	($406)	($654)
Share enrolled in Medicaid			0.223	0.228	0.239	0.250	0.268	0.309	0.580	0.821		
			(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)		
Share receiving SSI or DI (according to Medicare records)					0.147	0.167	0.189	0.228	0.279	0.325	0.324	0.356
					(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)	(0.005)	(0.006)
Sample Size	6,200	6,200	6,200	6,200	6,200	6,200	6,200	6,200	6,200	6,100	6,100	3,100
Panel B1: Houston - Adults in Families												
	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Share with earnings	0.717	0.737	0.749	0.731	0.756	0.744	0.744	0.794	0.806	0.791	0.761	0.732
	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.020)	(0.020)	(0.020)	(0.021)	(0.033)
50th percentile earnings (cond. on +)	$8,611	$10,250	$10,690	$11,130	$10,760	$11,320	$10,410	$10,550	$14,120	$15,040	$15,560	$14,270
	($658)	($810)	($816)	($872)	($711)	($523)	($546)	($767)	($601)	($590)	($685)	($1196)
Share enrolled in Medicaid			0.450	0.428	0.477	0.512	0.561	0.638	0.529	0.434		
			(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)	(0.036)		
Share receiving SSI or DI (according to Medicare records)												
Sample Size	400	400	400	400	400	400	400	400	400	400	400	200
Panel B2: Houston - Adults Not in Families												
	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Share with earnings	0.692	0.704	0.690	0.657	0.628	0.593	0.594	0.651	0.629	0.590	0.561	0.532
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.017)
50th percentile earnings (cond. on +)	$10,350	$11,180	$10,520	$9,421	$9,107	$8,401	$5,826	$7,186	$10,040	$11,370	$11,450	$11,990
	($520)	($453)	($419)	($432)	($320)	($395)	($285)	($334)	($431)	($582)	($582)	($1024)
Share enrolled in Medicaid			0.114	0.116	0.109	0.126	0.141	0.179	0.185	0.202		
			(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.014)		
Share receiving SSI or DI (according to Medicare records)					0.049	0.060	0.075	0.110	0.145	0.175	0.190	0.201
					(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)
Sample Size	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,700	1,700	850

Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, various administrative datasets
Note: Point-in-time samples consists of those who were in an HMIS shelter on March 30 of 2012 and 2013.

Table A.29: 2010 Income and Benefit Receipt among Sheltered and Unsheltered Homeless Individuals Ages 25-59 in the 2010 Census, by Race and Ethnicity

	Sheltered				
	White	Black	Other Race	Hispanic	Non-Hispanic
Share with earnings	0.496	0.547	0.514	0.535	0.516
	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)
50th percentile earnings (cond. on +)	$7,126	$9,567	$9,961	$10,510	$7,965
	($82)	($103)	($228)	($183)	($62)
75th percentile earnings (cond. on +)	$15,210	$17,100	$19,580	$19,190	$16,080
	($138)	($155)	($378)	($321)	($99)
50th percentile pre-tax income + in-kind transfers	$2,982	$4,996	$4,634	$4,617	$3,795
	($74)	($178)	($353)	($310)	($102)
75th percentile pre-tax income + in-kind transfers	$11,910	$14,710	$15,920	$15,420	$13,520
	($208)	($168)	($380)	($289)	($134)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)	0.852	0.923	0.883	0.910	0.888
	(0.004)	(0.003)	(0.006)	(0.004)	(0.002)
Share receiving SNAP	0.776	0.867	0.802	0.850	0.820
	(0.005)	(0.003)	(0.007)	(0.005)	(0.003)
Share enrolled in Medicaid	0.395	0.486	0.506	0.541	0.429
	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)
Share receiving SSI or DI (according to Medicare records)	0.180	0.207	0.181	0.172	0.194
	(0.003)	(0.003)	(0.006)	(0.005)	(0.002)
Share living in SNAP state in 2010	0.178	0.315	0.260	0.365	0.222
	Unsheltered				
	White	Black	Other Race	Hispanic	Non-Hispanic
Share with earnings	0.383	0.427	0.368	0.465	0.326
	(0.004)	(0.006)	(0.011)	(0.013)	(0.003)
50th percentile earnings (cond. on +)	$7,474	$8,946	$10,030	$12,300	$7,744
	($143)	($270)	($514)	($364)	($131)
75th percentile earnings (cond. on +)	$19,000	$19,160	$25,150	$27,630	$18,050
	($337)	($525)	($1261)	($717)	($328)
50th percentile pre-tax income + in-kind transfers	$2,694	$2,710	$3,495	$3,017	$2,710
	($70)	($58)	($520)	($980)	($17)
75th percentile pre-tax income + in-kind transfers	$10,690	$12,520	$17,520	$17,410	$11,310
	($1228)	($375)	($1262)	($2129)	($331)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)	0.777	0.832	0.736	0.739	0.816
	(0.011)	(0.006)	(0.016)	(0.021)	(0.005)
Share receiving SNAP	0.671	0.733	0.608	0.661	0.704
	(0.015)	(0.007)	(0.019)	(0.026)	(0.006)
Share enrolled in Medicaid	0.404	0.428	0.416	0.397	0.417
	(0.006)	(0.006)	(0.015)	(0.017)	(0.004)
Share receiving SSI or DI (according to Medicare records)	0.284	0.306	0.277	0.209	0.306
	(0.006)	(0.008)	(0.025)	(0.010)	(0.006)
Share living in SNAP state in 2010	0.130	0.240	0.162	0.231	0.165

Sources: Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)
Note: Sample includes PIKed adults in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.30: 2010 Income and Benefit Receipt among Sheltered and Unsheltered Homeless Individuals Ages 25-59 in the 2010 Census, by State

	Sheltered			Unsheltered		
	Californi a	New York	Other States	Californi a	New York	Other States
Share with earnings	0.471	0.497	0.531	0.347	0.368	0.422
	(0.005)	(0.004)	(0.002)	(0.008)	(0.014)	(0.004)
50th percentile earnings (cond. on +)	$10,330	$9,989	$7,534	$9,957	$11,310	$7,770
	($260)	($116)	($64)	($338)	($637)	($148)
75th percentile earnings (cond. on +)	$22,280	$16,000	$15,540	$24,840	$24,830	$18,030
	($485)	($248)	($106)	($825)	($1008)	($325)
50th percentile pre-tax income + in-kind transfers		$4,049	$3,426		$2,400	$2,699
		($180)	($103)		($103)	($54)
75th percentile pre-tax income + in-kind transfers		$40,000	$12,400		$36,780	$11,470
		($171)	($169)		($955)	($376)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)		0.932	0.839		0.814	0.788
		(0.002)	(0.004)		(0.009)	(0.006)
Share receiving SNAP		0.862	0.779		0.694	0.697
		(0.003)	(0.004)		(0.012)	(0.007)
Share enrolled in Medicaid	0.375	0.896	0.367	0.379	0.722	0.387
	(0.005)	(0.003)	(0.002)	(0.013)	(0.011)	(0.004)
Share receiving SSI or DI (according to Medicare records)	0.218	0.230	0.178	0.290	0.310	0.289
	(0.006)	(0.006)	(0.002)	(0.016)	(0.018)	(0.005)
Share living in SNAP state in 2010			0.143			0.128

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)

Note: Sample includes PIKed adults in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.31: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 - Point-in-Time and Interval-Based Results

	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t-0	t+1	t+2	t+3	t+4
Panel A1: Los Angeles Sample of First Spells in Year (2012-2013)												
Share with earnings	0.589	0.591	0.573	0.525	0.483	0.486	0.455	0.421	0.395	0.380	0.381	0.375
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
50th percentile earnings (cond. on +)	$9,975	$10,590	$10,750	$10,870	$10,780	$10,720	$9,704	$6,831	$9,013	$10,380	$11,350	$11,760
	($190)	($190)	($192)	($201)	($185)	($170)	($194)	($162)	($205)	($187)	($223)	($331)
Share enrolled in Medicaid		0.139	0.301	0.310	0.325	0.338	0.357	0.393	0.599	0.798	0.781	
		(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	
Share receiving SSI or DI (according to Medicare records)					0.151	0.163	0.179	0.198	0.227	0.255	0.277	0.293
					(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Sample Size	14,500	14,500	14,500	14,500	14,500	14,500	14,500	14,500	14,500	14,500	14,000	7,600
Panel A2: Los Angeles Point-in-Time Sample (2012-2013)	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t-0	t+1	t+2	t+3	t+4
Share with earnings	0.574	0.580	0.553	0.496	0.461	0.489	0.441	0.395	0.370	0.344	0.350	0.346
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
50th percentile earnings (cond. on +)	$10,170	$10,360	$10,010	$9,948	$10,140	$11,110	$9,124	$7,865	$9,726	$10,940	$11,780	$12,080
	($274)	($278)	($286)	($280)	($285)	($314)	($255)	($263)	($288)	($356)	($353)	($502)
Share enrolled in Medicaid		0.124	0.267	0.275	0.291	0.309	0.335	0.380	0.616	0.823	0.821	
		(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)		
Share receiving SSI or DI (according to Medicare records)					0.134	0.152	0.172	0.207	0.253	0.295	0.292	0.322
					(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.007)	(0.005)	(0.005)
Sample Size	7,200	7,200	7,200	7,200	7,200	7,200	7,200	7,200	7,100	7,100	7,000	3,600
Panel B1: Houston Sample of First Spells in Year (2012-2013)	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t-0	t+1	t+2	t+3	t+4
Share with earnings	0.659	0.663	0.666	0.632	0.587	0.588	0.578	0.598	0.572	0.545	0.519	0.507
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)
50th percentile earnings (cond. on +)	$8,610	$9,330	$10,020	$10,020	$10,660	$10,300	$8,911	$6,023	$8,436	$9,945	$10,330	$10,630
	($197)	($182)	($209)	($202)	($189)	($188)	($187)	($157)	($211)	($220)	($242)	($346)
Share enrolled in Medicaid		0.110	0.221	0.226	0.234	0.255	0.278	0.301	0.311	0.310		
		(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)		
Share receiving SSI or DI (according to Medicare records)					0.126	0.137	0.151	0.169	0.193	0.216	0.218	0.236
					(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Sample Size	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000	9,000	8,900	8,800	4,500
Panel B2: Houston Point-in-Time Sample (2012-2013)	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t-0	t+1	t+2	t+3	t+4
Share with earnings	0.697	0.710	0.701	0.671	0.652	0.621	0.622	0.678	0.662	0.628	0.599	0.567
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.015)
50th percentile earnings (cond. on +)	$9,891	$10,890	$10,600	$9,783	$9,495	$9,234	$6,796	$7,970	$10,790	$12,300	$12,470	$12,670
	($421)	($399)	($367)	($395)	($297)	($327)	($291)	($320)	($403)	($426)	($466)	($754)
Share enrolled in Medicaid		0.089	0.177	0.174	0.178	0.198	0.219	0.265	0.249	0.243		
		(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)		
Share receiving SSI or DI (according to Medicare records)					0.045	0.056	0.068	0.096	0.129	0.159	0.167	0.183
					(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
Sample Size	2,200	2,200	2,200	2,200	2,200	2,200	2,200	2,200	2,200	2,100	2,100	1,000

Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, various administrative datasets
Note: Interval-based sample consists of people who had a first homeless spell in 2012 or 2013. Point-in-time sample consists of those who were in an HMIS shelter on March 30 of 2012 and 2013.

Table A.32: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 and Census Homeless in Los Angeles and Houston

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Panel A1: Los Angeles HMIS Sample												
Share with earnings	0.515	0.514	0.491	0.462	0.401	0.499	0.484	0.341	0.355	0.314	0.298	0.317
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
50th percentile earnings (cond. on +)	$10,250	$10,650	$9,751	$9,119	$8,320	$12,750	$15,700	$12,890	$12,310	$13,770	$15,580	$16,140
	($419)	($405)	($439)	($430)	($433)	($501)	($572)	($503)	($527)	($568)	($612)	($683)
Share enrolled in Medicaid			0.308	0.318	0.347	0.391	0.426	0.449	0.465	0.752	0.768	
			(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	
Share receiving SSI or DI (according to Medicare records)						0.208	0.270	0.307	0.332	0.358		0.391
						(0.007)	(0.007)	(0.008)	(0.008)	(0.008)		(0.008)
Sample Size	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,200	3,100	3,100	3,000
Panel A2: Los Angeles Census Sample												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.529	0.531	0.509	0.471	0.411	0.506	0.503	0.378	0.382	0.349	0.336	0.351
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
50th percentile earnings (cond. on +)	$10,400	$10,950	$9,514	$9,173	$8,208	$12,850	$15,740	$12,970	$12,370	$13,500	$15,440	$16,240
	($419)	($405)	($439)	($430)	($433)	($501)	($572)	($503)	($527)	($568)	($612)	($683)
Share enrolled in Medicaid			0.271	0.283	0.306	0.358	0.389	0.423	0.444	0.720	0.764	
			(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	
Share receiving SSI or DI (according to Medicare records)						0.228	0.298	0.334	0.355	0.367		0.394
						(0.007)	(0.007)	(0.008)	(0.008)	(0.008)		(0.008)
Sample Size	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,500	3,400	3,400	3,300	3,300
Panel B1: Houston HMIS Sample												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.714	0.754	0.709	0.707	0.665	0.716	0.672	0.641	0.647	0.603	0.590	0.584
	(0.016)	(0.015)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
50th percentile earnings (cond. on +)	$8,716	$9,333	$9,097	$7,505	$6,855	$8,147	$11,850	$11,800	$10,840	$11,820	$12,590	$12,900
	($536)	($534)	($684)	($514)	($461)	($477)	($536)	($556)	($753)	($726)	($745)	($702)
Share enrolled in Medicaid			0.211	0.208	0.211	0.273	0.286	0.314	0.310	0.305		
			(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)		
Share receiving SSI or DI (according to Medicare records)						0.086	0.129	0.162	0.188	0.212		0.222
						(0.008)	(0.010)	(0.010)	(0.011)	(0.011)		(0.011)
Sample Size	800	800	800	800	800	800	800	800	800	800	750	750
Panel B2: Houston Census Sample												
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.605	0.633	0.607	0.618	0.596	0.563	0.543	0.515	0.525	0.503	0.475	0.479
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
50th percentile earnings (cond. on +)	$9,293	$8,484	$8,961	$8,661	$7,364	$8,098	$10,950	$11,770	$11,270	$12,370	$13,620	$13,050
	($624)	($569)	($625)	($540)	($388)	($443)	($675)	($658)	($674)	($773)	($925)	($907)
Share enrolled in Medicaid			0.138	0.153	0.175	0.223	0.266	0.300	0.307			
			(0.010)	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)	(0.014)			
Share receiving SSI or DI (according to Medicare records)						0.179	0.231	0.293	0.321	0.330		0.338
						(0.017)	(0.019)	(0.021)	(0.021)	(0.021)		(0.022)
Sample Size	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,100	1,100	1,100	1,100	1,100

Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, various administrative datasets

Note: Interval-based sample consists of people who had a first homeless spell in 2012 or 2013. Point-in-time sample consists of those who were in an HMIS shelter on March 30 of 2012 and 2013.

Table A.33: Income and Benefit Receipt Two Years Before and After Observed As Homeless, 2010-2014 ACS Sheltered Homeless Ages 25-59

	t-2	t-1	t	t+1	t+2
Share with earnings	0.5336	0.4908	0.5065	0.4627	0.4613
	(0.0181)	(0.0194)	(0.0221)	(0.0200)	(0.0205)
Mean earnings (cond. on receipt)	$12,940	$11,510	$11,260	$12,830	$13,430
	($629)	($594)	($528)	($610)	($555)
Median earnings (cond. on receipt)	$9,514	$7,350	$7,779	$10,140	$11,380
	($458)	($443)	($413)	($425)	($491)
75th percentile earnings (cond. on receipt)	$16,880	$14,400	$15,010	$17,730	$19,200
	($622)	($493)	($466)	($563)	($685)
Share receiving disability (SSI or DI)	0.1354	0.1397	0.1686	0.2095	0.2391
	0.0123	0.0112	0.0116	0.0145	0.0133
Share receiving any benefits, excl. SSI (SNAP, Medicaid, HUD, VA, or Medicare)	0.7872	0.8777	0.9386	0.9245	0.9077
	(0.0251)	(0.0211)	(0.0141)	(0.0166)	(0.0189)
Share receiving any benefits, incl. SSI (SNAP, Medicaid, HUD, VA, Medicare, or SSI)	0.8713	0.9218	0.9575	0.9321	0.9239
	(0.0217)	(0.0188)	(0.0135)	(0.0212)	(0.0269)
Mean cash income (pretax)	$7,801	$6,453	$6,451	$6,661	$6,834
	($450)	($458)	($431)	($469)	($460)
Median cash income	$1,150	$553	$600	$333	$136
	($243)	($141)	($151)	($86)	($92)
75th percentile cash income	$11,790	$9,667	$9,996	$11,440	$12,370
	($468)	($467)	($503)	($518)	($534)
Mean cash income + in-kind transfers, excl. SSI (SNAP, HUD, and VA)	$9,652	$9,009	$9,025	$9,169	$9,789
	($828)	($771)	($705)	($830)	($960)
Median cash income + in-kind transfers, excl. SSI	$3,911	$3,580	$3,661	$3,722	$5,012
	($697)	($642)	($665)	($664)	($800)
75th percentile cash income + in-kind transfers, excl. SSI	$14,430	$13,080	$13,260	$14,880	$16,120
	($804)	($694)	($849)	($739)	($817)
Mean cash income + in-kind transfers, incl. SSI (SNAP, HUD, VA, and SSI)	$10,280	$9,832	$9,941	$9,956	$10,710
	($641)	($765)	($650)	($706)	($958)
Median cash income + in-kind transfers, incl. SSI	$6,788	$6,676	$7,526	$7,328	$8,546
	($952)	($881)	($816)	($1009)	($1009)
75th percentile cash income + in-kind transfers, incl. SSI	$15,230	$14,000	$13,830	$15,340	$16,580
	($850)	($715)	($763)	($742)	($960)
Sample Size	4200	4200	4200	4100	4100

Sources: 2010-2014 ACS, various administrative datasets
Note: Sample includes sheltered homeless individuals ages 25-59 at the time of survey.

Table A.34: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, including TNSOLs, 2003-2016

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.549	0.535	0.522	0.485	0.412	0.397	0.399	0.361	0.358	0.342	0.342	0.341
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
50th percentile earnings (cond. on +)	$8,799	$8,926	$8,719	$8,096	$7,509	$8,589	$10,480	$10,650	$11,000	$11,250	$12,310	$12,670
	($146)	($143)	($228)	($123)	($162)	($150)	($473)	($258)	($268)	($301)	($319)	($206)
75th percentile earnings (cond. on +)	$20,610	$20,540	$20,070	$18,930	$18,370	$20,310	$22,580	$22,430	$23,250	$24,280	$26,190	$27,000
	($267)	($242)	($411)	($232)	($324)	($307)	($958)	($385)	($430)	($555)	($584)	($344)
50th percentile pre-tax income + in-kind transfers	$2,409	$2,472	$4,030	$2,264	$2,666	$2,710	$2,630	$2,579	$2,525	$2,389	$2,439	$2,417
	($176)	($163)	($324)	($98)	($22)	($25)	($29)	($17)	($31)	($4)	($9)	($26)
75th percentile pre-tax income + in-kind transfers	$12,330	$11,550	$14,580	$12,980	$11,490	$12,750	$13,120	$12,800	$12,640	$12,110	$13,230	$13,360
	($699)	($615)	($461)	($513)	($448)	($486)	($476)	($485)	($453)	($487)	($503)	($503)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.643	0.691	0.745	0.791	0.790	0.781	0.788	0.796	0.817	0.000
			(0.011)	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	
Share receiving SSI or DI (according to Medicare records)						0.270	0.303	0.334	0.351	0.361		0.373
						(0.006)	(0.006)	(0.007)	(0.007)	(0.007)		(0.007)
Sample Size	54,000	54,000	54,000	54,000	54,000	54,000	53,500	52,500	52,000	51,000	50,500	49,500

Sources: Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)
Note: Sample includes PIKed adults enumerated at unsheltered locations in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. We include individuals who were counted in TNSOLs. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.35: Income and Benefit Receipt among Sheltered Homeless Ages Individuals 25-59 in 2010 Decennial Census, excluding individuals counted in multiple housing statuses in the Census, 2003-2016

	Sheltered Homeless											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.619	0.616	0.600	0.573	0.490	0.509	0.486	0.449	0.441	0.423	0.422	0.423
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50th percentile earnings (cond. on +)	$9,135	$9,146	$8,896	$7,541	$5,938	$7,775	$10,440	$10,690	$10,880	$11,150	$12,190	$12,700
	($73)	($77)	($72)	($70)	($67)	($60)	($72)	($78)	($80)	($88)	($105)	($110)
75th percentile earnings (cond. on +)	$19,260	$18,910	$17,790	$15,690	$13,600	$15,380	$18,910	$19,260	$19,680	$20,360	$22,310	$23,410
	($128)	($106)	($104)	($93)	($103)	($86)	($113)	($110)	($128)	($139)	($163)	($156)
50th percentile pre-tax income + in-kind transfers	$5,607	$4,937	$3,841	$2,797	$2,666	$3,388	$3,748	$3,383	$3,348	$3,085	$3,391	$3,564
	($265)	($237)	($134)	($75)	($17)	($82)	($122)	($105)	($113)	($111)	($132)	($139)
75th percentile pre-tax income + in-kind transfers	$14,450	$14,210	$13,550	$12,210	$10,940	$13,270	$14,960	$14,700	$14,750	$14,350	$15,260	$15,720
	($453)	($414)	($164)	($157)	($150)	($118)	($149)	($151)	($153)	($149)	($172)	($174)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.687	0.734	0.834	0.906	0.890	0.862	0.848	0.849	0.851	
			(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	
Share receiving SSI or DI (according to Medicare records)						0.181	0.238	0.283	0.309	0.326		0.343
						(0.002)	(0.002)	(0.002)	(0.003)	(0.003)		(0.003)
Sample Size	74,500	74,500	74,500	74,500	74,500	74,500	74,000	73,000	72,000	71,500	70,000	69,000
	Unsheltered Homeless											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.555	0.542	0.519	0.480	0.395	0.377	0.361	0.324	0.322	0.299	0.301	0.303
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
50th percentile earnings (cond. on +)	$7,088	$7,108	$7,136	$6,324	$5,507	$7,128	$8,230	$8,177	$8,476	$8,844	$9,912	$10,100
	($181)	($183)	($210)	($141)	($217)	($138)	($217)	($209)	($220)	($193)	($198)	($198)
75th percentile earnings (cond. on +)	$16,910	$16,670	$16,450	$14,940	$14,470	$15,600	$18,030	$17,840	$18,120	$18,990	$20,260	$21,180
	($291)	($312)	($338)	($212)	($315)	($300)	($458)	($317)	($359)	($300)	($323)	($324)
50th percentile pre-tax income + in-kind transfers	$2,057	$2,223	$2,224	$1,962	$2,284	$2,505	$2,578	$2,443	$2,441	$2,255	$2,346	$2,370
	($213)	($228)	($102)	($58)	($53)	($30)	($28)	($34)	($29)	($34)	($34)	($31)
75th percentile pre-tax income + in-kind transfers	$10,120	$10,030	$10,840	$8,806	$6,809	$8,426	$9,600	$8,819	$8,370	$8,229	$9,200	$9,961
	($843)	($694)	($345)	($444)	($419)	($424)	($422)	($417)	($425)	($417)	($454)	($427)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.653	0.695	0.757	0.819	0.814	0.805	0.811	0.823	0.846	
			(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.009)	
Share receiving SSI or DI (according to Medicare records)						0.236	0.277	0.312	0.332	0.344		0.363
						(0.007)	(0.008)	(0.008)	(0.007)	(0.007)		(0.007)
Sample Size	29,500	29,500	29,500	29,500	29,500	29,500	29,500	29,000	28,500	28,000	27,500	27,000

Sources: 2010 Decennial Census, 2019 Numident, 2003-2016 IRS 1040 Datasets, 2006-2016 W2 Datasets, 2004-2016 IRS 1099R Datasets, 2004-2016 HUD PIC and TRACS, 2007-2015 Administrative VA Dataset, 2006-2014 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016)
Note: Sample includes PIKed adults enumerated as homeless in the 2010 Decennial Census who have a non-missing birthdate in the 2019 Numident who were between the ages of 25 and 59 (inclusive) as of March 30, 2010. We exclude individuals who were counted in a housed or other group quarters status in addition to being counted as homeless in the Census. Table displays the weighted means, percentiles, and shares for individuals who link to income and benefits datasets from 2003-2016. For disclosure purposes, percentiles are calculated as the average of the twelve observations above and the twelve observations below the weighted percentile. Sample sizes are rounded to comply with Census Bureau requirements. Dollars are expressed as Chained CPI-U-adjusted 2018 dollars.

Table A.36: Migration-Adjusted SNAP Receipt

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Panel A: Migration Adjustment Approach #1													
Baseline consists of all those who lived in SNAP state in 2010. Migration-adjusted sample consists of those who lived in the same SNAP state in 2000 and 2010.													
	Baseline												
Sheltered Homeless	Migration Adjusted	0.4366	0.4498	0.5852	0.6432	0.7668	0.8435	0.8090	0.7604	0.7363	0.7123	0.6846	0.6519
	SE	0.0138	0.0139	0.0060	0.0059	0.0047	0.0040	0.0044	0.0048	0.0050	0.0051	0.0053	0.0055
Sample size	Baseline												
	Migration Adjusted	1,300	1,300	6,800	6,800	8,100	8,100	8,100	8,000	7,900	7,800	7,700	7,600
	Baseline												
Unsheltered Homeless	Migration Adjusted	0.5004	0.4959	0.5364	0.5704	0.6445	0.7024	0.6941	0.6902	0.6739	0.6658	0.6492	0.6275
	SE	0.0183	0.0183	0.0103	0.0102	0.0089	0.0086	0.0086	0.0087	0.0089	0.0090	0.0092	0.0094
Sample size	Baseline												
	Migration Adjusted	750	750	2,400	2,400	3,000	3,000	3,000	2,900	2,900	2,800	2,800	2,700
	Baseline												
Single Housed Poor	Migration Adjusted	0.4082	0.4496	0.4428	0.4689	0.5417	0.5873	0.5951	0.5818	0.5647	0.5500	0.5342	0.5137
	SE	0.0202	0.0212	0.0131	0.0131	0.0112	0.0110	0.0110	0.0110	0.0111	0.0113	0.0114	0.0114
Sample size	Baseline												
	Migration Adjusted	1,800	1,800	4,300	4,300	5,800	5,800	5,800	5,800	5,700	5,700	5,600	5,600
Panel B: Migration Adjustment Approach #2													
Baseline consist of 2010 Medicaid recipients in SNAP state in 2010. Migration-adjusted sample consists of Medicaid recipients in SNAP state in pre- and post-2010 window.													
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
	Baseline			0.6097	0.6810	0.8409	0.9174	0.8689	0.8113	0.7734	0.7429	0.7082	0.6848
Sheltered Homeless	SE			0.0043	0.0041	0.0031	0.0023	0.0028	0.0033	0.0036	0.0037	0.0039	0.0040
	Migration Adjusted			0.6872	0.7580	0.8786	0.9197	0.8992	0.8574	0.8222	0.7914	0.7537	0.7284
	SE			0.0039	0.0036	0.0025	0.0019	0.0018	0.0025	0.0029	0.0030	0.0030	0.0025
Sample size	Baseline			13,500	13,500	14,500	14,500	14,500	14,500	14,000	14,000	14,000	13,500
	Migration Adjusted			11,500	11,500	12,500	12,500	12,500	12,000	12,000	12,000	12,000	11,500
	Baseline			0.6410	0.7165	0.8046	0.8558	0.8288	0.8008	0.7844	0.7688	0.7509	0.7319
Unsheltered Homeless	SE			0.0207	0.0115	0.0084	0.0069	0.0079	0.0086	0.0090	0.0095	0.0101	0.0108
	Migration Adjusted			0.6869	0.7603	0.8236	0.8527	0.8464	0.8304	0.8197	0.8030	0.7841	0.7696
	SE			0.0266	0.0078	0.0046	0.0044	0.0040	0.0052	0.0049	0.0055	0.0056	0.0050
Sample size	Baseline			3,600	3,600	4,000	4,000	4,000	4,000	3,900	3,800	3,800	3,700
	Migration Adjusted			3,300	3,300	3,700	3,700	3,700	3,700	3,600	3,600	3,500	3,400
	Baseline			0.6473	0.6930	0.7959	0.8432	0.8205	0.7911	0.7574	0.7459	0.7151	0.6951
Single Housed Poor	SE			0.0130	0.0127	0.0097	0.0086	0.0093	0.0097	0.0102	0.0103	0.0107	0.0110
	Migration Adjusted			0.6932	0.7304	0.8081	0.8446	0.8474	0.8304	0.8041	0.7895	0.7573	0.7317
Sample size	SE			0.0111	0.0096	0.0051	0.0049	0.0044	0.0046	0.0063	0.0065	0.0074	0.0078
	Baseline			3,900	3,900	5,100	5,100	5,100	5,100	5,000	5,000	4,900	4,900
	Migration Adjusted			3,600	3,600	4,800	4,800	4,800	4,700	4,700	4,600	4,600	4,500

Sources: 2000 and 2010 Census, 2010 ACS, various states' SNAP datasets, various states' Medicaid datasets
Note: Sample for Approach 1 consists of people who lived in a SNAP state in 2010 and in the same state in 2000 according to that year's Census. Sample for Approach 2 consists of people who received Medicaid in a SNAP state in a three-year window before 2010 and a three-year window after 2010; baseline consists of those who received Medicaid in a SNAP state in 2010.

A.3 Chapter 4 Appendix

A.4 Exhibits

Table A.37: Homeless Population Summary Statistics by Gender and Sheltered Status Demographic Characteristics and Region

	Sheltered Homeless		Unsheltered Homeless	
Age in 2010	Ages 18-54		Ages 18-54	
Gender	Males	Females	Males	Females
Mean Age	40.8	35.5	41.2	38.6
Ages 18-24	0.1090	0.2250	0.0982	0.1507
25-29	0.0881	0.1539	0.0856	0.1102
30-34	0.0953	0.1275	0.0921	0.1076
35-39	0.1081	0.1155	0.1086	0.1234
40-44	0.1580	0.1264	0.1658	0.1572
45-49	0.2135	0.1341	0.2206	0.1817
50-54	0.2280	0.1175	0.2291	0.1690
Race and Ethnicity				
White	0.5055	0.4459	0.5300	0.5572
Black	0.4020	0.4465	0.3691	0.3276
Other Race	0.0925	0.1076	0.1008	0.1152
Hispanic	0.1494	0.1753	0.1659	0.1527
Region				
Northeast	0.2524	0.3415	0.1769	0.1785
Midwest	0.1830	0.1691	0.1640	0.2013
South	0.3095	0.2622	0.2815	0.2462
West	0.2552	0.2272	0.3776	0.3739
Weighted Count	80,380	48,290	95,720	37,140
N	55,000	34,000	35,000	15,000

Note: Weighted counts reflect inverse probability weighting to account for non-linkage. All reported ages reflect age in 2010.

Table A.38: Homeless Population Summary Statistics by Gender and Sheltered Status Disability, Economic Status, Family Connections, and State

	Sheltered Homeless		Unsheltered Homeless	
Age in 2010	Ages 18-54		Ages 18-54	
Gender	Males	Females	Males	Females
SSI receipt (2009)	0.1572	0.1516	0.2080	0.2564
DI receipt (2009)	0.0656	0.0474	0.1051	0.0944
SSI or DI	0.1726	0.1599	0.2309	0.2711
Employed in 2009	0.5186	0.5578	0.4412	0.4551
Top Half of Prior Income	0.5371	0.5105	0.4649	0.4324
Has Spouse or Former Spouse	0.1208	0.1630	0.1261	0.2076
Also Recorded in Housing	0.1702	0.2056	0.3505	0.4755
Has Child	0.2408	0.5140	0.2197	0.4056
Any Indicator of Family Connection	0.3791	0.6289	0.4840	0.6814
New York	0.1290	0.2209	0.0706	0.0726
California	0.1352	0.1257	0.2256	0.2263
Other State	0.7358	0.6534	0.7037	0.7011
Weighted Count	80,380	48,290	95,720	37,140
N	55,000	34,000	35,000	15,000

Note: Weighted counts reflect inverse probability weighting to account for non-linkage. All reported ages reflect age in 2010.

Table A.39: Mortality Hazard of Homeless and Housed (Ages 18-54 in 2010)

Period	Empirical Hazard			Covariate-Adjusted Hazard		
	Homeless	Housed Poor	Housed	Homeless	Housed Poor	Housed
1	0.00382	0.00180	0.00087	0.00379	0.00296	0.00113
2	0.00459	0.00184	0.00093	0.00456	0.00304	0.00121
3	0.00456	0.00160	0.00109	0.00454	0.00266	0.00142
4	0.00503	0.00163	0.00104	0.00502	0.00271	0.00135
5	0.00510	0.00160	0.00111	0.00510	0.00269	0.00144
6	0.00593	0.00201	0.00124	0.00595	0.00337	0.00162
7	0.00521	0.00182	0.00122	0.00524	0.00307	0.00160
8	0.00562	0.00210	0.00125	0.00567	0.00354	0.00163
9	0.00611	0.00211	0.00129	0.00618	0.00357	0.00169
10	0.00620	0.00242	0.00140	0.00628	0.00408	0.00183
11	0.00669	0.00228	0.00140	0.00680	0.00386	0.00183
12	0.00695	0.00243	0.00154	0.00709	0.00412	0.00202
13	0.00659	0.00226	0.00152	0.00674	0.00385	0.00199
14	0.00703	0.00264	0.00166	0.00723	0.00451	0.00218
15	0.00702	0.00253	0.00158	0.00724	0.00433	0.00208
16	0.00740	0.00286	0.00172	0.00765	0.00491	0.00226
17	0.00790	0.00311	0.00171	0.00819	0.00535	0.00225
18	0.00764	0.00294	0.00184	0.00795	0.00509	0.00242
19	0.00748	0.00286	0.00188	0.00781	0.00495	0.00247
20	0.00847	0.00326	0.00218	0.00887	0.00565	0.00286
21	0.01074	0.00418	0.00235	0.01128	0.00725	0.00309
22	0.01093	0.00406	0.00259	0.01155	0.00708	0.00341
23	0.01187	0.00469	0.00290	0.01262	0.00824	0.00384
24	0.01185	0.00471	0.00296	0.01269	0.00833	0.00392

Note: Covariate-adjusted hazard indicates simulated hazard using age and gender distribution of homeless sample.

Table A.40: Survivor Function of Homeless and Housed (Ages 18-54 in 2010)

Period	Empirical Hazard			Covariate-Adjusted Hazard		
	Homeless	Housed Poor	Housed	Homeless	Housed Poor	Housed
1	0.99618	0.99820	0.99913	0.99621	0.99704	0.99887
2	0.99161	0.99637	0.99820	0.99167	0.99402	0.99766
3	0.98709	0.99477	0.99711	0.98717	0.99137	0.99625
4	0.98212	0.99315	0.99608	0.98221	0.98868	0.99491
5	0.97712	0.99156	0.99498	0.97720	0.98603	0.99348
6	0.97132	0.98957	0.99374	0.97138	0.98270	0.99187
7	0.96626	0.98777	0.99252	0.96630	0.97969	0.99028
8	0.96083	0.98569	0.99128	0.96082	0.97622	0.98867
9	0.95496	0.98361	0.99000	0.95489	0.97274	0.98700
10	0.94904	0.98123	0.98862	0.94889	0.96877	0.98520
11	0.94269	0.97899	0.98723	0.94244	0.96504	0.98339
12	0.93614	0.97661	0.98572	0.93576	0.96106	0.98141
13	0.92997	0.97440	0.98422	0.92945	0.95736	0.97946
14	0.92343	0.97182	0.98258	0.92273	0.95304	0.97732
15	0.91695	0.96937	0.98103	0.91605	0.94892	0.97530
16	0.91017	0.96659	0.97935	0.90905	0.94426	0.97310
17	0.90298	0.96359	0.97767	0.90160	0.93920	0.97091
18	0.89608	0.96075	0.97587	0.89444	0.93442	0.96855
19	0.88937	0.95800	0.97403	0.88745	0.92980	0.96616
20	0.88184	0.95488	0.97191	0.87958	0.92455	0.96339
21	0.87237	0.95089	0.96962	0.86966	0.91785	0.96041
22	0.86283	0.94703	0.96712	0.85961	0.91135	0.95714
23	0.85259	0.94259	0.96431	0.84876	0.90384	0.95346
24	0.84249	0.93815	0.96146	0.83799	0.89631	0.94973

Note: Covariate-adjusted survivor function derived from simulated hazard using age and gender distribution of homeless sample.

Table A.41: Mortality Hazard of Homeless by Gender and Sheltered Status (Ages 18-54 in 2010)

Period	Empirical Hazard				Covariate-Adjusted Hazard			
	Sheltered		Unsheltered		Sheltered		Unsheltered	
	Men	Women	Men	Women	Men	Women	Men	Women
1	0.00382	0.00180	0.00180	0.00087	0.00379	0.00296	0.00296	0.00113
2	0.00459	0.00184	0.00184	0.00093	0.00456	0.00304	0.00304	0.00121
3	0.00456	0.00160	0.00160	0.00109	0.00454	0.00266	0.00266	0.00142
4	0.00503	0.00163	0.00163	0.00104	0.00502	0.00271	0.00271	0.00135
5	0.00510	0.00160	0.00160	0.00111	0.00510	0.00269	0.00269	0.00144
6	0.00593	0.00201	0.00201	0.00124	0.00595	0.00337	0.00337	0.00162
7	0.00521	0.00182	0.00182	0.00122	0.00524	0.00307	0.00307	0.00160
8	0.00562	0.00210	0.00210	0.00125	0.00567	0.00354	0.00354	0.00163
9	0.00611	0.00211	0.00211	0.00129	0.00618	0.00357	0.00357	0.00169
10	0.00620	0.00242	0.00242	0.00140	0.00628	0.00408	0.00408	0.00183
11	0.00669	0.00228	0.00228	0.00140	0.00680	0.00386	0.00386	0.00183
12	0.00695	0.00243	0.00243	0.00154	0.00709	0.00412	0.00412	0.00202
13	0.00659	0.00226	0.00226	0.00152	0.00674	0.00385	0.00385	0.00199
14	0.00703	0.00264	0.00264	0.00166	0.00723	0.00451	0.00451	0.00218
15	0.00702	0.00253	0.00253	0.00158	0.00724	0.00433	0.00433	0.00208
16	0.00740	0.00286	0.00286	0.00172	0.00765	0.00491	0.00491	0.00226
17	0.00790	0.00311	0.00311	0.00171	0.00819	0.00535	0.00535	0.00225
18	0.00764	0.00294	0.00294	0.00184	0.00795	0.00509	0.00509	0.00242
19	0.00748	0.00286	0.00286	0.00188	0.00781	0.00495	0.00495	0.00247
20	0.00847	0.00326	0.00326	0.00218	0.00887	0.00565	0.00565	0.00286
21	0.01074	0.00418	0.00418	0.00235	0.01128	0.00725	0.00725	0.00309
22	0.01093	0.00406	0.00406	0.00259	0.01155	0.00708	0.00708	0.00341
23	0.01187	0.00469	0.00469	0.00290	0.01262	0.00824	0.00824	0.00384
24	0.01185	0.00471	0.00471	0.00296	0.01269	0.00833	0.00833	0.00392

Note: Covariate-adjusted hazard indicates simulated hazard using age distribution of sheltered men.

Table A.42: Proportional Hazard Model (Ages 18-54 in 2010)

	No Controls	Age Controls	Age and Gender Controls	All Demographic Controls	Region Fixed Effects	State Fixed Effects
Group Indicators (Pooled Sheltered and Unsheltered):						
Homeless	4.368***	3.771***	3.439***	3.395***	3.486***	3.514***
	(0.228)	(0.160)	(0.143)	(0.115)	(0.119)	(0.144)
Housed Poor	1.625***	2.073***	2.124***	2.209***	2.195***	2.183***
	(0.0945)	(0.123)	(0.127)	(0.0880)	(0.0638)	(0.0513)
Group Indicators (Separate Sheltered and Unsheltered):						
Sheltered Homeless	4.072***	3.695***	3.402***	3.340***	3.412***	3.446***
	(0.287)	(0.173)	(0.151)	(0.119)	(0.116)	(0.137)
Unsheltered Homeless	4.658***	3.839***	3.471***	3.445***	3.552***	3.575***
	(0.198)	(0.156)	(0.141)	(0.117)	(0.128)	(0.157)
Housed Poor	1.625***	2.073***	2.124***	2.209***	2.195***	2.183***
	(0.0945)	(0.123)	(0.127)	(0.0880)	(0.0638)	(0.0513)
Covariates:						
Ages 18-24		0.0293***	0.0296***	0.0308***	0.0308***	0.0306***
		(0.00333)	(0.00338)	(0.00356)	(0.00353)	(0.00348)
25-29		0.0451***	0.0458***	0.0472***	0.0471***	0.0468***
		(0.00529)	(0.00540)	(0.00568)	(0.00567)	(0.00561)
30-34		0.0512***	0.0523***	0.0537***	0.0536***	0.0532***
		(0.00498)	(0.00511)	(0.00528)	(0.00522)	(0.00519)
35-39		0.0781***	0.0804***	0.0841***	0.0839***	0.0830***
		(0.00828)	(0.00852)	(0.00915)	(0.00907)	(0.00891)
40-44		0.124***	0.128***	0.135***	0.135***	0.133***
		(0.0100)	(0.0102)	(0.0113)	(0.0112)	(0.0109)
45-49		0.199***	0.203***	0.213***	0.212***	0.211***
		(0.0169)	(0.0172)	(0.0189)	(0.0187)	(0.0185)
50-54		0.300***	0.304***	0.315***	0.314***	0.312***
		(0.0263)	(0.0268)	(0.0287)	(0.0284)	(0.0283)
55-59		0.451***	0.455***	0.463***	0.462***	0.459***
		(0.0340)	(0.0345)	(0.0354)	(0.0353)	(0.0351)
60-64		0.633***	0.638***	0.641***	0.640***	0.637***
		(0.0593)	(0.0601)	(0.0597)	(0.0596)	(0.0596)
Female			0.655***	0.653***	0.652***	0.651***
			(0.0184)	(0.0190)	(0.0191)	(0.0189)
Black				1.033	1.002	1.011
				(0.0380)	(0.0334)	(0.0356)
Other Race				0.679***	0.702***	0.708***
				(0.0308)	(0.0293)	(0.0281)
Hispanic				0.633***	0.640***	0.664***
				(0.0504)	(0.0480)	(0.0516)
Northeast					1.035	0.531***
					(0.0630)	(0.0542)
Midwest					1.119**	0.888***
					(0.0616)	(0.0189)
South					1.229***	1.298***
					(0.0743)	(0.0288)
Obs (N x Periods)	36,770,000	36,770,000	36,770,000	36,770,000	36,770,000	36,770,000
Standard Error Cluster	State x Group	State x Group	State x Group	State x Group	State x Group	State x Group
Fixed Effects	Duration	Duration	Duration	Duration	Duration	Duration, State

*** p<0.01, ** p<0.05, * p<0.1

Table A.43: Proportional Mortality Hazard by Housing Status and Race

Group	No Age Controls	Age Controls
Homeless Black	3.754***	3.255***
	(0.209)	(0.120)
Homeless Other	3.601***	3.564***
	(0.278)	(0.238)
Homeless White	5.000***	4.469***
	(0.199)	(0.188)
Housed Black	1.292***	1.432***
	(0.0409)	(0.0440)
Housed Other	0.685***	0.799***
	(0.0318)	(0.0395)
Poor Black	1.891***	2.443***
	(0.0913)	(0.114)
Poor Other	0.94	1.262***
	(0.0646)	(0.0941)
Poor White	1.686***	2.225***
	(0.0855)	(0.118)
Baseline Group	Housed Whites	Housed Whites
Covariates	None	Age
Standard Errors	State x Group	State x Group
Fixed Effects	Duration	Duration
Age Group	18-54	18-54

*** p<0.01, ** p<0.05, * p<0.1

Table A.44: Proportional Mortality Hazard by Housing Status and Gender

Group	No Age Controls	Age Controls
Homeless Female	2.463***	2.542***
	(0.172)	(0.125)
Homeless Male	4.124***	3.267***
	(0.174)	(0.122)
Housed Female	0.640***	0.633***
	(0.00919)	(0.00937)
Poor Female	1.069	1.369***
	(0.0689)	(0.0906)
Poor Male	1.679***	2.099***
	(0.0920)	(0.116)
Baseline Group	Housed Males	Housed Males
Covariates	None	Age
Standard Errors	State x Group	State x Group
Fixed Effects	Duration	Duration
Age Group	18-54	18-54

*** p<0.01, ** p<0.05, * p<0.1

Table A.45: Proportional Mortality Hazard by Housing Status and Hispanic Ethnicity

Group	No Age Controls	Age Controls
Homeless Hispanic	3.018***	3.117***
	(0.185)	(0.149)
Homeless Non-Hispanic	4.435***	3.823***
	(0.203)	(0.156)
Housed Hispanic	0.755***	0.896**
	(0.0322)	(0.0389)
Poor Hispanic	0.937	1.252**
	(0.0828)	(0.118)
Poor Non-Hispanic	1.753***	2.273***
	(0.0795)	(0.108)
Baseline Group	Housed Non-Hispanic	Housed Non-Hispanic
Covariates	None	Age
Standard Errors	State x Group	State x Group
Fixed Effects	Duration	Duration
Age Group	18-54	18-54

*** p<0.01, ** p<0.05, * p<0.1

Table A.46: Proportional Mortality Hazard by Housing Status and Disability Status

Group	No Age Controls	Age Controls
Homeless Disabled	8.479***	6.230***
	(0.361)	(0.244)
Homeless Non-Disabled	4.399***	3.976***
	(0.259)	(0.186)
Housed Disabled	6.236***	4.727***
	(0.131)	(0.100)
Poor Disabled	6.726***	5.170***
	(0.343)	(0.263)
Poor Non-Disabled	1.404***	1.855***
	(0.0760)	(0.110)
Baseline Group	Housed Non-Disabled	Housed Non-Disabled
Covariates	None	Age
Standard Errors	State x Group	State x Group
Fixed Effects	Duration	Duration
Age Group	18-54	18-54

*** p<0.01, ** p<0.05, * p<0.1

Table A.47: Proportional Mortality Hazard by Housing Status and Age

Group	
Homeless 18-24	2.062***
	(0.324)
Homeless 25-34	4.561***
	(0.489)
Homeless 35-44	8.705***
	(0.765)
Homeless 45-54	18.69***
	(1.486)
Homeless 55-67	32.91***
	(2.689)
Housed 25-34	1.356***
	(0.072)
Housed 35-44	2.042***
	(0.130)
Housed 45-54	4.463***
	(0.227)
Housed 55-67	9.153***
	(0.541)
Poor 18-24	1.134
	(0.136)
Poor 25-34	1.830***
	(0.185)
Poor 35-44	3.835***
	(0.377)
Poor 45-54	9.732***
	(0.870)
Poor 55-67	20.13***
	(1.933)
Baseline Group	Housed Ages 18-24
Covariates	None
Standard Errors	State x Group
Fixed Effects	Duration
Age Group	18-54

*** p<0.01, ** p<0.05, * p<0.1

Table A.48: Proportional Mortality Hazard by Housing Status and Age (Ages 30-79)

Proportional Mortality Hazard by Housing Status and Age (Ages 30-79)						
Age	Age Only			Age x Duration Interactions		
(lower bound of 2-yr bin)	Homeless	Housed Poor	Housed	Homeless	Housed Poor	Housed
30	3.584	1.036		3.583	1.049	
32	4.13	1.95	1.169	4.121	1.952	1.168
34	4.903	1.848	1.204	4.698	1.795	1.159
36	4.769	2.256	1.321	4.412	2.118	1.228
38	5.961	2.781	1.469	5.514	2.599	1.365
40	6.496	3.869	1.634	16.48	9.77	4.139
42	7.694	3.759	1.825	19.6	9.5	4.629
44	8.584	4.657	2.137	18.86	10.34	4.737
46	10.35	6.009	2.582	20.08	11.87	5.079
48	11.97	6.781	2.973	23.29	13.4	5.856
50	14.15	7.554	3.708	30.01	16.03	7.865
52	14.87	9.879	4.25	31.56	20.95	9.02
54	18.23	11.96	5.212	37.48	24.6	10.72
56	20.16	13.86	5.982	40.19	27.63	11.92
58	22.46	15.54	6.856	44.8	30.99	13.67
60	25.08	17.17	8.055	59.85	41.09	19.27
62	29	21.31	9.697	69.17	51.05	23.2
64	32.74	23.34	11.01	75.98	54.47	25.66
66	33.62	23.95	13.02	75.69	54.42	29.55
68	39.57	27.68	15.03	88.85	62.76	34.06
70	38.9	32.55	17.95	74.11	61.63	33.93
72	45.13	36.43	21.65	85.81	69.02	40.98
74	46.11	39.14	26.28	85.65	72.58	48.72
76	50.66	46.59	31.84	91.45	84.6	57.68
78	55.52	54.68	39.46	100.6	99.58	71.55
Baseline Group	Housed Ages 30-31			Housed Ages 30-31		
Covariates	Gender, Age			Gender, Age, Duration		
Std Errors	State x Group			State x Group		
Fixed Effects	Period			Period		
Age Group	30-79			30-79		

*** p<0.01, ** p<0.05, * p<0.1

Table A.49: Proportional Mortality Hazard by Housing Status and Race (Homeless Ages 18-54 in 2010)

Group	Coefficient	95% CI	
Sheltered Female Black	0.523	0.488	0.561
Sheltered Female Other	0.528	0.4538	0.6149
Sheltered Female White	0.715	0.6799	0.7529
Sheltered Male Black	0.631	0.5923	0.6727
Sheltered Male Other	0.794	0.7236	0.872
Unsheltered Female Black	0.596	0.54	0.6584
Unsheltered Female Other	0.764	0.6217	0.9395
Unsheltered Female White	0.678	0.6347	0.7253
Unsheltered Male Black	0.685	0.6394	0.7341
Unsheltered Male Other	0.914	0.8133	1.027
Unsheltered Male White	0.992	0.9503	1.036
Baseline Group	Sheltered Male White		
Covariates	Age, Region, Hispanic		
Standard Errors	Robust		
Fixed Effects	Duration		
Age Group	18-54		

*** p<0.01, ** p<0.05, * p<0.1

Table A.50: Proportional Mortality Hazard by Housing Status and Age (Homeless Ages 18-54 in 2010)

Group	Coefficient	95% CI	
Sheltered 25-34	2.082	1.622	2.673
Sheltered 35-44	3.866	2.936	5.092
Sheltered 45-54	8.295	6.203	11.09
Sheltered 54-67	14.34	10.67	19.27
Unsheltered 18-24	1.128	0.7743	1.644
Unsheltered 25-34	2.328	1.712	3.167
Unsheltered 35-44	4.267	3.277	5.556
Unsheltered 45-54	8.678	6.454	11.67
Unsheltered 54-67	14.41	10.69	19.41
Baseline Group	Sheltered 18-24		
Covariates	Age, Gender, Hispanic, Race, Region		
Standard Errors	Robust		
Fixed Effects	Duration		
Age Group	18-54		

*** p<0.01, ** p<0.05, * p<0.1

Table A.51: Proportional Mortality Hazard by Geography, Family Connections, and Employment and INcome (Homeless Ages 18-54 in 2010)

	Coefficient	95% CI	
Geography			
New York	0.866	0.827	0.9058
California	1.029	0.9342	1.132
Baseline group	Other states		
Additional Covariates	Income		
Family Connections			
Has/Had Spouse	0.787	0.7466	0.8303
Baseline group	No Spouse		
Additional Covariates	Income		
Has Child	0.784	0.7431	0.8269
Baseline group	No Child		
Additional Covariates	Income		
Census Duplicate	0.864	0.8287	0.9017
Baseline group	No Census Duplicate		
Additional Covariates	Income		
Any Family Connection	0.827	0.7951	0.8608
Baseline group	No Observed Family Connection		
Additional Covariates	Income		
Employment and Income			
Employed	0.654	0.6115	0.6995
Baseline group	Not Employed		
Additional Covariates	None		
Top Half Income	0.673	0.6407	0.7073
Baseline group	Bottom Half Income		
Additional Covariates	None		
Covariates	Age, Gender, Hispanic, Race, Region, Sheltered		
Standard Errors	Robust		
Fixed Effects	Duration		
Age Group	18-54		

*** p<0.01, ** p<0.05, * p<0.1

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