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

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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.

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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 2 discusses related prior work, Section 3 describes our data, and Section 4 describes our methodology, including a discussion of how we define homelessness and link datasets. Section 5 presents our main results, as well as analyses of heterogeneity by demographic characteristics and geography and Section 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 7 compares our findings to prior work and Section 8 concludes.

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 5.

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 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. Data

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.[1] 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 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. 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 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.[2] 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

[1] 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.

[2] We test the robustness of our findings to differences between the Census and PIT definitions of a homeless shelter in Section 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.

differences in the sources' methodologies – suggests that the Census covered this population reasonably well.

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 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 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 6).

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.[3] 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.[4] 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 include DI amounts, Unemployment Insurance (UI) among people who do not file 1040s, and workers'

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

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.

4. Methods

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).[5] 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 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 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

[5] 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.

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.

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.[6] 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 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.[7]

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,

[6] 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.
[7] 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 Appendix A.

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 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.[8] 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 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

[8] Given exceptionally low linkage rates at TNSOLs, we exclude people recorded at these locations from our main results, although we show in Section 6 that our findings are robust to their inclusion.

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.

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 during the 2010 Census.[9] 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.

5.1 Characteristics of the Homeless and Housed Comparisons Samples

Table 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 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

[9] 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 on Appendix Tables A1-A7 contain detailed information about the definitions and methodology underlying income and program receipt measures.

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 housed person living in poverty in the United States.

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 2a and 2b.[10]

Connections to Formal Employment and the Safety Net

Figure 1a displays the share of the Census homeless population and single housed poor comparison group receiving various benefits and earnings in 2010.[11] 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 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.[12]

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

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[10] Detailed additional results are available in Appendix Tables A1-A7.

[11] 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.

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

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 1b). 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 1a, we find that people experiencing homelessness have extremely low incomes, indicating severe material deprivation. 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.[13]

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 Tables A3-A4). The safety net appears to provide crucial assistance to many people experiencing homelessness.

Comparisons to the Single Housed Poor

[13] 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.

Figures 1a and 1b 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.[14] W-2 records offer suggestive evidence of slightly elevated employment instability in the homeless population, with sheltered and unsheltered homeless 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 Tables A3-A5). 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 1b, 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.

[14] 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.

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

Persistence of Deprivation

Moving beyond static levels of deprivation, Figure 2 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 3a) and median earnings among those who are employed (Figure 3b) 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.[15] 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 $1,500 to $1,700 lower in 2009 relative to the two surrounding years, and for unsheltered homeless workers it was $500 to

[15] 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.

$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 4a and Figure 4b). 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 5a and 5b 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.[16] 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.

[16] 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 6 suggest that most of the rise preceding 2010 and fall after 2010 reflect true changes in SNAP receipt.

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.[17] 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 6 displays monthly SNAP enrollment among Chicago HMIS users relative to their first observed shelter entry.[18][19] 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.

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[17] 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).

[18] See Appendix Table A8.

[19] 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).

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.).[20]

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 7a) and had higher average earnings conditional on working (Figure 7b) 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).[21] 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 of

[20] See Appendix Tables A9-A12.

[21] 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.

individuals indicated as being enrolled in HMIS shelters in Los Angeles and Houston on March 30 of 2012 and 2013.[22] 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 8).

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 9a) and Hispanic ethnicity (Figure 9b). 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.

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

[22] 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.

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 10a, 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 10b 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 11c). 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.

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.

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 3a). 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 3b).[23] 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

[23] 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.

housed poor (28 percent) and overall housed population (7.7 percent).[24] 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 show sufficient error for income sources that a reliance solely on survey responses is likely to lead to substantial bias.

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.

[24] 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.

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.[25] 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

[25] 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.

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 11a), median earnings conditional being employed (Figure 11b), and benefit receipt (Table A13) 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 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.

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.[26] 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 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.

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

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.[27] Figures 12a and 12b 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.[28]

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 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

[27] 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.

[28] Table A14 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.

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 6.1, self-reported values of income and program receipt, while sometimes misreported, are nevertheless highly correlated with true values.[29] Including these self-reported measures in the IPW model should therefore account for most of any unobservable characteristics that are potentially associated with the 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 13a and 13b 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 13a, 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 A15 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.

[29] Table 3b 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.

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.[30]

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 A1-A4 (Tables A16 and A17) 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

[30] 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.

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.

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 4 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.[31] 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 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.

[31] 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.

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.[32] 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 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 5, 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 timeframe 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

[32] 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.

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.

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.

9. Citations

Bollinger, Christopher R., Barry T. Hirsch, Charles M. Hokayem, and James P. Ziliak. 2019. “Trouble in the Tails? What We Know about Earnings Nonresponse 30 Years after Lillard, Smith, and Welch.” *Journal of Political Economy* 127 (5): 2143–85. https://doi.org/10.1086/701807.

Browning, Martin, Pierre-Andre Chiappori, and Yoram Weiss. 2014. *Economics of the Family*. Cambridge University Press.

Burt, Martha R. 2001. “Homeless Families, Singles, and Others: Findings from the 1996 National Survey of Homeless Assistance Providers and Clients.” *Housing Policy Debate* 12 (4): 737–80. https://doi.org/10.1080/10511482.2001.9521428.

Burt, Martha R, Cohen, Barbara E. 1989. “America’s Homeless: Numbers, Characteristics, and Programs That Serve Them.” *Urban Institute Press*.

Burt, Martha R, United States, Interagency Council on the Homeless, and Urban Institute. 1999. *Homelessness: Programs and the People They Serve.* Collingdale, Penn.: DIANE Pub. Co.

Evans, William, James X Sullivan, and Melanie Wallskog. 2016. “The Impact of Homelessness Prevention Programs on Homelessness.” *Science* 353 (6300).

Han, Jeehoon, Bruce D. Meyer, and James X. Sullivan. 2021. “The Consumption, Income, and Well-Being of Single Mother–Headed Families 25 Years After Welfare Reform.” *National Tax Journal* 74 (3): 791–824. https://doi.org/10.1086/716242.

IOM (Institute of Medicine), and NRC (National Research Council). 2013. *Supplemental Nutrition Assistance Program: Examining the Evidence to Define Benefit Adequacy*. Washington, D.C.: The National Academies Press.

Kuhn, Randall, and Dennis P. Culhane. 1998. “Applying Cluster Analysis to Test a Typology of Homelessness by Pattern of Shelter Utilization: Results from the Analysis of Administrative Data.” *American Journal of Community Psychology* 26 (2): 207–32. https://doi.org/10.1023/A:1022176402357.

Lee, Barrett A., Kimberly A. Tyler, and James D. Wright. 2010. “The New Homelessness Revisited.” *Annual Review of Sociology* 36 (1): 501–21. https://doi.org/10.1146/annurev-soc-070308-115940.

Metraux, Stephen, Jamison D. Fargo, Nicholas Eng, and Dennis P. Culhane. 2018. “Employment and Earnings Trajectories During Two Decades Among Adults in New York City Homeless Shelters.” *Cityscape: A Journal of Policy Development and Research* 20 (2): 173–202.

Metraux, Stephen, Janna Manjelievskaia, Dan Treglia, Roy Hoffman, Dennis P. Culhane, and Bon S. Ku. 2016. “Posthumously Assessing a Homeless Population: Services Use and Characteristics.” *Psychiatric Services* 67 (12): 1334–39. https://doi.org/10.1176/appi.ps.201500388.

Meyer, Bruce D., and Nikolas Mittag. 2019. “Using Linked Survey and Administrative Data to Better Measure Income: Implications for Poverty, Program Effectiveness, and Holes in the Safety Net.” *American Economic Journal: Applied Economics* 11 (2): 176–204. https://doi.org/10.1257/app.20170478.

———. 2021. “An Empirical Total Survey Error Decomposition Using Data Combination.” *Journal of Econometrics* 224 (2): 286–305. https://doi.org/10.1016/j.jeconom.2020.03.026.

Meyer, Bruce D., Wallace K.C. Mok, and James X. Sullivan. 2015. “The Underreporting of Transfers in Household Surveys: Its Nature and Consequences.” University of Chicago Working Paper. Harris School of Public Policy.

Meyer, Bruce D, Derek Wu, Victoria Mooers, and Carla Medalia. 2021. “The Use and Misuse of Income Data and Extreme Poverty in the United States.” *Journal of Labor Economics* 39.

Meyer, Bruce D, Angela Wyse, and Kevin Corinth. 2022. “The Size and Census Coverage of the U.S. Homeless Population.” *NBER Working Paper Series*, no. No. 30163.

Meyer, Bruce D., Angela Wyse, and Kevin Corinth. 2023. “The Size and Census Coverage of the U.S. Homeless Population.” *Journal of Urban Economics* 136 (July): 103559. https://doi.org/10.1016/j.jue.2023.103559.

Meyer, Bruce D., Angela Wyse, Alexa Grunwaldt, Carla Medalia, and Derek Wu. 2021. “Learning about Homelessness Using Linked Survey and Administrative Data.” w28861. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w28861.

Meyer, Bruce, Angela Wyse, and Ilina Logani. 2023. “Life and Death at the Margins of Society: The Mortality of the U.S. Homeless Population.” *NBER Working Paper Series* w21843.

O’Flaherty, Brendan. 2011. *Homelessness in the United States*. Oxford Handbook of Urban Economics and Planning. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195380620.013.0013.

Phillips, David, and James X Sullivan. 2023. “Do Homelessness Prevention Programs Prevent Homelessness? Evidence from a Randomized Controlled Trial.” *The Review of Economics and Statistics*.

Rolston, Howard, Judy Geyer, Gretchen Locke, Stephen Metraux, and Dan Treglia. 2013. “Evaluation of the Homebase Community Prevention Program: Final Report.” *NYC Department of Homeless Services*.

Rossi, Peter. 1989. *Down and Out in America: The Origins of Homelessness*. Chicago, IL: The University of Chicago Press.

Russell, Deborah, and Diane Barrett. 2013. “2010 Census Service-Based Enumeration Assessment Report.” U.S. Census Bureau.

Shinn, Marybeth, Andrew L. Greer, Jay Bainbridge, Jonathan Kwon, and Sara Zuiderveen. 2013. “Efficient Targeting of Homelessness Prevention Services for Families.” *American Journal of Public Health* 103 (S2): S324–30. https://doi.org/10.2105/AJPH.2013.301468.

Social Security Administration (SSA). 2024. “Supplemental Security Income (SSI) Spotlight on Homelessness -- 2024 Edition.” https://www.ssa.gov/ssi/spotlights/spot-homeless.htm.

United States Department of Agriculture (USDA). 2013. “SNAP - Clarification of Policies Barriers Facing Homeless Youth.” https://www.fns.usda.gov/snap/snap-clarification-policies-barriers-facing-homeless-youth.

U.S. Department of Agriculture. 2013. “SNAP - Clarification of Policies Barriers Facing Homeless Youth.” https://www.fns.usda.gov/snap/snap-clarification-policies-barriers-facing-homeless-youth.

U.S. Department of Housing and Urban Development. 2010. “The 2009 Annual Homeless Assessment Report.”

———. 2022. “The 2022 Annual Homelessness Assessment Report to Congress, Part 1: Point-in-Time Estimates of Homelessness.”

Von Wachter, Till, Robert Santillano, Janey Rountree, Maya Buenaventura, Landon Gibson, April Nunn, Nino Migineishvili, and Alyssa Arbolante. 2021. “Preventing Homelessness:

Evidence-Based Methods to Screen Adults and Families at Risk of Homelessness in Los Angeles." *California Policy Lab: Policy Brief*.
Wachter, Till Von, Geoffrey Schnorr, and Nefara Riesch. 2020. "Employment and Earnings Among LA County Residents Experiencing Homelessness." *California Policy Lab: Policy Brief*.
Wagner, Deborah, and Layne, Mary. 2014. "The Person Identification Validation System (PVS): Applying the Center for Administrative Records Research and Applications' (CARRA) Record Linkage Software." *CARRA Working Paper Series* Working Paper #2014-01 (July).

10. Tables

Table 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.

Table 2a: 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

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: See notes on Tables A1-A6 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 2b: 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: 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: See notes on Tables A1-A6 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 3a: 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

Notes: 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 3b: 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

Notes: 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 4: 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

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.

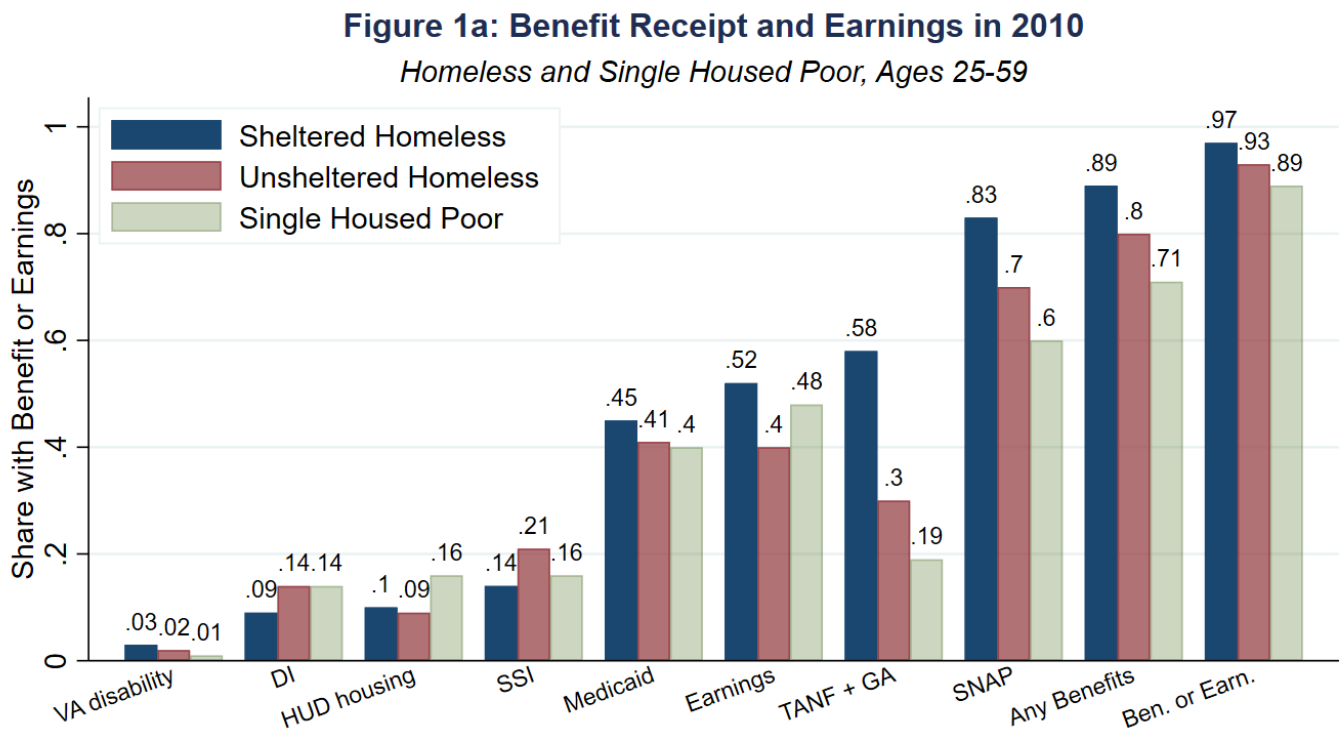
[2]Pre-tax cash income amounts reported in main tables do not include the value of SSI or TANF/GA from New York. We calculate pre-tax cash income with these benefits by adding the share receiving these benefits times the mean benefit amount conditional on receipt.

[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.

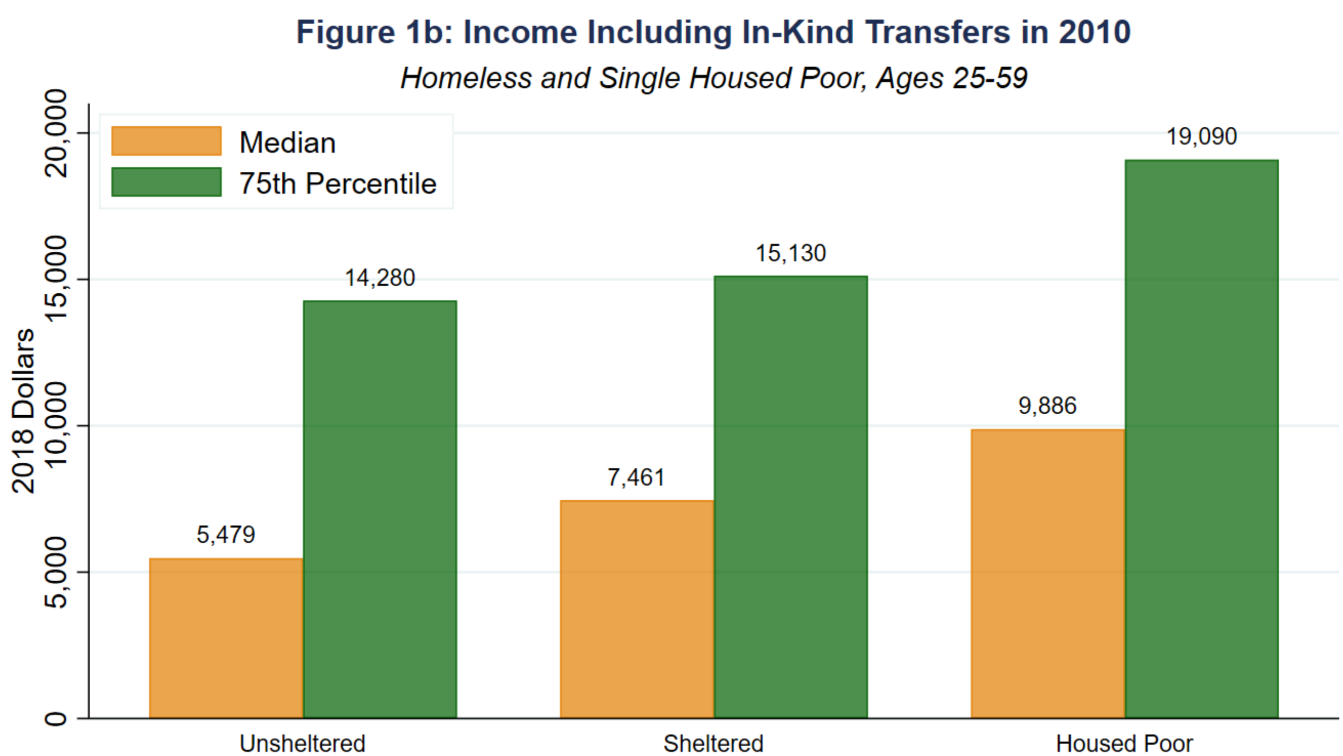
[4]We omit 2009 from the pre-period because we count people as homeless in the beginning of 2010, meaning that many individuals in our sample may have become homeless in 2009 rather than 2010.

[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.

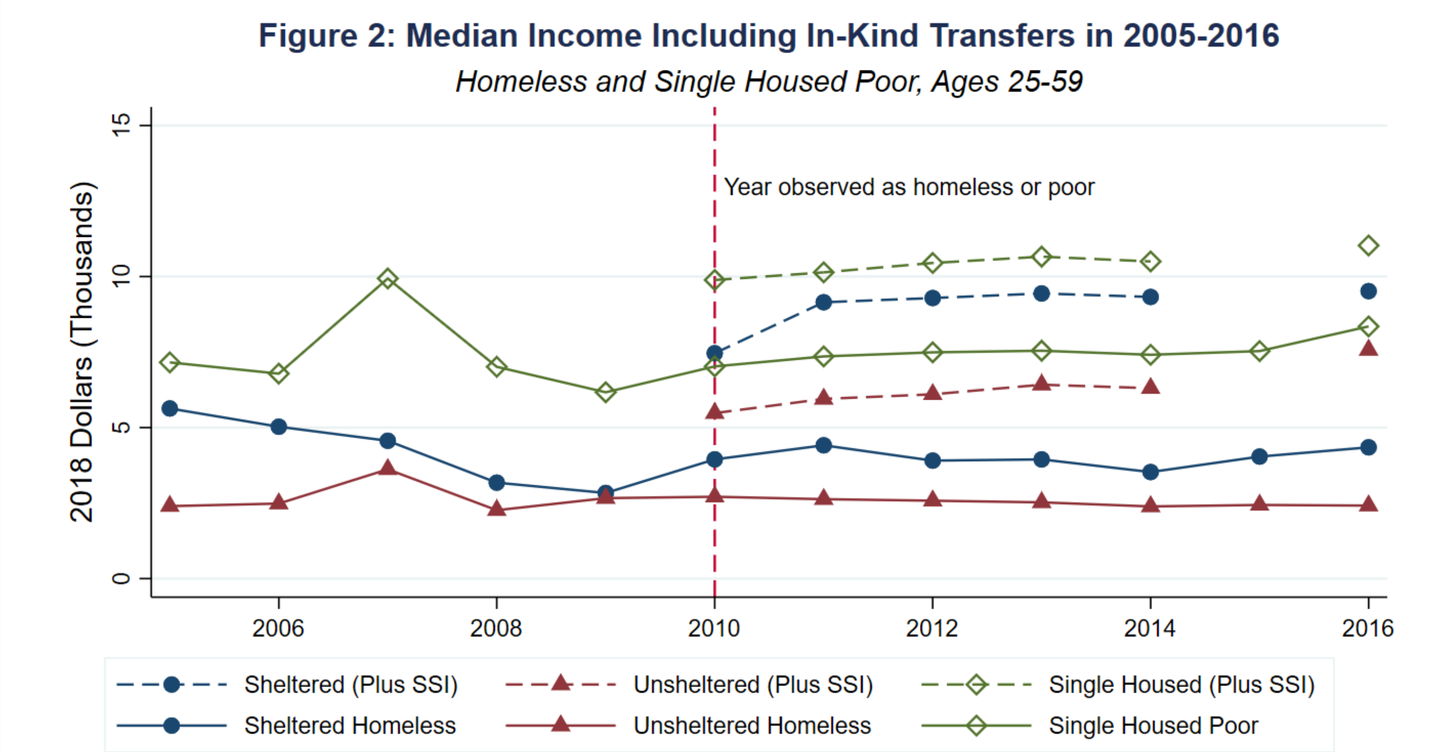
11. Figures



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



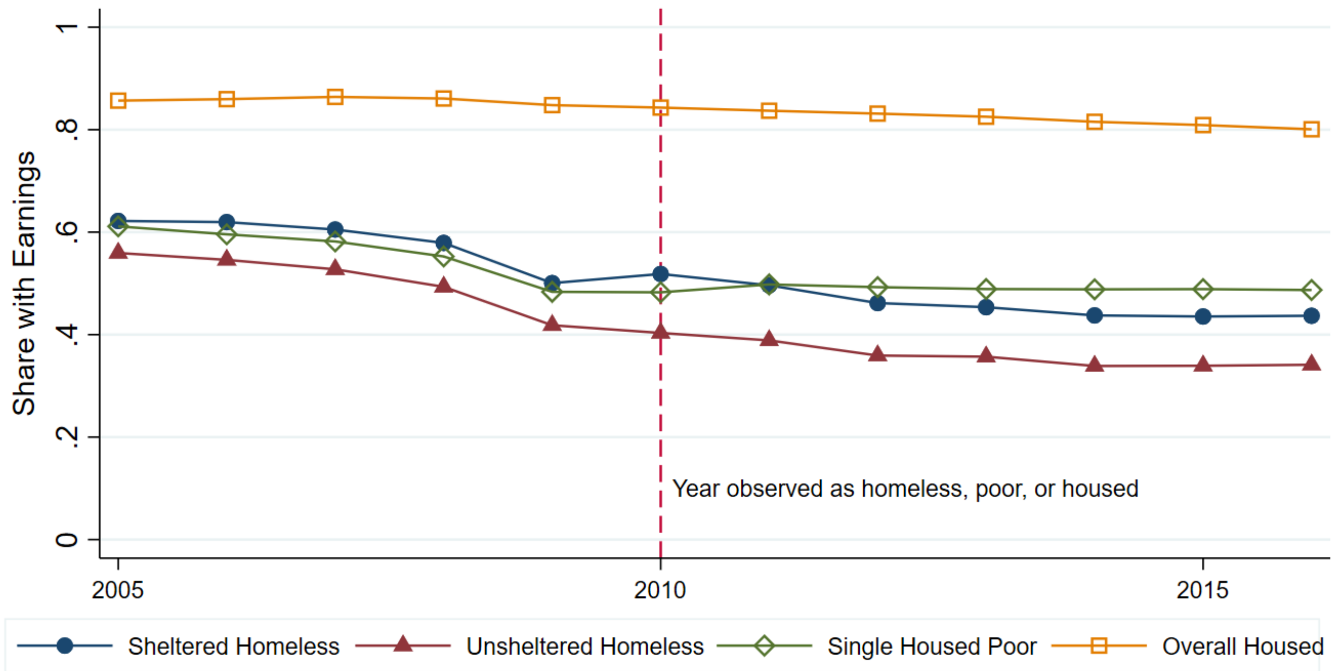
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015) SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. In-kind transfers from SNAP and HUD.



Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), SSI (2010-2014, 2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 3a: Share with Earnings, 2005-2016

Homeless, Single Housed Poor, and Overall Housed, Ages 25-59



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

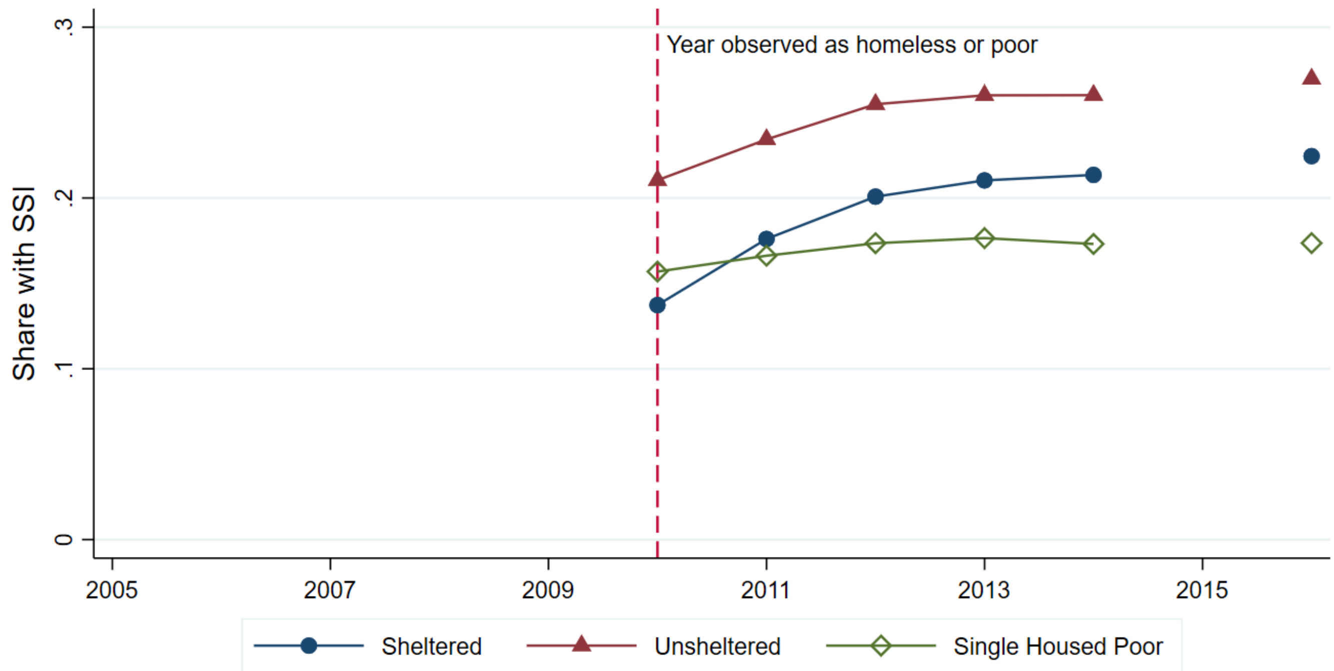
Figure 3b: Median Earnings (Conditional on Working), 2005-2016

Homeless, Single Housed Poor, and Overall Housed, Ages 25-59

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

Figure 4a: SSI Receipt, 2010-2016

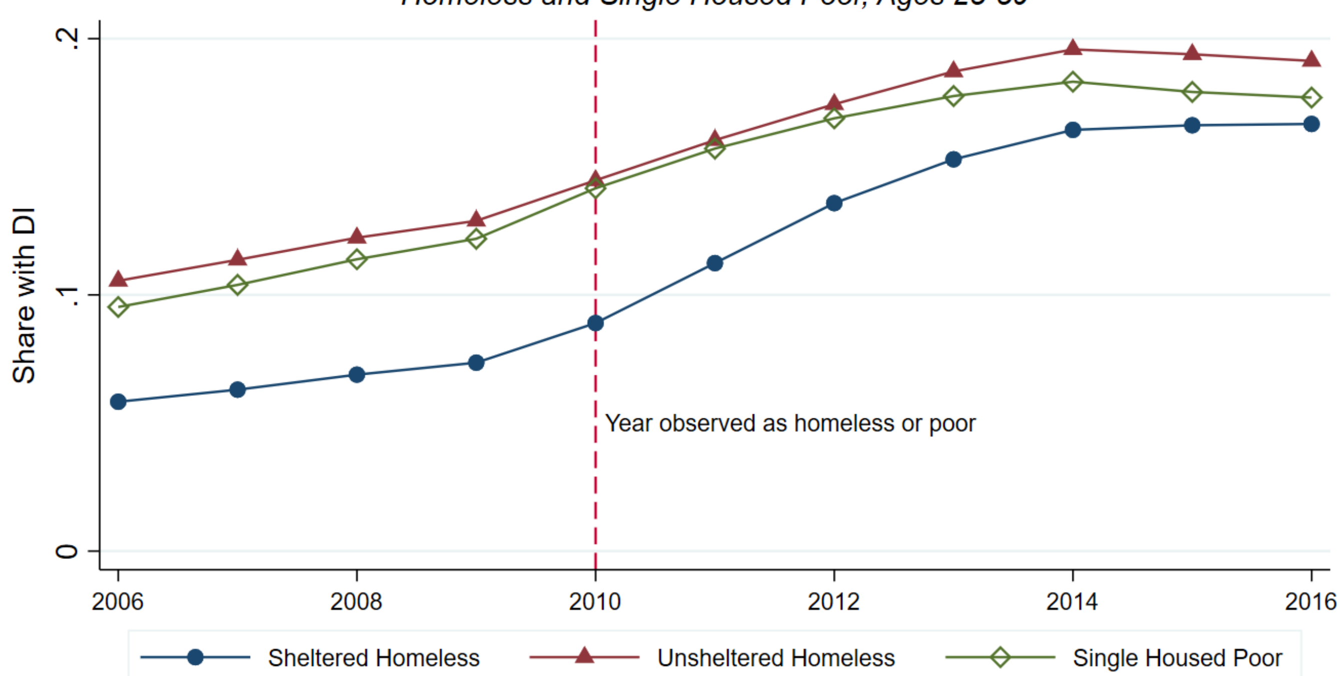
Homeless and Single Housed Poor, Ages 25-59



Sources: SSI Datasets (2010-2014, 2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 4b: DI Receipt (According to Medicare Records), 2006-2016

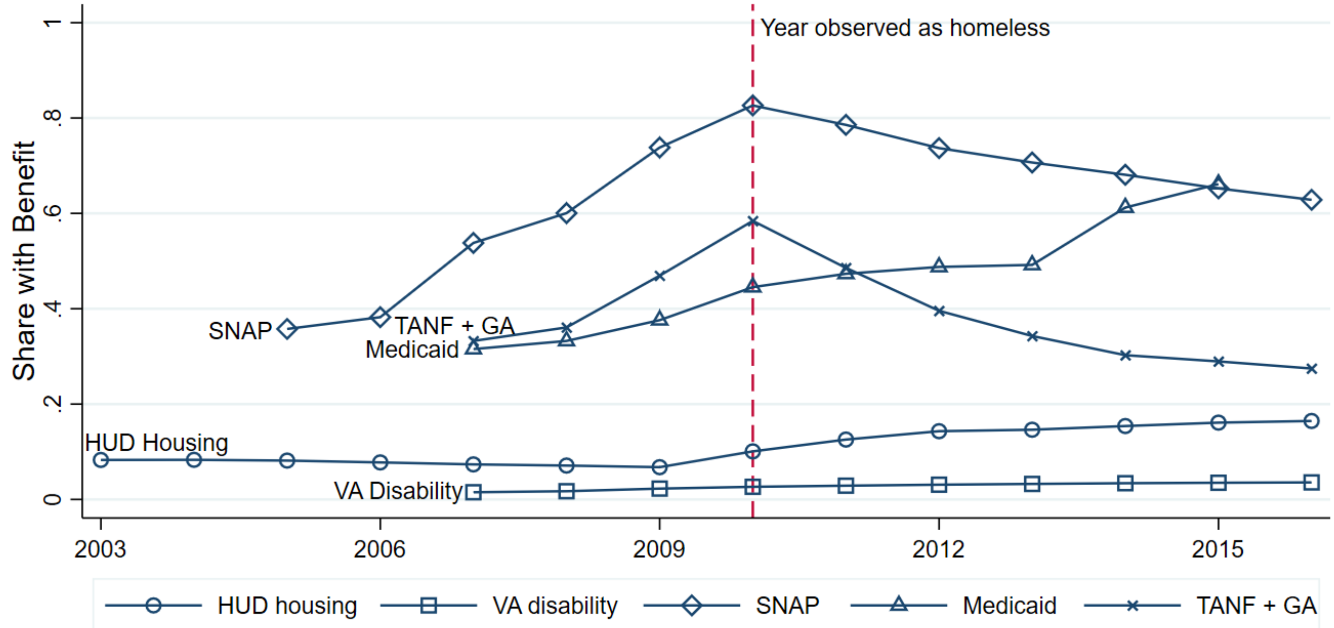
Homeless and Single Housed Poor, Ages 25-59



Sources: 2006-2016 Medicare Datasets, 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 5a: Program Receipt of Sheltered Homeless, 2003-2016

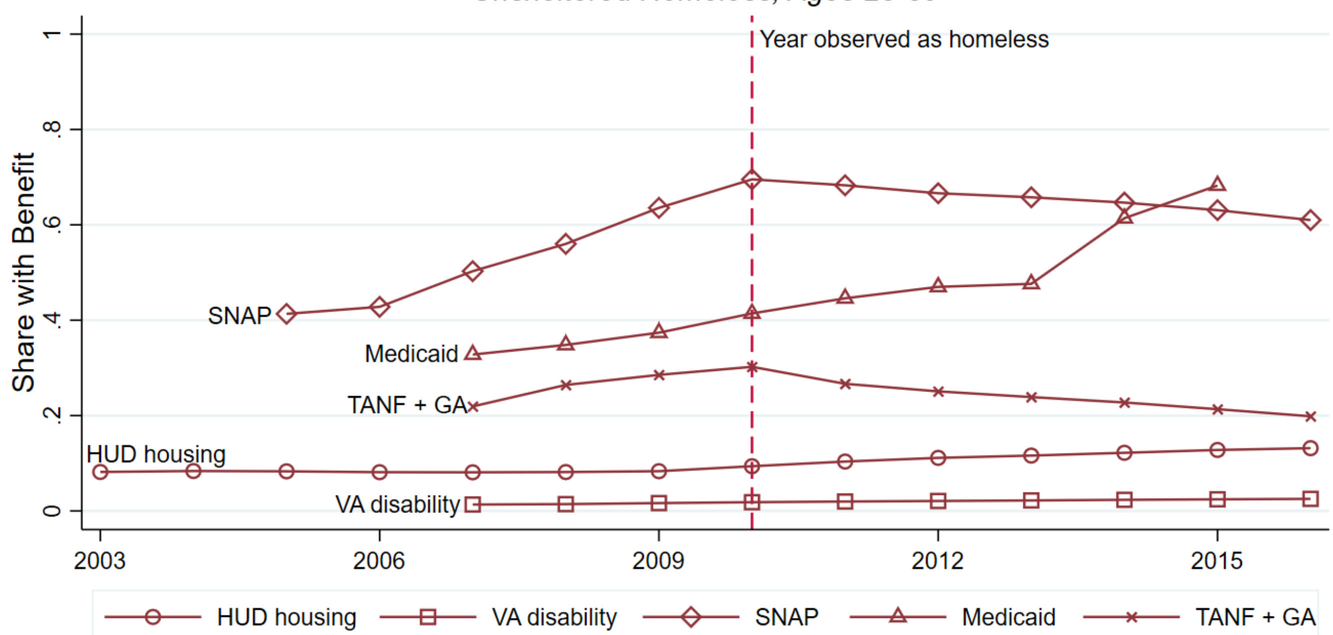
Sheltered Homeless, Ages 25-59



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

Figure 5b: Program Receipt of Unsheltered Homeless, 2003-2016

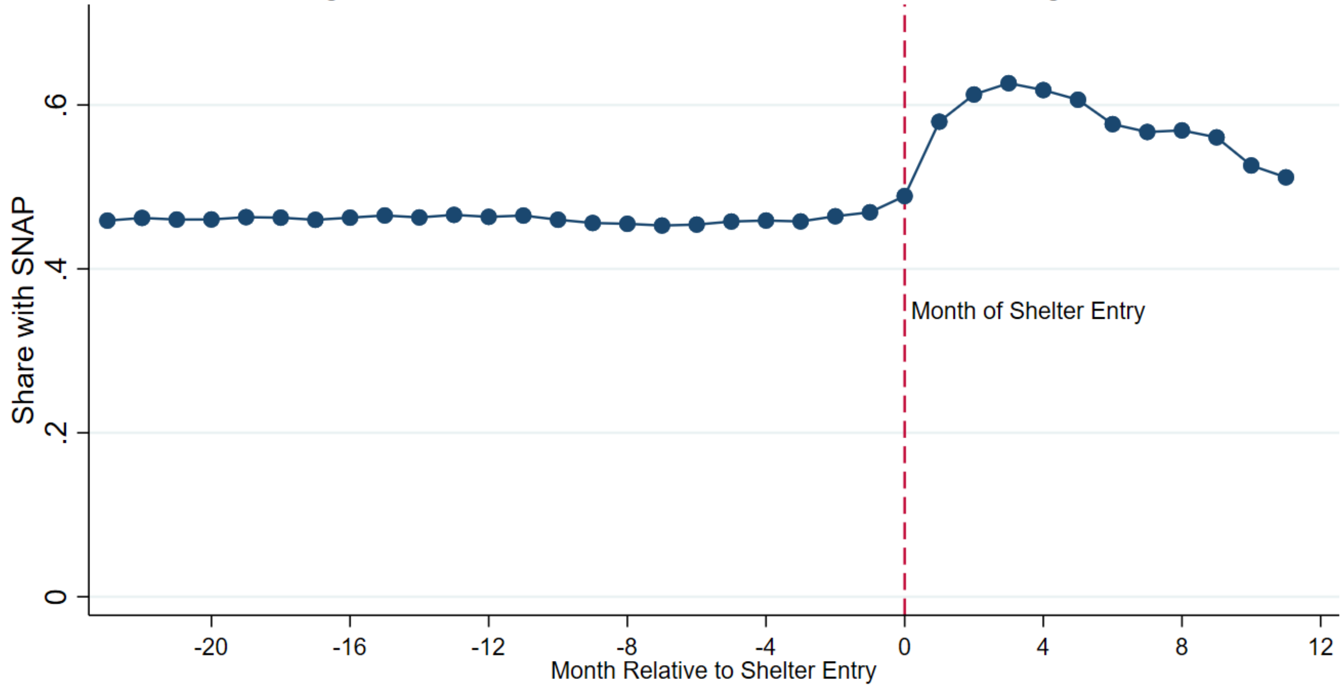
Unsheltered Homeless, Ages 25-59



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

Figure 6: Monthy SNAP Receipt in Chicago HMIS Data

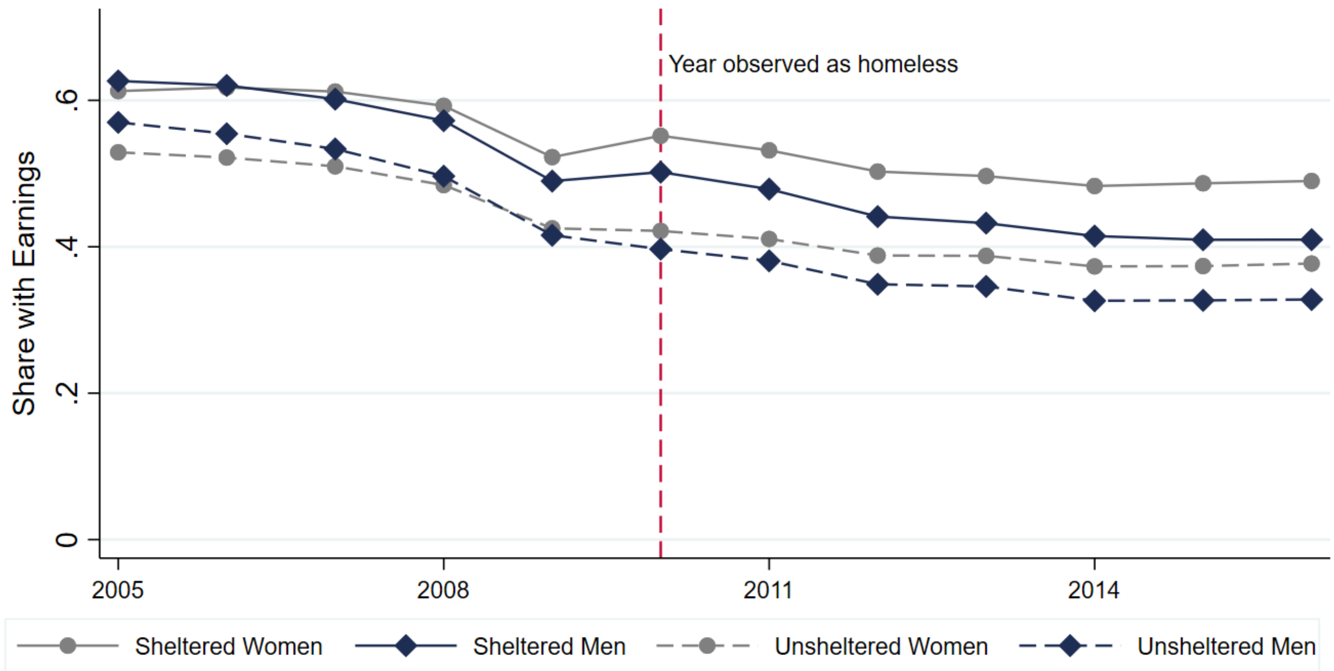
Chicago HMIS Shelter Users with First Enrollment in 2016, Ages 25-59



Sources: Chicago (2014-2019) HMIS dataset, Illinois SNAP dataset (2009-2016).
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 7a: Share with Earnings by Gender, 2005-2016

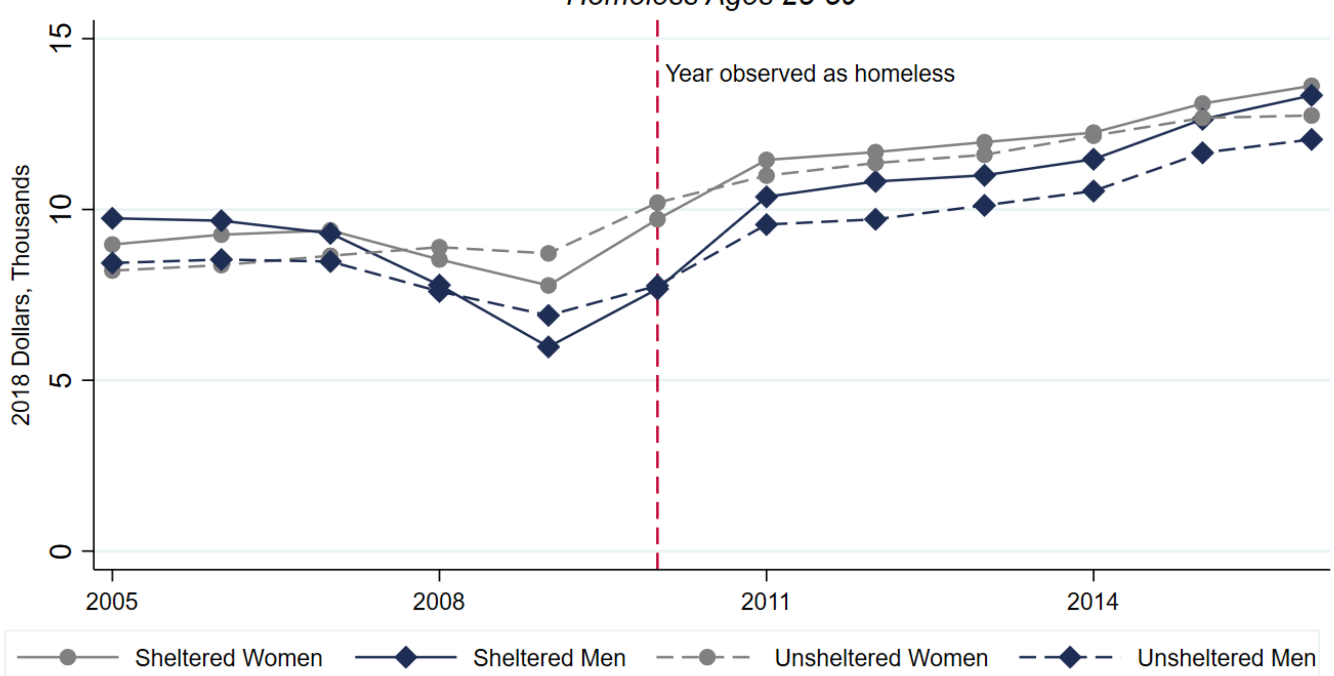
Homeless Ages 25-59



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

Figure 7b: Median Earnings by Gender (Conditional on Working), 2005-2016

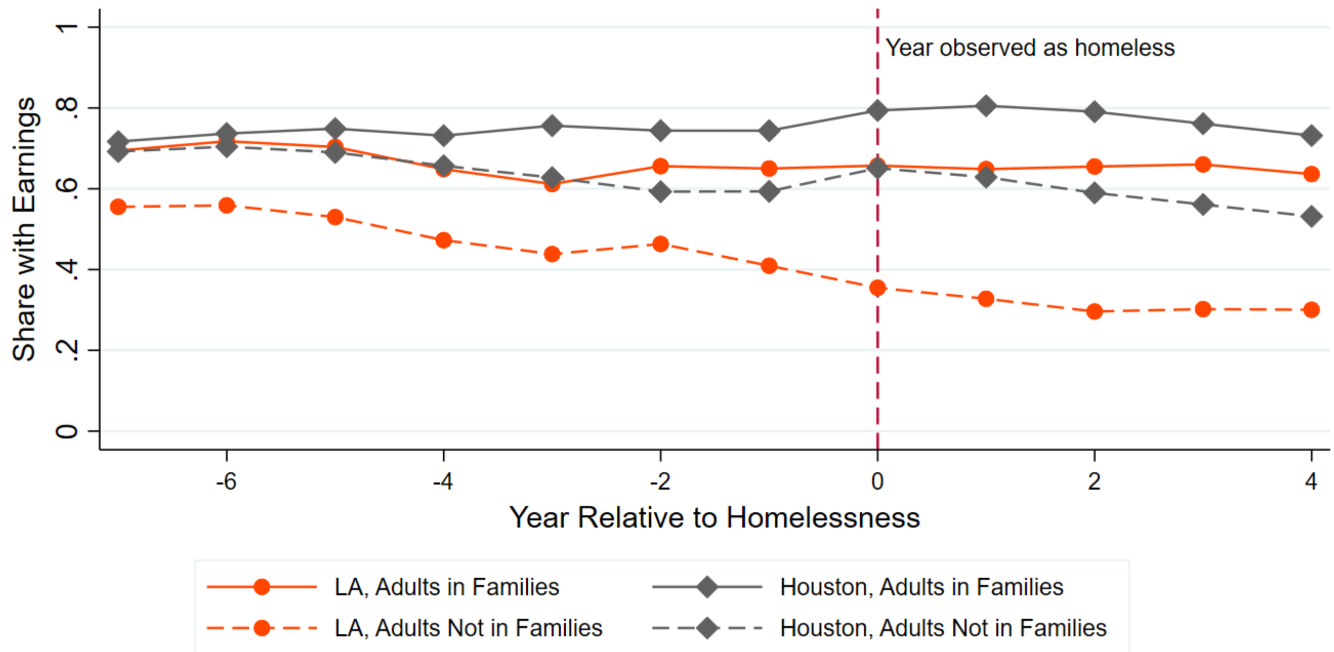
Homeless Ages 25-59



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

Figure 8: Share with Earnings by Family Status

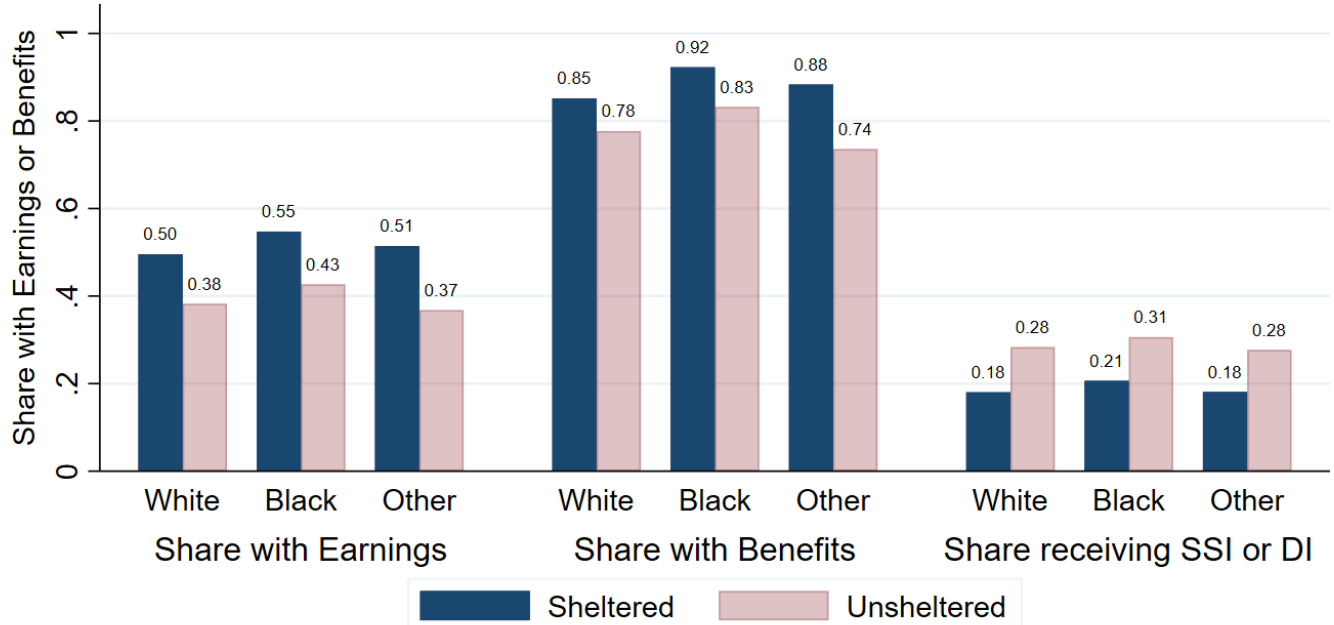
Los Angeles and Houston HMIS Shelter Users, 2012 and 2013



Sources: IRS 1040s (2003-2015), W2s (2005-2016), Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Sample contains those enrolled in HMIS shelters on March 30, 2012 or 2013.

Figure 9a: Share with Earnings, Benefits, and Disability by Race, 2010

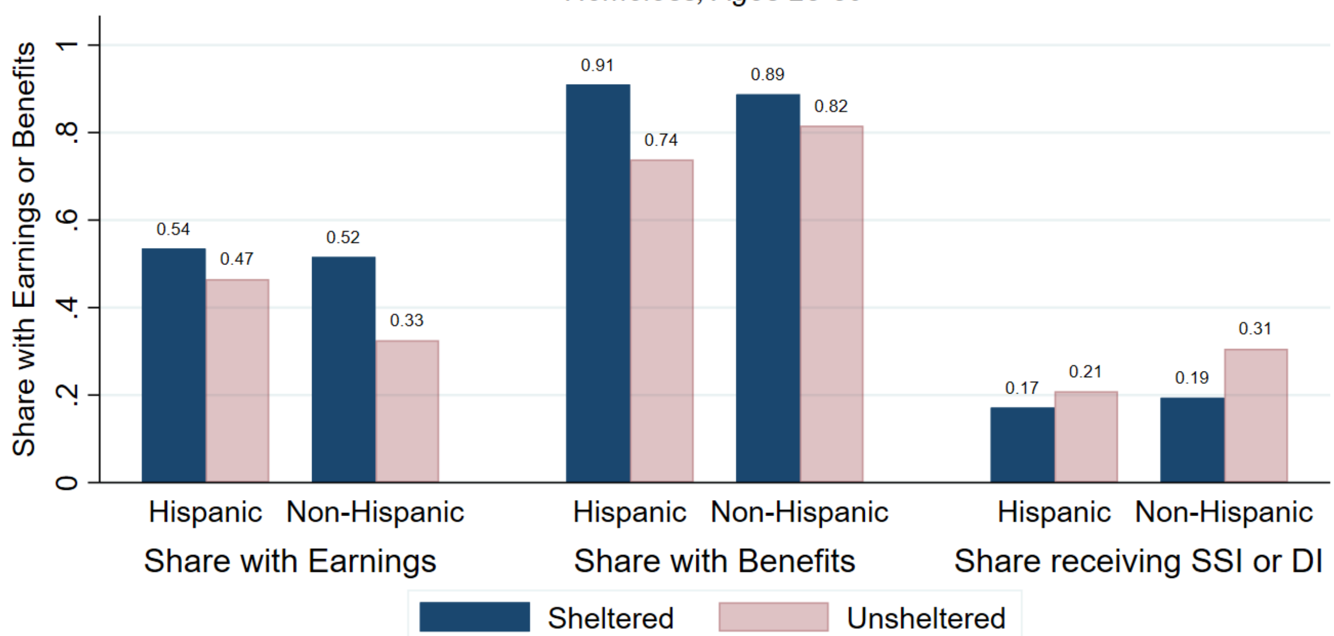
Homeless, Ages 25-59



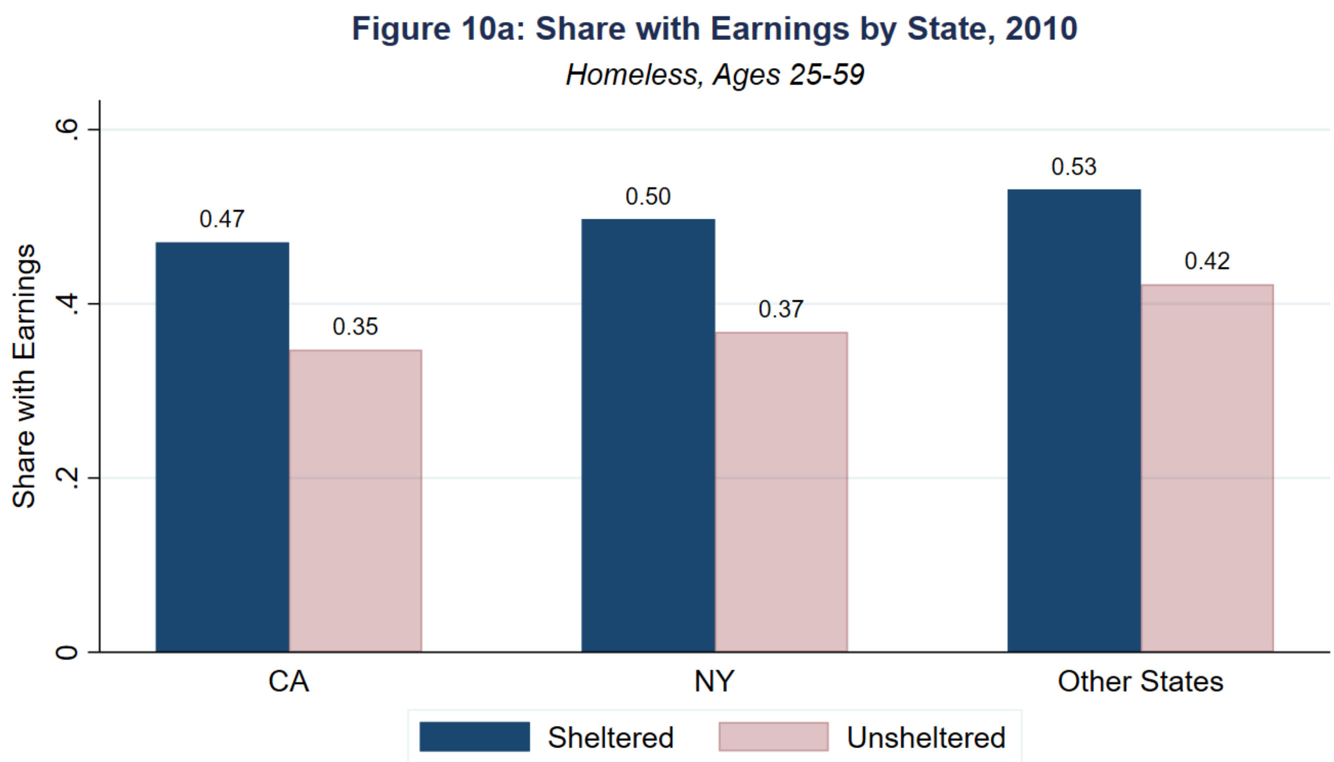
Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 9b: Share with Earnings, Benefits, and Disability by Ethnicity, 2010

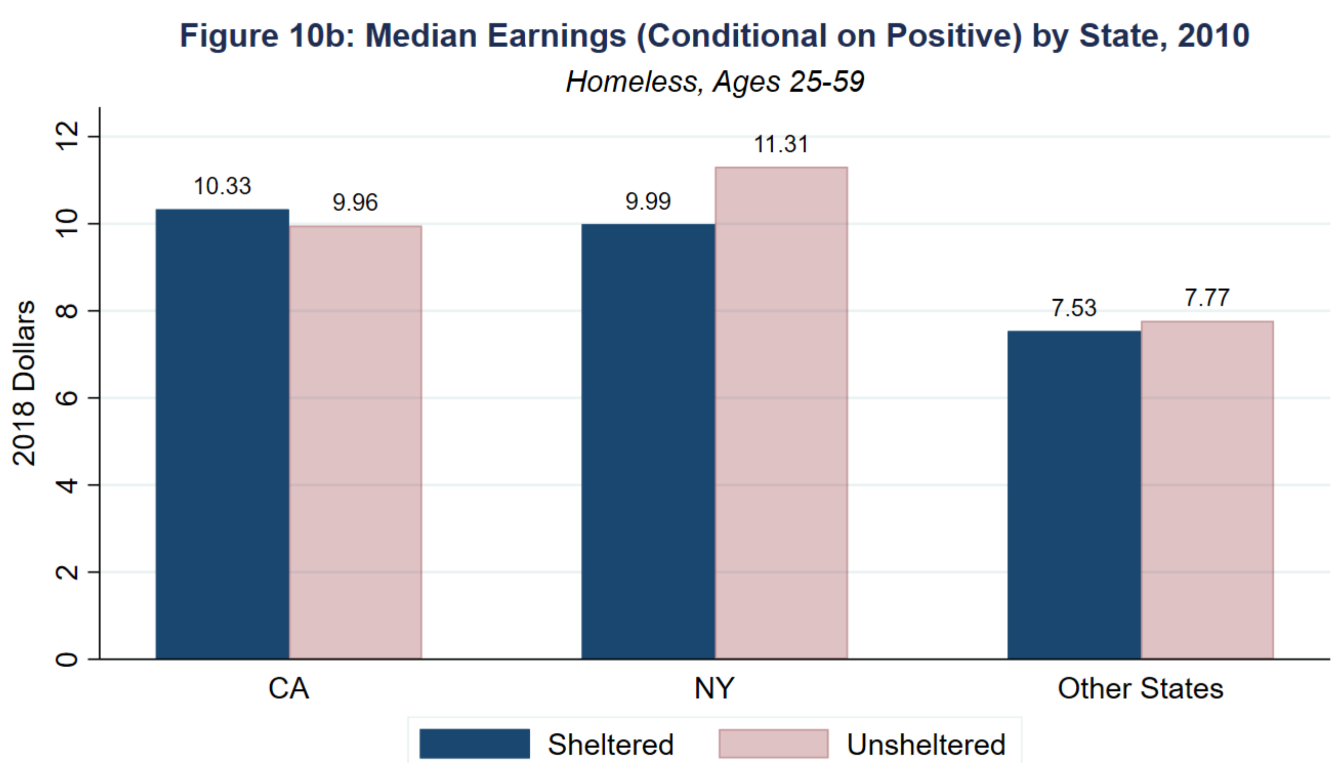
Homeless, Ages 25-59



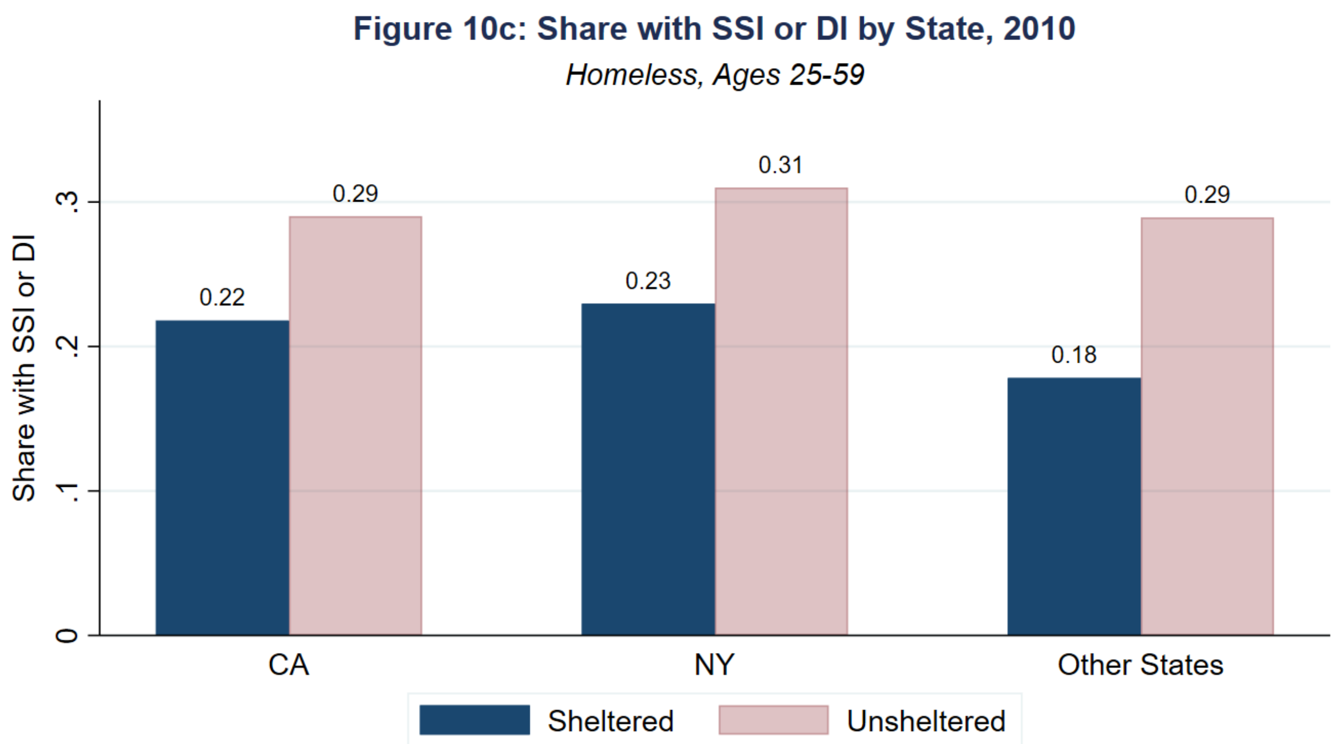
Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



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



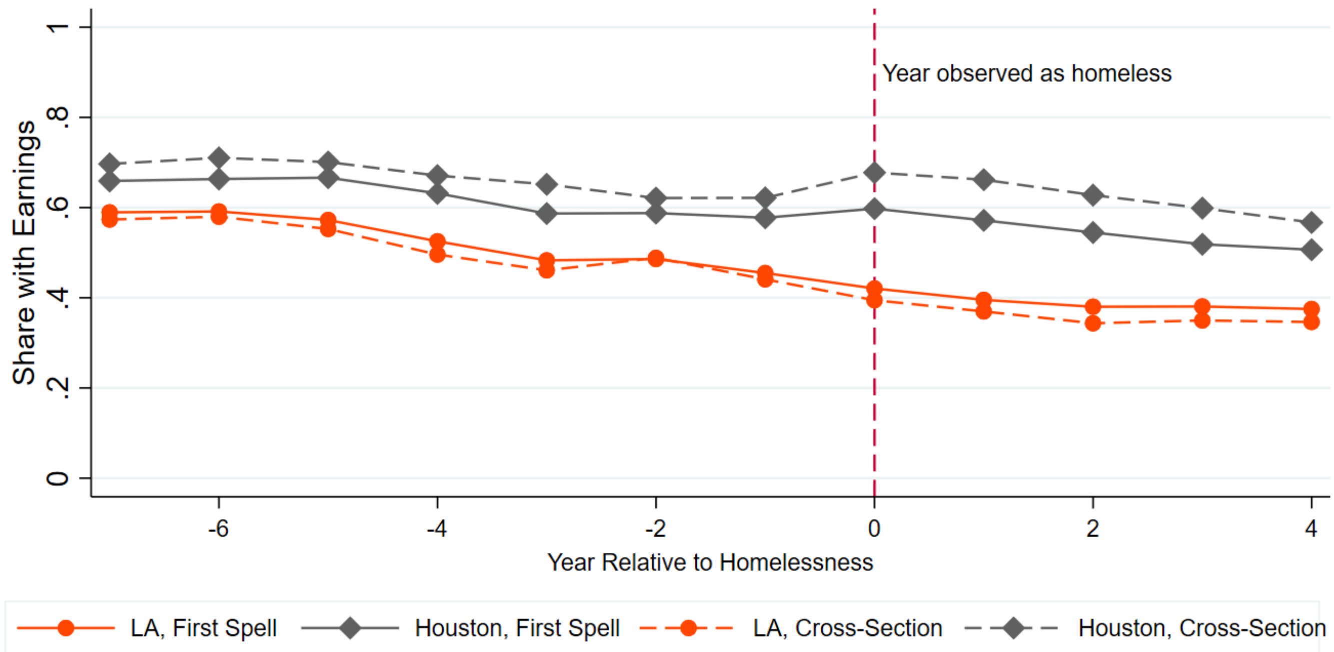
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



Sources: Medicare (2006-2014), Medicaid (2007-2015), SSI (2010-2014, 2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure 11a: Share with Earnings in HMIS Data, Comparison of Sample Time-Frames

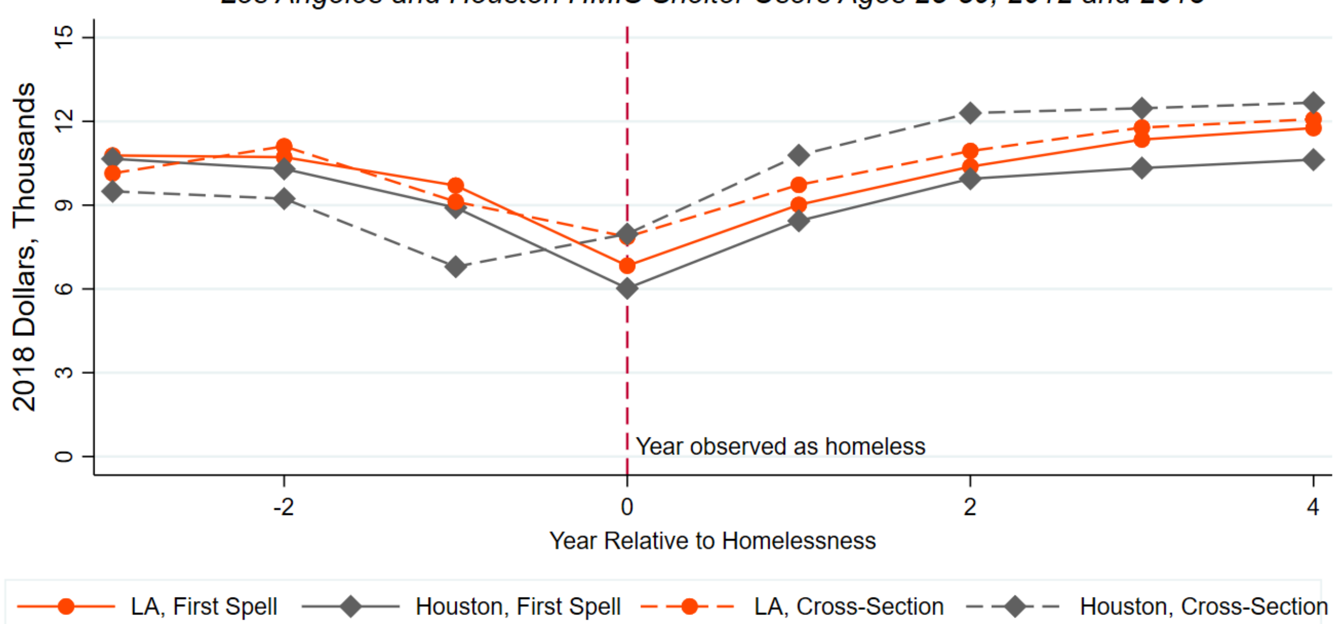
Los Angeles and Houston HMIS Shelter Users Ages 25-59, 2012 and 2013



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, 2003-2016 IRS 1040 Datasets, 2005-2016 W2 Datasets.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. "First spell" sample consists of those with first observed HMIS enrollment in 2012 or 2013. "Cross section" includes those enrolled on March 30, 2012 or March 30, 2013.

Figure 11b: Median Earnings (Conditional on Working), Comparison of Sample Time-Frames

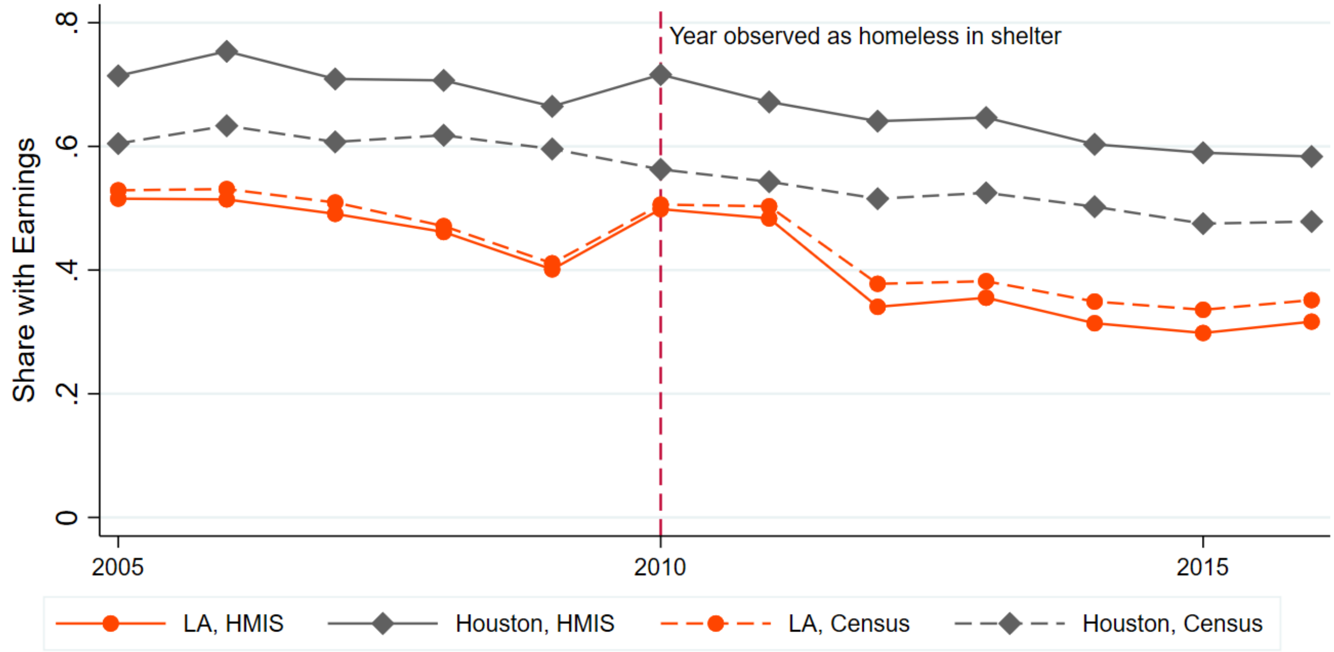
Los Angeles and Houston HMIS Shelter Users Ages 25-59, 2012 and 2013



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, IRS 1040s (2003-2015), W2s (2005-2016).
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. "First spell" sample consists of those with first observed HMIS enrollment in 2012 or 2013. "Cross section" includes those enrolled on March 30, 2012 or March 30, 2013.

Figure 12a: Share with Earnings, Comparison of HMIS and Census Samples

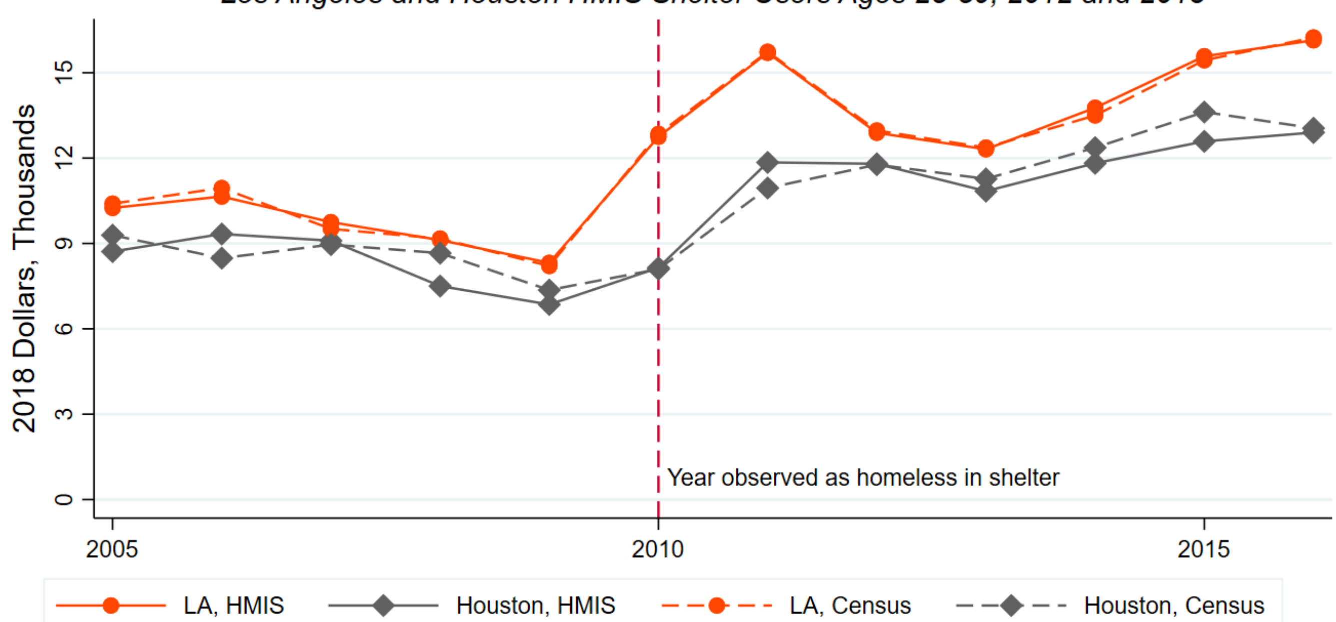
Los Angeles and Houston Census and HMIS Shelter Users Ages 25-59, 2012 and 2013



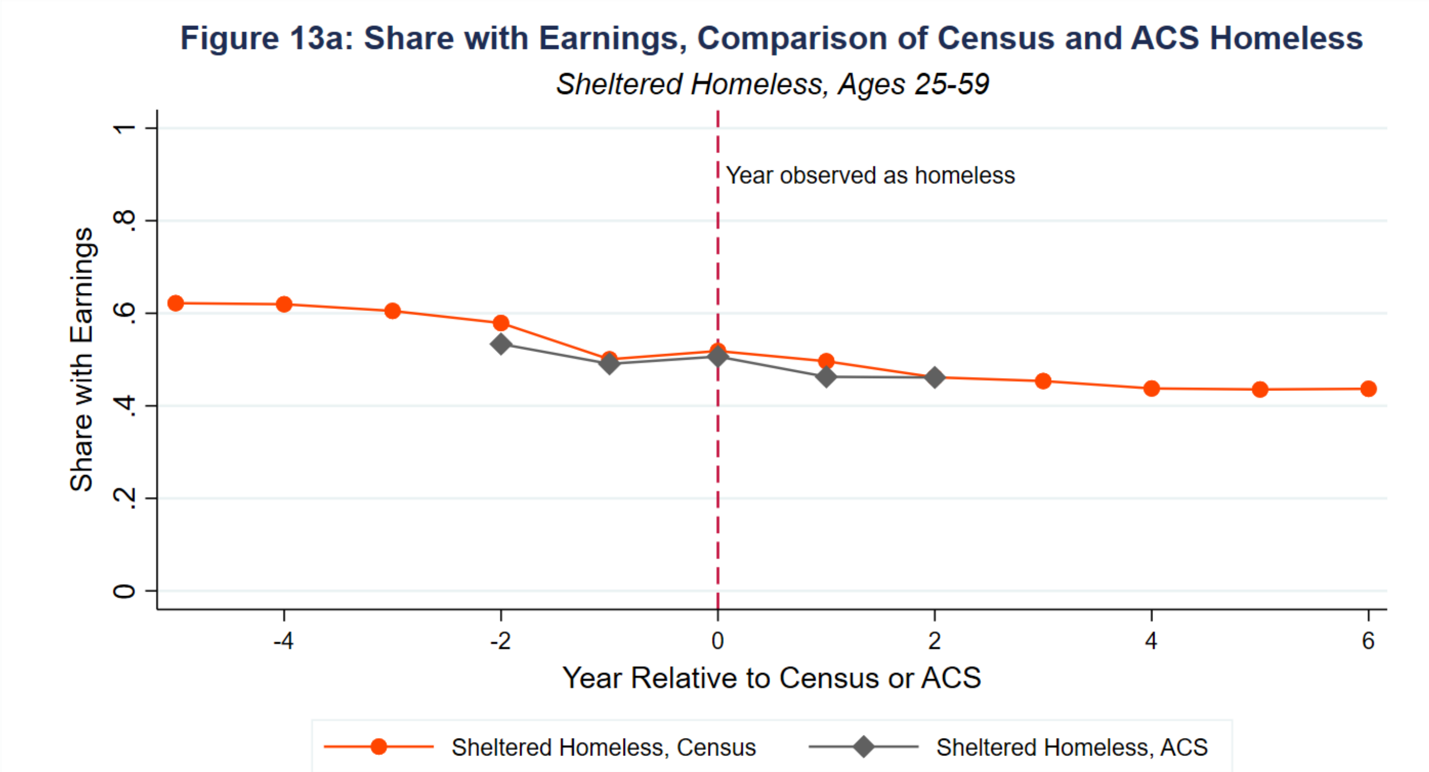
Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, 2010 Census, 2003-2016 IRS 1040 Datasets, 2005-2016 W2 Datasets.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Census sample consists of sheltered homeless 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 12b: Median Earnings (Conditional on Working), Comparison of HMIS and Census Samples

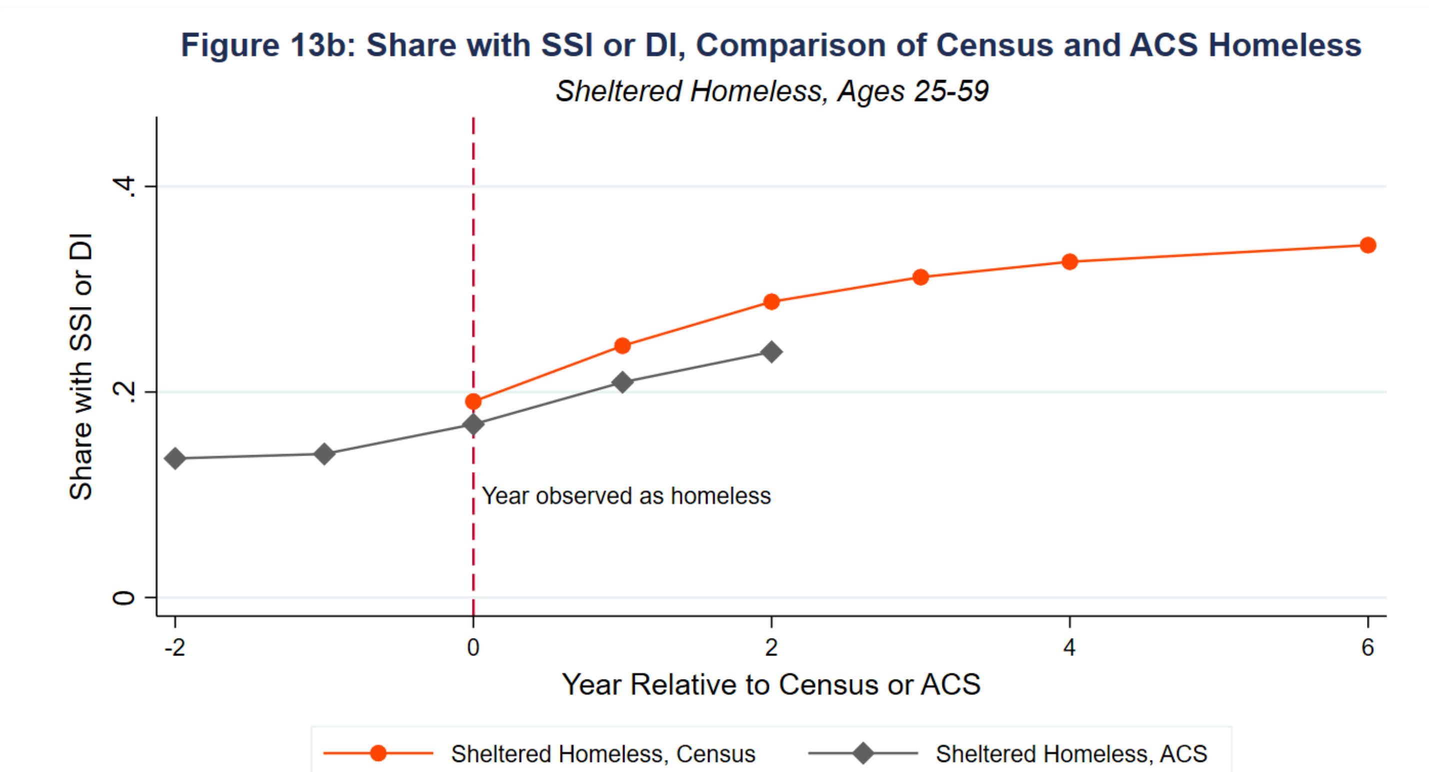
Los Angeles and Houston HMIS Shelter Users Ages 25-59, 2012 and 2013



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



Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010-2014 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



Sources: SSI Datasets (2010-2014, 2016), 2006-2016 Medicare Datasets, 2010 Census, 2010-2014 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.