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July 26, 2024

Via E-Filing

Ms. Lisa Felice
Executive Secretary
Michigan Public Service Commission
7109 West Saginaw Highway
Lansing, MI 48917

RE: MPSC Case No. U-21534

Dear Ms. Felice:

Please find enclosed the Accompanying Exhibits DAO-260 to DAO-270 (Part 2 of 4) for the Direct Testimony of Arjun Makhijani on Behalf of Soulardarity and We Want Green, Too, along with proof of service for electronic filing in the above-referenced matter. Please do not hesitate to contact me with any questions or comments.

Sincerely,

Mark N. Templeton, *pro hac vice*
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xc: Parties to Case No. U-21534

Health Care Utilization Patterns of Homeless Individuals in Boston: Preparing for Medicaid Expansion Under the Affordable Care Act

Monica Bharel, MD, MPH, Wen-Chieh Lin, PhD, Jianying Zhang, MD, MPH, Elizabeth O'Connell, MS, Robert Taube, PhD, MPH, and Robin E. Clark, PhD

Objectives. We studied 6494 Boston Health Care for the Homeless Program (BHCHP) patients to understand the disease burden and health care utilization patterns for a group of insured homeless individuals.

Methods. We studied merged BHCHP data and MassHealth eligibility, claims, and encounter data from 2010. MassHealth claims and encounter data provided a comprehensive history of health care utilization and expenditures, as well as associated diagnoses, in both general medical and behavioral health services sectors and across a broad range of health care settings.

Results. The burden of disease was high, with the majority of patients experiencing mental illness, substance use disorders, and a number of medical diseases. Hospitalization and emergency room use were frequent and total expenditures were 3.8 times the rate of an average Medicaid recipient.

Conclusions. The Affordable Care Act provides a framework for reforming the health care system to improve the coordination of care and outcomes for vulnerable populations. However, improved health care coverage alone may not be enough. Health care must be integrated with other resources to address the complex challenges presented by inadequate housing, hunger, and unsafe environments. (*Am J Public Health.* 2013;103:S311–S317. doi:10.2105/AJPH.2013.301421)

Several million Americans experience being homeless every year, and the majority of them cannot afford health insurance.[1] These individuals live on the periphery of society, struggling in abject poverty. They must prioritize basic shelter, safety, and food, and therefore often forgo medical care until conditions become urgent or irreversible. Unmanaged and worsening medical conditions can further extend the duration of homelessness and associated economic problems (e.g., unemployment). Additionally, many homeless individuals are held in the grip of addiction and have mental illness.[2] Given this complex set of circumstances, often compounded by a lack of health insurance coverage, providing medical care for these individuals can be challenging. Care often remains fragmented, taking place in emergency departments (EDs) and multiple inpatient and outpatient settings.

The Medicaid expansion through the Affordable Care Act (ACA) will be an unprecedented opportunity to improve access to health services for poor and homeless individuals around the country. Starting in 2014, individuals with incomes up to 138% of the federal poverty level will be eligible for Medicaid in states that choose to expand their Medicaid program. Given the high uninsured rate and low incomes among homeless people, they stand to benefit immensely from this expansion.

Although expanded coverage will almost certainly increase access to health care for many, little information is available on what types of services homeless patients will use when insurance is available. Homeless individuals have high rates of mental illness (e.g., depression) and certain medical illnesses (e.g., HCV or diabetes mellitus).[3–5] Previous investigations have shown a high level of health care utilization.[6–8] For example, in a survey of 2578 homeless patients, Kushel et al.[9] found that 40% of respondents had 1 or more ED visit in the last year, and 7.9% had 3 or more visits in the last year. These previous studies mainly used survey data, relied on self-reported data, or examined medical records of a single clinic, and many of the study populations were uninsured. Although these studies provide important information on the homeless population, the disease profiles obtained this way are not always complete, and there is incomplete information on health care utilization. Furthermore, they do not show utilization patterns for an insured homeless population. With health insurance, homeless individuals may have greater access to medications and preventive care that could reduce use of EDs and inpatient care. In the context of high rates of addiction, mental illness, and cognitive impairment, these crisis-driven utilization patterns may also persist in insured patients while expanding access to a wider range of services.

In Massachusetts, early Medicaid expansions since the 1990s have allowed a high percentage of homeless individuals to be insured under Medicaid, perhaps higher than most states in the country. Although Massachusetts is perhaps best known for its 2006 Medicaid expansion, unaccompanied homeless men and women were most beneficially affected by its 1115 waiver expansion in 1996. This expansion opened MassHealth (Massachusetts Medicaid) to chronically unemployed residents, and doubled the percentage of unaccompanied adults with Medicaid benefits from 30% to 60%. This expanded access to a variety of services for homeless men and women. The 2006 expansion built on this base and increased the percentage of insured homeless men and women; internal Boston Health Care for the Homeless Program (BHCHP) data demonstrated nearly 80% of patients have Medicaid or Medicare coverage.

Therefore, Massachusetts served as a unique environment in which to identify patterns of

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medical care utilization in the Medicaid enrolled homeless population. We examined Massachusetts Medicaid claims data in 2010 for a large cohort of homeless individuals seen at BHCHP. The program provides care to approximately 40% of the homeless population in Massachusetts.[10] Augmenting previous studies, this study provided a unique perspective by analyzing claims data for a large sample of homeless people with health insurance coverage. In addition to providing a comprehensive understanding of the disease burden among homeless individuals, this data set included both behavioral health services for mental illness and substance use disorders (SUDs) and general medical care. This provided an opportunity to understand current service use across these sectors in preparation for the integrated care envisioned in future care models.

METHODS

BHCHP was established in 1985 under a Robert Wood Johnson Foundation grant to improve access to high quality medical care to homeless individuals in and around Boston. Since then, the program has become a federally qualified neighborhood health center and now serves more than 12 000 individuals in an outreach model, at dozens of different sites. The model of care is a person-centered multidisciplinary and culturally competent holistic approach to patients. Clinic visits are a mix of urgent care, episodic care, chronic disease management, and preventive health care. Services include outreach directly to the street, soup kitchens, and adult and family shelters. The program also runs a 104-bed medical respite unit, providing 24-hour medical care for homeless individuals who are too sick for the shelter or street but do not meet criteria for admission into an acute hospital bed. The program is integrated into the medical community, providing critical health care to homeless individuals in Boston.[11]

We studied merged BHCHP data and MassHealth eligibility, claims, and encounter data from 2010. MassHealth claims and encounter data provided a comprehensive history of health care utilization and expenditures, as well as associated diagnoses, in both general medical and behavioral health services sectors and across a broad range of health care settings.

Study Population

The final study population included 6494 BHCHP patients with Medicaid in 2010. Although the BHCHP database showed 6846 potential Medicaid recipients, 343 individuals were excluded because they were not eligible for Medicaid and 9 individuals were enrolled in Medicaid managed care programs (Program for All-inclusive Care for Elderly and Senior Care Option); we did not have access to their health care utilization records.

The analysis followed the framework of the Andersen Health Care Utilization model, which classifies variables associated with health care utilization and expenditures into 3 sets of factors: predisposing, enabling, and need factors.[12] We incorporated population characteristics in the domains of predisposing and enabling factors, and included disability and disease burden for need factors. We obtained demographic characteristics information from MassHealth data, including member age, gender, disability status, and Medicare enrollment. Race/ethnicity was derived from BHCHP data, which provided more comprehensive information than MassHealth data. Disability status was determined by the Social Security Administration or Massachusetts Disability Evaluation Services. Major MassHealth coverage types included standard coverage with full Medicaid benefits and basic and essential coverage that were similar to the standard coverage, except for long-term support and services.

Disease Burden

We identified members with mental illness, and selected physical conditions using the *International Classification of Diseases, Ninth Revision, Clinical Modifications*[13] (*ICD-9-CM*) diagnosis codes in MassHealth claims and encounter data. The grouping of *ICD-9-CM* codes for diseases was based on the Clinical Classification Software developed by the Agency for Healthcare Research and Quality.[14]

Mental illness diagnoses included schizophrenia and other psychosis, bipolar disorders, depression, anxiety, and other mental illness. SUDs included alcohol abuse or dependence and drug abuse or dependence. In some instances, behavioral health disorder was used and referred to mental illness or SUDs. Members with co-occurring mental illness and SUDs were identified. We specifically identified patients with several prevalent medical diseases, including HCV, HIV, cirrhosis, asthma or chronic obstructive pulmonary disease (COPD), hypertension, congestive heart failure, ischemic heart disease, and diabetes.

We used the DxCG score to evaluate the overall disease burden for the study population. DxCG is a subsidiary of Verisk Analytics and is a provider of predictive modeling software. The DxCG score is a predictive modeling tool that uses the Diagnostic Cost Group (DCG) methodology and benchmark data to estimate a populations' disease rate.[15,16] In the DxCG model for the Medicaid population, the DxCG score is set to 1.0 for its original development sample of the general Medicaid population. In other words, DxCG scores greater than 1.0 indicate higher disease burden and scores less than 1.0 indicate that the disease burden is less than the average disease burden.

Health Care Utilization and Expenditures

We based the analysis of health care utilization and expenditures on paid MassHealth fee-for-service claims and those reported in managed care encounter data by MassHealth contracted managed care plans. Medicare services that generated "cross-over" Medicaid claims (for supplementing Medicare services) were included in the analysis. However, Medicare Part D pharmacy utilization and expenditures were not available for this analysis. General medical care and behavioral health services were reported, then analyzed separately and combined. Major health service categories and settings included hospitals, EDs, ambulatory care visits, prescriptions, dental, and outpatient detoxification. Inpatient detoxification was embedded in the overall hospitalization numbers. To assess the distribution of total annual expenditures, we ranked individuals by annual expenditures per person and then classified them into 5 expenditure groups.

Homeless individuals are at increased risk for exposure to HCV, and previous studies have shown increased prevalence rates. Therefore, we included a separate analysis of utilization among patients with HCV.[17]

Additionally, previous studies showed that treatment complexity increases for individuals with mental illness and SUDs[18,19]; therefore, we also conducted a separate analysis of utilization for this group. Finally, we compared the overall health care utilization between those with and without co-occurring mental illness and SUDs and between those with and without HCV. The χ^2 test was used for comparisons for categorical variables, and the *t*-test was used for continuous variables.

All analyses were performed with SAS statistical software, version 9.2 (SAS Institute, Inc., Cary, North Carolina).

RESULTS

We focused on results from the combined analysis for the 6494 BHCHP patients included in the study regardless of their dual eligibility for Medicare and Medicaid. (Data available as a supplement to the online version of this article at http://www.ajph.org provide detailed results from separate analyses for dual eligibles and Medicaid-only members.) The majority of BHCHP MassHealth patients were male (71%), and the mean age was 45.5 years. Forty-four percent were non-Latino White, 32% non-Latino African American, and 15% Latino; 58% had disabilities, and 27% were eligible for both Medicare and Medicaid (Table 1). On average, homeless individuals were enrolled in MassHealth for at least 11 months in 2010.

Homeless individuals experienced a high disease burden, including chronic diseases, infections, mental illness, and SUDs (Table 1). More than two thirds of the study population had some form of mental illness, with depression being the most prevalent diagnosis. SUDs were also highly prevalent (60%). Furthermore, almost half of homeless individuals (48%) had co-occurring mental illness and SUDs. The study population also had a high prevalence of several selected medical illnesses. There was a high prevalence of infectious diseases, including HCV (23%) and HIV (6%). Chronic diseases were also prevalent; 37% of the study population had a diagnosis of hypertension, 26% had COPD or asthma, and 18% had diabetes mellitus. The overall disease burden represented by the DxCG score was 3.8, which indicated a substantially higher burden than the general Medicaid population.[16]

On average, this homeless population had 10 ambulatory care visits annually. They also used EDs frequently, with an annual average of 4 visits and were hospitalized, on average, at least once a year. Notably, 20% of the population had 6 or more ED visits and 12% had 3 or more hospitalizations in a year. Moreover, approximate one third of ED visits and half of hospitalizations were attributable to behavioral health disorders (Table 2).

Homeless individuals with co-occurring mental illness and SUDs and those with HCV

TABLE 1—Population Characteristics: Boston Health Care for the Homeless Program (BHCHP) Users With Medicaid, 2010

Characteristic[a]	No. (%) or Mean ±SD
Age, y	45.5 ±13.3
Male	4587 (71)
Race/ethnicity	
Non-Latino White	2868 (44)
Non-Latino African American	2058 (32)
Latino	986 (15)
Others	214 (3)
Unknown	368 (6)
Disability status[b]	3734 (58)
Dually eligible for Medicare and Medicaid	1761 (27)
Behavioral health disorders[c,d]	5139 (79)
Any mental illness	4384 (68)
Schizophrenia	1264 (19)
Bipolar disorders	1889 (30)
Depression	3068 (47)
Anxiety	2627 (40)
Others	1765 (27)
Any substance use disorders	3890 (60)
Alcohol use disorder	2628 (40)
Drug use disorder	3118 (48)
Co-occurring mental illness and substance use disorders	3135 (48)
Selected physical conditions[c,d]	4177 (64)
HCV	1473 (23)
HIV	410 (6)
Cirrhosis	254 (4)
Asthma/COPD	1712 (26)
Hypertension	2395 (37)
Congestive heart failure	265 (4)
Ischemic heart disease	560 (10)
Diabetes	1191 (18)
Overall disease burden[e]	3.8 ±3.8

Note. COPD = chronic obstructive pulmonary disease. The sample size was n = 6494.
[a]Based on the last segment of MassHealth eligibility or enrollment data in 2010, except for race/ethnicity, which was based on BHCHP data.
[b]Determined by the Social Security Administration or Massachusetts Disability Evaluation Services.
[c]Both MassHealth claims data and managed care encounter data were used for the prevalence analysis; however, laboratory claims and radiology claims were not included.
[d]Diseases listed are not mutually exclusive.
[e]Disease burden is represented by the DxCG score. A DxCG score of 1 equals average expected expenditures or average disease burden in DxCG's original development sample of the general Medicaid population. Scores > 1 indicate higher than average disease burden and scores < 1 indicate lower than average disease burden. The median disease burden was 2.6.

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TABLE 2—Health Care Utilization: Boston Health Care for the Homeless Program Users With Medicaid, 2010

Types of Health Services[a]	Behavioral Health Services, No. (%) or Mean ±SD	General Medical Care, No. (%) or Mean ±SD	Both, No. (%) or Mean ±SD
Ambulatory care visits	1.0 ±3.2	9.0 ±10.4	10.0 ±11.0
None	4503 (69)	356 (5)	262 (4)
1–2	1394 (21)	1244 (19)	1089 (17)
3–5	320 (5)	1520 (24)	1433 (22)
> 5	277 (4)	3374 (52)	3710 (57)
ED visits	1.3 ±4.2	2.7 ±4.7	4.0 ±7.3
None	4464 (69)	2292 (35)	1990 (31)
1–2	1157 (18)	2126 (33)	1932 (30)
3–5	454 (7)	1139 (18)	1168 (18)
> 5	419 (6)	937 (14)	1404 (21)
Hospitalizations[b]	0.5 ±1.5	0.5 ±1.6	1.0 ±2.4
None	5369 (83)	4958 (76)	4287 (66)
1–2	765 (12)	1143 (18)	1436 (22)
> 2	360 (5)	393 (6)	771 (12)
Hospital length of stay, d[c]	8.0 ±12.4	5.7 ±9.5	7.0 ±11.4
Outpatient detoxification[d]			
None	4952 (76)	NA	4952 (76)
1	391 (6)	NA	391 (6)
≥ 2	1151 (18)	NA	1151 (18)
Mean ±SD	1.4 ±4.6	NA	1.4 ±4.6

Note. ED = emergency department. The sample size was n = 6494.
[a]Based on MassHealth fee-for-service claims and managed care encounter data.
[b]Including acute inpatient, psychiatric inpatient, semiacute hospitals, chronic inpatient hospital, and state hospitals.
[c]For members with at least 1 hospitalization in 2010. Median hospital length of stay was 4.0 for both behavioral health and general medical care.
[d]Inpatient detoxifications are included in hospitalizations.

had high health care utilization (Table 3). More than one third of them had 6 or more ED visits and more than 20% of them had 3 or more hospitalizations. Except for hospital length of stay, health care utilization for these 2 groups was substantially higher than among those without these conditions ($P < .001$).

Homeless individuals had high health care expenditures—$2036 per member per month compared with $568 per month for all MassHealth members.[20] Almost half of total annual expenditures were incurred by 10% of the study population (Table 4). The 2 highest categories of health care expenditure were hospitalizations and ED visits, which represented 40% and 11% of total expenditures, respectively.

DISCUSSION

Medicaid expansion under the ACA could improve access to care for homeless individuals across the country. This study was a unique analysis of a Medicaid claims database for homeless individuals in Boston, Massachusetts, who already had health insurance. Our findings reinforced the understanding that homeless individuals have a great deal of physical illness, mental illness and addictions. This high disease burden adds to the existing life stress created by unsafe and uncertain housing and the daily search for food and clothing.[21,22] In this context, conditions that could be managed in stably housed patients become life threatening.

Diabetes mellitus was an example of a disease made much worse by the social circumstances of homelessness, including limited access to nutritious food, an irregular meal schedule, inability to refrigerate insulin, and challenges of carrying needles. The prevalence of diabetes mellitus was extremely high in this population (18%) compared with the general population (8.3%).[23] HCV was another example of a disease made worse by the social circumstances of homelessness. The prevalence in this cohort was 24% compared with 1.8% of the general population.[24] Treatment and management of HCV typically requires access to sophisticated technology and medications and management of multiple medical appointments and procedures. Adherence to treatment regimens are complicated by being homeless. Mental illness and substance use disorders, prevalent in staggering proportions in this group of patients, further complicate management of chronic physical illness. Previous studies showed that these behavioral health disorders are associated with lower quality indicators, lower adherence with prescribed treatment, and higher health care expenditures.[19,25–27] In this analysis, we found that the presence of HCV resulted in higher utilization of many services, including the ED, hospitals, and outpatient services.

Overall, our findings showed that homeless individuals used the ED 4 times a year on average, and 20% of the cohort had 6 or more ED visits per year. In comparison, only 1% of the general population and 5% of Medicaid recipients used the ED 4 or more times a year.[28] Hospitalization rates were also high, with these individuals using the hospital more than domiciled patients. Hospital stays averaged 1 per year with an average length of stay of 7 days. Additionally, 12% of the study population had 3 or more hospitalizations in a year. Previous studies of homeless individuals showed that lack of health insurance was associated with more use of acute hospital facilities and fewer ambulatory services,[6] but in this insured cohort, rates of ED and hospitalization remained high.

Behavioral health disorders appeared to be a factor associated with higher utilization. One third of ED visits and half of all hospitalizations were attributable to behavioral health disorders. This was consistent with previous studies that showed that behavioral health disorders were associated with increased Medicaid expenditures.[19] High use of the medical system was reflected in health care costs, including a per-member-per-month expenditure of $2036, of which one third were for services directly related to mental illness or SUDs.

TABLE 3—Overall Health Care Utilization: Subgroups of Boston Health Care for the Homeless Program Users With Medicaid, 2010

	Co-Occurring Mental Illness and SUDs,[b] No. (%) or Mean ±SD		HCV,[c] No. (%) or Mean ±SD	
Types of Health Services[a]	With (n = 3135)	Without (n = 3359)	With (n = 1473)	Without (n = 5021)
Ambulatory care visits	11.6 ±11.5	8.5 ±10.1	13.5 ±12.6)	9.0 ±10.2
None	2	5	1	5
1–2	11	22	9	19
3–5	20	24	17	24
> 5	67	48	73	52
ED visits	6.3 ±9.1	1.8 ±3.6	6.3 ±9.5	3.3 ±6.2
None	15	46	19	34
1–2	26	33	23	32
3–5	23	13	23	17
> 5	35	8	35	17
Hospitalizations[d]	1.8 ±3.1	0.3 ±0.9	2.0 ±3.4	0.7 ±1.8
None	48	83	45	82
1–2	31	14	30	5
> 2	22	3	25	13
Hospital length of stay, d[e]	6.8 ±11.0	7.4 ±12.7	6.7 ±12.4	7.0 ±10.9
Outpatient detoxification[f]	2.7 ±6.1	0.3 ±1.6	2.9 ±6.4	1.0 ±3.7
None	58	93	58	82
1	10	2	10	5
≥ 2	32	5	32	13

Note. ED = emergency department; SUDs = substance use disorders.
[a]Based on MassHealth fee-for-service claims and managed care encounter data.
[b]Homeless individuals with co-occurring mental illness and SUDs had significantly higher health care utilization than those without co-occurring mental illness and SUDs ($P < .001$ from the χ^2 test for categorical variables and the *t*-test for interval variables), except for hospital length of stay.
[c]Homeless individuals with HCV had significantly higher health care utilization than those without HCV ($P < 0.0001$ from the χ^2 test for categorical variables and the *t*-test for interval variables), except for hospital length of stay.
[d]Including acute inpatient, psychiatric inpatient, semiacute hospitals, chronic inpatient hospital, and state hospitals.
[e]For members with at least 1 hospitalization in 2010.
[f]Inpatient detoxifications are included in hospitalizations.

Even among this population with higher than average costs, there was a subgroup of very high service users (n = 650; 10%) who were responsible for 48% of total expenditures (Table 4). The greater flexibility in payment and service delivery provided by the ACA could be used to provide intensive, targeted services to high need groups.

In implementing the ACA, which is designed to profoundly enhance access to care, states must determine how to incorporate the new recipients of Medicaid into the health care delivery system in the most effective way. Our findings provided a window into the health care utilization patterns of one of the most vulnerable subgroups for Medicaid expansion. There are several implications to these findings.

First of all, states that begin to enroll homeless individuals in Medicaid systems should understand that these individuals will have many unmet needs and require enhanced coordination of services. There might be concern about the costs of medical care for this population. As our findings suggested, the burden of medical and behavioral health needs are high. Therefore, it is not surprising that costs are consequently higher because the burden of disease is up to 4 times that of the general Medicaid population. However, states are already likely to be paying for services for homeless individuals in less effective and fragmented systems. In a recent policy paper from the Kaiser Family Foundation, Holahan et al.[29] evaluated the cost of coverage under ACA Medicaid expansion and found that extending coverage could actually reduce costs, and some states might see a net savings with Medicaid expansion.

Enrolling and caring for this population in an effective manner can be challenging, and health care for the homeless programs can be crucial partners in outreach and engagement efforts. Specialized health care programs, such as BHCHP, work to improve the fragmented use of the medical system by assisting in Medicaid enrollment and providing integrated care that follows the Institute of Medicine's core principles of public health, including identifying community health problems, mobilizing community partners, linking people to needed health services, and promoting health and safety.[11] Following this framework has allowed many homeless individuals to start to access the medical care and services that they need in a timelier manner. Furthermore, integration of care under patient-centered and integrated behavioral health and medical service models hold future promise.

Second, as more homeless individuals obtain needed health insurance under the ACA Medicaid expansion, it will be critical for providers to establish care models that take into account the high prevalence of behavioral health disorders. Our findings confirmed that a majority of individuals have mental illness and SUDs, either alone or co-occurring. Better integration of behavioral health services with primary care will be critical. Although BHCHP improved the integration of primary care and behavioral health services through co-location of providers, shared medical records, and shared case conferencing, the development of Health Homes under the ACA could further provide additional funding to better align health care financing and delivery.

Third, our findings showed that, even within this cohort of high users of the medical system, there was a group of super-high users. The top 10% people incurred almost half of health care expenditures for homeless people, and a significant proportion of the study population had frequent ED visits or hospitalizations. This group needs to be targeted with new programs and more efficient payment models based on community outreach and engagement. Current efforts on targeting

TABLE 4—Health Care Expenditures for Boston Health Care for the Homeless Program Users With Medicaid, 2010

Variable	Behavioral Health Services, No. (%) or Mean ±SD	General Medical Care, No. (%) or Mean ±SD	Both, No. (%) or Mean ±SD
Overall expenditures[a]			
PMPM, $	653	1383	2036
Annual expenditures[b], $	7355 ±15 502	15 579 ±31 071	22 934 ±36 510,
Distribution of total annual expenditures[b]			
Total annual expenditures, $	47 756 358	101 156 508	148 912 866
Population ranked by annual expenditures per person, $			
Lowest 25% (n = 1623)	739 (0)	1 310 109 (1)	2 058 769 (1)
25%–50% (n = 1623)	668 020 (1)	5 136 725 (5)	9 737 568 (7)
50%–75% (n = 1623)	6 277 094 (13)	14 654 616 (15)	27 727 537 (19)
75%–90% (n = 974)	12 786 808 (27)	23 631 322 (23)	37 979 192 (26)
90%–100% (n = 650)	28 023 698 (59)	56 423 736 (56)	71 409 801 (48)
Total annual expenditures by type of service			
Hospitalizations	18 797 235 (39.4)	39 412 510 (39.0)	58 209 745 (39.1)
ED visits	3 428 304 (7.2)	12 589 927 (12.4)	16 011 738 (10.8)
Ambulatory care visits	642 807 (1.3)	9 278 497 (9.2)	9 921 304 (6.7)
Outpatient detoxification	6 291 717 (13.2)	NA	6 291 717 (4.2)
Prescription	2 973 794 (6.2)	6 655 325 (6.6)	9 629 119 (6.5)
Dental visits	NA	1 642 729 (1.6)	1 642 729 (1.1)
Others[c]	15 622 501 (33.0)	31 577 520 (31.4)	47 206 514 (31.6)

Note. ED = emergency department; NA = not applicable; PMPM = per member per month. One member was excluded from the calculation because of extremely high payments. The sample size was n = 6493.
[a]Includes MassHealth fee-for-service payments, managed care payment amount to their contracting providers, Medicare payments, third-party payments, and out-of-pocket payments reported in MassHealth fee-for-service claims and managed care encounter data.
[b]Median annual expenditure for both behavioral health and general medical care was 10 172
[c]Includes expenditures for intensive alcohol or drug services, psychotherapy, crisis intervention, drug screen, methadone treatment, skilled nursing in home health setting, and nonemergent transportation.

high users tend to focus at the practice level and result in improved quality of care but do not address the more systemic issues that require better alignment of incentives and data integration across different sectors of the health care system. The ACA is an important step towards more systemic improvement across the spectrum of health services. As the ACA promotes investigation of alternative models of care, there will need to be a focus on data-driven coordination of care across the medical care system.

Fourth, although out of the scope of this study, it is difficult to address the health care needs and disparities of this population without addressing their housing needs. Studies show that housing homeless individuals results in lower health care utilization and improvement in health.[4,5,30,31] Housing should be considered as a benefit that improves health and is a potential cost-saving intervention.

There were several limitations to this study. One limitation was the use of *ICD-9-CM* codes instead of chart reviews because claims-based *ICD-9-CM* codes might not capture the entire clinical picture because of underreporting or underdiagnosis.[32] The high burden of disease identified might still be understated. Furthermore, these analyses were based on analysis from a single year and did not allow comparisons over a longer period of time. The Massachusetts Medicaid expansion has been a slow process since the 1990s, and made a pre-expansion cohort difficult to discern. Additionally, since 2010, several new interventions have been initiated at BHCHP, including a patient-centered medical home initiative, which might change utilization patterns. We did not have access to utilization data on the 20% of homeless patients who did not have Medicaid. They might exhibit a different pattern of health care utilization, but we were not able to comment on this. Additionally, because of data availability, this study focused on 1 city in Massachusetts, and therefore, we could not comment on any regional variations. Given these limitations, these baseline data could be used for comparison purposes for future investigations. Future studies should focus on further clarifying the effects of being homeless on health status and risk stratification, as well as controlled trials on the use of housing interventions and integrated care models.

This study demonstrated the clinical characteristics and medical use patterns in a homeless population with Medicaid coverage. Medicaid expansion will provide a unique opportunity and will significantly improve access to care for homeless individuals. However, it will take extensive collaboration across different state offices, provider networks, community and human service organizations to manage the care for this population in a cost-effective manner while ensuring high quality of care. The data provided in our analysis should provide clinicians, administrators, and policymakers with important information on an understudied and vulnerable population with a high burden of illness and need for coordinated, high-quality care. ■

About the Authors

Monica Bharel is with the Boston Health Care for the Homeless Program and the Department of Medicine, Massachusetts General Hospital and Boston Medical Center, Boston. Wen-Chieh Lin, Jianying Zhang, Elizabeth O'Connell, and Robin E. Clark are with the Center for Health Policy and Research, University of Massachusetts Medical School, Boston. Wen-Chieh Lin and Robin E. Clark are with the Department of Family Medicine and Community Health, University of Massachusetts Medical School. At the time of the study, Robert Taube was with the Boston Health Care for the Homeless Program.

Correspondence should be sent to Monica Bharel, Boston Health Care for the Homeless Program, 780 Albany Street, Boston, MA 02118 (e-mail: mbharel@bhchp.org). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

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Contributors

M. Bharel conceptualized the study and developed the article, including writing, statistical analysis, and interpretation. W-C. Lin helped conceptualize the study, led the study design and statistical analysis, and

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developed the article together with M. Bharel. J. Zhang conducted the statistical analysis, assisted in data interpretation, and reviewed drafts of the article. E. O'Connell assisted in the statistical analysis and data interpretation, and reviewed drafts of the article. R. E. Clark helped conceptualize the study; supervised and participated in all aspects of the implementation, statistical analysis, and data interpretation; and reviewed drafts of the article. R. Taube helped conceptualize the study, participated in data interpretation, and reviewed drafts of the article.

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Note. This article is solely the responsibility of the authors and does not necessarily reflect the opinions or policies of MassHealth or of the Commonwealth of Massachusetts Executive Office of Health and Human Services.

Human Participant Protection

The institutional review board at the University of Massachusetts Medical School approved this study and waived the need for informed consent.

References

1. Kaiser Commission on Medicaid and the Uninsured. Medicaid coverage and care for the homeless population: key lessons to consider for the 2014 Medicaid expansion. 2012. Available at: http://www.kff.org/medicaid/upload/8355.pdf. Accessed on December 21, 2012.

2. Koegel P, Sullivan G, Burnam A, Morton SC, Wenzel S. Utilization of mental health and substance abuse services among homeless adults in Los Angeles. *Med Care.* 1999;37(3):306–317.

3. O'Toole TP, Pollini R, Gray P, Jones T, Bigelow G, Ford DE. Factors identifying high-frequency and low-frequency health service utilization among substance-using adults. *J Subst Abuse Treat.* 2007;33(1):51–59.

4. Basu A, Kee R, Buchanan D, Sadowski LS. Comparative cost analysis of housing and case management program for chronically ill homeless adults compared to usual care. *Health Serv Res.* 2012;47(1 Pt 2):523–543.

5. Larimer ME, Malone DK, Garner MD, et al. Health care and public service use and costs before and after provision of housing for chronically homeless persons with severe alcohol problems. *JAMA.* 2009;301(13):1349–1357.

6. Kushel MB, Vittinghoff E, Haas JS. Factors associated with the health care utilization of homeless persons. *JAMA.* 2001;285(2):200–206.

7. Yoon C, Ju YS, Kim CY. Disparities in health care utilization among urban homeless in South Korea: a cross sectional study. *J Prev Med Pub Health.* 2011;44(6):267–274.

8. Poulin SR, Maguire M, Metraux S, Culhane DP. Service use and costs for persons experiencing chronic homelessness in Philadelphia: a population based study. *Psychiatr Serv.* 2010;61(11):1093–1098.

9. Kushel MB, Perry S, Bangsberg D, Clark R, Moss AR. Emergency department use among the homeless and marginally housed: results from a community-based study. *Am J Public Health.* 2002;92(5):778–784.

10. Department of Housing and Urban Development, Office of Community Planning and Development. The 2010 annual homeless assessment report to Congress. Available at: https://www.onecpd.info/resources/documents/2010HomelessAssessmentReport.pdf. Accessed on December 19, 2012.

11. O'Connell JJ, Oppenheimer SC, Judge CM, et al. The Boston Health Care for the Homeless Program: a public health framework. *Am J Public Health.* 2010;100(8):1400–1408.

12. Andersen RM. Revisiting the behavioral model and access to medical care: does it matter? *J Health Soc Behav.* 1995;36(1):1–10.

13. *International Classification of Diseases, Ninth Revision, Clinical Modification.* Hyattsville, MD: National Center for Health Statistics; 1980. DHHS publication PHS 80–1260.

14. Agency for Healthcare Research and Quality. Clinical classification software for ICD-9-CM. Available at: http://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp. Accessed December 1, 2012.

15. Pope GC, Kautter J, Ellis RP, et al. Risk adjustment of Medicare capitation payments using the CMS-HCC model. *Health Care Financ Rev.* 2004;25(4):119–141.

16. Verisk Health. DxCG intelligence site. Available at: http://www.veriskhealth.com/solutions/enterprise-analytics/dxcg-intelligence. Accessed December 1, 2012.

17. Beijer U, Wolf A, Fazel S. Prevalence of tuberculosis, hepatitis C virus and HIV in homeless people: a systematic review and meta-analysis. *Lancet Infect Dis.* 2012;12(11):859–870.

18. Dickey B, Normand SL, Weiss RD, Drake RE, Azeni H. Medical morbidity, mental illness, and substance use disorders. *Psychiatr Serv.* 2002;53(7):861–867.

19. Clark RE, Samnaliev M, McGovern MP. Impact of substance disorders on medical expenditures for medicaid beneficiaries with behavioral health disorders. *Psychiatr Serv.* 2009;60(1):35–42.

20. Seifert R, Anthony S. The basics of MassHealth. 2011. Available at: http://www.umassmed.edu/uploadedFiles/CWM_CHLE/Included_Content/Right_Column_Content/MassHealth%20Basics%202011-FINAL.pdf. Accessed December 26, 2012.

21. Hwang SW, Orav EJ, O'Connell JJ, Lebow JM, Brennan TA. Causes of death in homeless adults in Boston. *Ann Intern Med.* 1997;126(8):625–628.

22. Hwang SW, Wilkins R, Tjepkema M, O'Campo PJ, Dunn JR. Mortality among residents of shelters, rooming houses, and hotels in Canada: 11 year follow-up study. *BMJ.* 2009;339:b4036.

23. CDC National Diabetes Fact Sheet. 2011. Available at: http://www.cdc.gov/diabetes/pubs/pdf/ndfs_2011.pdf. Accessed December 26, 2012.

24. Alter MJ, Kruszon-Moran D, Nainan OV, et al. The prevalence of hepatitis C virus infection in the United States, 1988 through 1994. *N Engl J Med.* 1999;341(8):556–562.

25. Clark RE, Weir S, Ouellette RA, Zhang J, Baxter JD. Beyond health plans: behavioral health disorders and quality of diabetes and asthma care for Medicaid beneficiaries. *Med Care.* 2009;47(5):545–552.

26. Druss BG, Rosenheck RA, Desai MM, Perlin JB. Quality of preventive medical care for patients with mental disorders. *Med Care.* 2002;40(2):129–136.

27. Bartels SJ, Clark RE, Peacock WJ, Dums AR, Pratt SI. Medicare and Medicaid costs for schizophrenia patients by age cohort compared with costs for depression, dementia, and medically ill patients. *Am J Geriatr Psychiatry.* 2003;11(6):648–657.

28. Garcia TC, Bernstein AB, Bush MA. Emergency department's visitors and visits: who used the emergency room in 2007? 2007. Available at: http://www.cdc.gov/nchs/data/databriefs/db38.pdf. Accessed December 19, 2012.

29. Kaiser Family Foundation Commission on Medicaid and the Uninsured. The cost and coverage implications of the ACA Medicaid expansion. National and state-by-state analysis. 2012. Available at: http://www.kff.org/medicaid/upload/8384.pdf. Accessed December 26, 2012.

30. Sadowski LS, Kee RA, VanderWeele TJ, Buchanan D. Effect of housing and case management program on emergency department visits and hospitalizations among chronically ill homeless adults: a randomized trial. *JAMA.* 2009;301(17):1771–1778.

31. Buchanan D, Doblin B, Sai T, Garcia P. The effect of respite care for homeless patients. A cohort study. *Am J Public Health.* 2006;96(7):1278–1281.

32. Quan H, Parsons GA, Ghali WA. Validity of information on comorbidity derived from ICD-9-CCM administrative data. *Med Care.* 2002;40(8):675–685.

FRED Graph Observations
Federal Reserve Economic Data
Link: https://fred.stlouisfed.org
Help: https://fredhelp.stlouisfed.org
Economic Research Division
Federal Reserve Bank of St. Louis

CPIMEDSL Consumer Price Index for All Urban Consumers: Medical Care in U.S. City Average, Index 1982-1984=100, Annual, Seasonally Adjusted

Frequency: Annual

observation_date	CPIMEDSL
1947-01-01	13.542
1948-01-01	14.392
1949-01-01	14.833
1950-01-01	15.100
1951-01-01	15.825
1952-01-01	16.708
1953-01-01	17.292
1954-01-01	17.825
1955-01-01	18.250
1956-01-01	18.900
1957-01-01	19.675
1958-01-01	20.633
1959-01-01	21.492
1960-01-01	22.258
1961-01-01	22.908
1962-01-01	23.525
1963-01-01	24.083
1964-01-01	24.592
1965-01-01	25.183
1966-01-01	26.300
1967-01-01	28.150
1968-01-01	29.867
1969-01-01	31.917
1970-01-01	33.958
1971-01-01	36.133
1972-01-01	37.325
1973-01-01	38.758
1974-01-01	42.367
1975-01-01	47.492
1976-01-01	52.000
1977-01-01	56.975
1978-01-01	61.750
1979-01-01	67.475
1980-01-01	74.858
1981-01-01	82.925
1982-01-01	92.617
1983-01-01	100.658
1984-01-01	106.975

1985-01-01	113.617
1986-01-01	122.167
1987-01-01	130.175
1988-01-01	138.625
1989-01-01	149.250
1990-01-01	162.808
1991-01-01	177.017
1992-01-01	190.058
1993-01-01	201.400
1994-01-01	211.025
1995-01-01	220.450
1996-01-01	228.267
1997-01-01	234.592
1998-01-01	242.125
1999-01-01	250.558
2000-01-01	260.750
2001-01-01	272.767
2002-01-01	285.633
2003-01-01	297.058
2004-01-01	310.142
2005-01-01	323.225
2006-01-01	336.192
2007-01-01	351.065
2008-01-01	364.072
2009-01-01	375.608
2010-01-01	388.423
2011-01-01	400.241
2012-01-01	414.923
2013-01-01	425.133
2014-01-01	435.306
2015-01-01	446.762
2016-01-01	463.678
2017-01-01	475.317
2018-01-01	484.704
2019-01-01	498.402
2020-01-01	518.852
2021-01-01	525.249
2022-01-01	546.532
2023-01-01	549.068
2024-01-01	#N/A

Fiscal Year	Grantee	Percent of Income-Eligible Households Served by Any Type of LIHEAP Assistance		
2001	Michigan	N/A		
2002	Michigan	N/A		
2003	Michigan	N/A		
2004	Michigan	N/A		
2005	Michigan	N/A		
2006	Michigan	N/A		
2007	Michigan	N/A		
2008	Michigan	N/A		
2009	Michigan	N/A		
2010	Michigan	N/A		
2011	Michigan	47.31%		
2012	Michigan	41.50%		
2013	Michigan	39.23%		
2014	Michigan	38.33%		
2015	Michigan	42.48%		
2016	Michigan	38.51%		
2017	Michigan	36.85%		
2018	Michigan	32.47%		
2019	Michigan	32.09%		
2020	Michigan	30.00%		
2021*	Michigan	22.16%		
2022*	Michigan	31.11%		
2023*	Michigan	39.60%	Five year average:	30.99%

Source: LIHEAP Performance Measurement Web Site(https://liheappm.acf.hhs.gov)

Fiscal Year	Grantee	State Income-Eligible Households - Total		
2001	Michigan	1,015,505	1,015,505	
2002	Michigan	1,110,048	1,110,048	
2003	Michigan	442,046		
2004	Michigan	517,152		
2005	Michigan	499,991		
2006	Michigan	506,621		
2007	Michigan	526,177		
2008	Michigan	526,177		
2009	Michigan	602,149		
2010	Michigan	568,604		
2011	Michigan	580,475		
2012	Michigan	580,475		
2013	Michigan	607,768		
2014	Michigan	622,384		
2015	Michigan	617,346		
2016	Michigan	603,886		
2017	Michigan	598,929		
2018	Michigan	575,917		
2019	Michigan	551,897		
2020	Michigan	542,727		
2021*	Michigan	528,387		
2022*	Michigan	497,332		
2023*	Michigan	481,913	Five year average:	520,451

Source: LIHEAP Performance Measurement Web Site(https://liheappm.acf.hhs.gov)

Fiscal Year	Grantee	Federally Income-Eligible Households - Total		
2001	Michigan	1,015,505		
2002	Michigan	1,110,048		
2003	Michigan	1,249,438		
2004	Michigan	1,376,703		
2005	Michigan	1,298,359		
2006	Michigan	1,202,113		
2007	Michigan	1,204,341		
2008	Michigan	1,204,341		
2009	Michigan	1,219,874		
2010	Michigan	1,279,202		
2011	Michigan	1,302,893		
2012	Michigan	1,302,893		
2013	Michigan	1,245,264		
2014	Michigan	1,221,328		
2015	Michigan	1,200,571		
2016	Michigan	1,180,137		
2017	Michigan	1,198,808		
2018	Michigan	1,178,417		
2019	Michigan	1,150,627		
2020	Michigan	1,137,840		
2021*	Michigan	1,159,876		
2022*	Michigan	1,145,560		
2023*	Michigan	1,090,396	Five year average:	1,136,860

Source: LIHEAP Performance Measurement Web Site(https://liheappm.acf.hhs.gov)

Table 1. 2022 Summary statistics
Michigan

	Value	Rank
Primary energy source	**Natural Gas**	
Net summer capacity (megawatts)	**30,538**	**11**
..Electric utilities	22,471	8
..IPP and CHP	8,067	15
Net generation (megawatthours)	**117,497,052**	**11**
..Electric utilities	81,577,914	9
..IPP and CHP	35,919,138	13
Emissions (thousand metric tons)		
..Sulfur dioxide (short tons)	53,778	5
..Nitrogen oxide (short tons)	53,786	6
..Carbon dioxide (thousand metric tons)	58,510	6
..Sulfur dioxide (lbs/MWh)	0.9	10
..Nitrogen oxide (lbs/MWh)	0.9	15
..Carbon dioxide (lbs/MWh)	1,096	16
Total sales to ultimate customers (megawatthours)	**100,639,262**	**12**
..Full service provider and facility direct sales (megawatthours)	91,766,110	10
..Energy-only provider sales (megawatthours)	8,873,152	10
Direct use (megawatthours)	**2,536,443**	**11**
Average price to ultimate customers (cents/kWh)	**13.20**	**14**

Sources: U.S. Energy Information Administration, Form EIA-860, Annual Electric Generator Report. U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report. U.S. Energy Information Administration, Form EIA-923, Power Plant Operations Report and predecessor forms.

Table 2A. Ten largest plants by capacity, 2022
Michigan

	Plant	Primary energy source	Operating company	Net summer capacity (MW)
1	Monroe (MI)	Coal	DTE Electric Company	3,080
2	Ludington	Pumped storage	Consumers Energy Co	2,186
3	Donald C Cook	Nuclear	Indiana Michigan Power Co	2,177
4	Midland Cogeneration Venture	Natural gas	Midland Cogeneration Venture	1,865
5	Dan E Karn	Natural gas	Consumers Energy Co	1,689
6	Belle River	Coal	DTE Electric Company	1,508
7	J H Campbell	Coal	Consumers Energy Co	1,400
8	Fermi	Nuclear	DTE Electric Company	1,192
9	Blue Water Energy Center	Natural gas	DTE Electric Company	1,146
10	New Covert Generating Facility	Natural gas	New Covert Generating Company LLC	1,085

Source: U.S. Energy Information Administration, Form EIA-860, Annual Electric Generator Report.

Table 2B. Ten largest plants by generation, 2022
Michigan

	Plant	Primary energy source	Operating company	Generation (MWh)
1	Donald C Cook	Nuclear	Indiana Michigan Power Co	16,621,031
2	Monroe (MI)	Coal	DTE Electric Company	15,349,520
3	J H Campbell	Coal	Consumers Energy Co	7,677,054
4	Midland Cogeneration Venture	Natural gas	Midland Cogeneration Venture	7,411,985
5	New Covert Generating Facility	Natural gas	New Covert Generating Company LLC	7,328,022
6	Belle River	Coal	DTE Electric Company	6,818,124
7	Fermi	Nuclear	DTE Electric Company	6,662,563
8	Dearborn Industrial Generation	Natural gas	Dearborn Industrial Gen Inc	4,803,433
9	Blue Water Energy Center	Natural gas	DTE Electric Company	4,496,030
10	Zeeland Generating Station	Natural gas	Consumers Energy Co	4,316,479

Source: U.S. Energy Information Administration, Form EIA-923, Power Plant Operations Report and predecessor forms.

Table 3. Top five retailers of electricity, with end use sectors, 2022
Michigan

megawatthours

	Entity	Type of provider	All sectors	Residential	Commercial	Industrial	Transportation
1	DTE Electric Company	Investor-owned	40,897,642	15,844,478	16,500,656	8,548,188	4,320
2	Consumers Energy Co	Investor-owned	33,249,141	12,976,844	11,817,172	8,455,125	0
3	Constellation NewEnergy, Inc	Retail power marketer	4,802,062	0	2,980,246	1,821,816	0
4	Indiana Michigan Power Co	Investor-owned	2,619,737	1,175,727	767,758	676,252	0
5	City of Lansing - (MI)	Public	2,027,546	578,323	1,101,975	347,248	0
	Total sales, top five providers		83,596,128	30,575,372	33,167,807	19,848,629	4,320
	Percent of total state sales		83	87	89	70	100

Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Table 4. Electric power industry capacity by primary energy source, 1990 through 2022

Michigan

megawatts

	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005
Electric utilities	22,471.1	22,741.0	22,355.4	22,440.5	22,684.7	22,625.3	22,361.2	23,386.9	22,259.5	22,147.5	22,515.8	22,401.4	21,639.2	21,758.9	21,885.1	21,894.0	22,734.0	23,029.0
Battery	1.3	1.3	1.0	1.0	1.0	.	.	.	.	.	.	.	.	.	.	.	.	.
Coal	6,225.3	7,969.1	8,263.5	8,524.5	9,124.6	9,150.9	9,346.4	10,743.7	10,847.8	10,785.4	10,937.4	11,033.2	11,217.8	11,431.2	11,543.1	11,533.0	11,534.0	11,633.0
Hydroelectric	246.2	245.6	246.5	244.7	241.2	238.2	234.3	302.2	304.4	302.7	207.3	209.7	208.6	223.0	221.9	221.0	229.0	225.0
Natural gas	8,145.5	6,785.8	6,532.6	6,674.1	6,640.7	6,758.8	6,384.1	6,219.8	5,085.1	5,170.9	5,488.8	5,463.1	4,618.4	4,445.9	4,446.8	4,461.0	3,695.0	3,669.0
..Natural gas - CC	2,614.8	1,289.6	1,300.6	1,306.6	1,289.9	1,294.3	1,167.8	1,185.2	621.2	539.4	546.3	552.9	20.5	20.5	22.0	.	.	.
..Natural gas - GT	3,154.0	3,106.4	3,104.9	3,108.1	3,129.2	3,224.4	3,231.3	2,696.8	1,898.6	1,960.3	1,975.2	1,965.3	1,653.0	1,424.1	1,423.7	.	.	.
..Natural gas - IC	349.4	349.4	350.6	344.4	161.6	180.1	128.0	134.3	121.8	121.8	128.8	135.9	135.9	135.3	135.1	.	.	.
..Natural gas - ST	2,027.3	2,040.4	1,776.5	1,915.0	2,060.0	2,060.0	1,857.0	2,203.5	2,443.5	2,549.4	2,838.5	2,809.0	2,809.0	2,866.0	2,866.0	.	.	.
Nuclear	3,318.0	3,318.0	3,318.0	3,318.0	3,318.0	3,318.0	3,318.0	3,193.0	3,193.0	3,154.0	3,154.0	3,154.0	3,154.0	3,175.0	3,191.0	3,191.0	4,006.0	3,982.0
Other gas	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Petroleum	420.7	420.7	435.9	441.9	440.1	467.0	475.0	519.6	514.6	518.9	544.1	567.4	568.4	611.8	610.3	616.0	1,397.0	1,647.0
..Petroleum - GT	214.3	214.3	231.7	231.7	231.7	262.7	262.7	300.2	312.2	314.5	314.5	318.4	319.5	340.0	338.7	.	.	.
..Petroleum - IC	206.4	206.4	204.2	210.2	208.4	204.3	212.3	219.4	202.4	204.4	229.6	249.0	248.9	271.8	271.6	.	.	.
Pumped storage	2,185.6	2,143.8	2,235.0	2,232.0	2,152.0	2,134.0	2,103.0	1,964.0	1,872.0	1,872.0	1,871.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0
Solar	61.8	62.8	62.5	62.5	62.5	62.5	12.5	2.0	.	.	.	.	.	.	.	.	.	.
..Solar- PV	61.8	62.8	62.5	62.5	62.5	62.5	12.5	2.0	.	.	.	.	.	.	.	.	.	.
Wind	1,866.7	1,793.9	1,260.4	941.8	704.6	495.9	487.9	442.6	442.6	343.6	313.2	102.0	.	.	.	.	.	.
..Wind - Onshore	1,866.7	1,793.9	1,260.4	941.8	704.6	495.9	.	.	.	.	.	.	.	.	.	.	.	.
IPP, commercial and industrial	8,066.9	7,399.7	7,247.4	7,016.4	7,035.3	7,009.4	6,721.9	6,675.6	8,175.4	7,980.7	7,815.0	7,500.5	8,186.1	8,543.4	8,527.9	8,411.0	7,456.0	7,393.0
Coal	65.8	65.8	65.8	65.8	65.8	65.8	67.8	93.8	100.6	161.1	324.4	313.4	313.4	362.3	377.5	378.0	325.0	349.0
Hydroelectric	17.9	17.9	17.9	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.7	28.1	28.1	28.1	28.1	28.0	28.0	28.0
Natural gas	5,155.6	4,035.7	4,030.7	4,042.8	4,022.4	4,027.0	4,010.0	3,971.0	5,814.6	5,770.7	5,586.8	5,564.5	6,409.0	6,754.5	6,764.8	6,774.0	6,628.0	6,618.0
..Natural gas - CC	4,250.0	3,153.0	3,153.0	3,145.3	3,123.7	3,126.7	3,126.7	3,111.3	3,670.4	3,670.7	4,230.7	4,209.4	4,738.9	4,729.4	4,889.7	.	.	.
..Natural gas - GT	742.0	742.0	742.0	744.8	744.8	746.4	733.6	731.7	1,658.2	1,654.1	1,344.1	1,348.6	1,663.6	2,018.6	1,868.6	.	.	.
..Natural gas - IC	37.2	9.0	4.0	4.0	4.0	4.0	4.0	4.0	0.8	0.8	0.8	.	.	.	.	.	.	.
..Natural gas - ST	126.4	131.7	131.7	148.7	149.9	149.9	145.7	124.0	485.2	445.1	11.2	6.5	6.5	6.5	6.5	.	.	.
Nuclear	.	795.8	768.5	771.6	804.2	801.8	787.4	783.5	789.0	775.1	782.2	803.4	793.0	778.0	778.0	778.0	.	.
Other	3.8	.	.	.	.	.	.	.	0.9	.	.	.	.	7.6	.	8.0	.	.
Other biomass	168.4	162.0	170.0	166.0	224.0	221.1	222.5	222.5	215.5	198.8	195.7	182.9	175.9	168.0	168.8	156.0	149.0	157.0
Other gas	250.0	250.0	250.0	250.0	250.0	250.0	250.0	250.0	.	.	.	.	.	.	.	.	12.0	5.0
Petroleum	66.3	70.1	70.1	70.1	70.6	70.6	70.6	70.6	70.6	70.6	72.0	72.0	72.0	72.0	56.8	57.0	102.0	27.0
..Petroleum - GT	.	.	.	.	.	.	.	.	.	.	1.4	1.4	1.4	1.4	1.4	.	.	.
..Petroleum - IC	19.1	22.9	22.9	22.9	23.4	23.4	23.4	23.4	23.4	23.4	23.4	23.4	23.4	23.4	23.4	.	.	.
..Petroleum - ST	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	32.0	.	.	.
Solar	645.9	290.5	162.5	39.5	35.7	10.5	.	.	.	.	.	.	.	.	.	.	.	.
..Solar- PV	645.9	290.5	162.5	39.5	35.7	10.5	.	.	.	.	.	.	.	.	.	.	.	.
Wind	1,372.3	1,373.9	1,373.9	1,243.9	1,195.9	1,195.9	946.9	917.5	917.5	736.7	561.6	272.6	162.6	142.6	123.6	2.0	2.0	1.0
..Wind - Onshore	1,372.3	1,373.9	1,373.9	1,243.9	1,195.9	1,195.9	.	.	.	.	.	.	.	.	.	.	.	.
Wood	320.9	338.0	338.0	338.0	338.0	338.0	338.0	338.0	238.0	239.0	263.6	263.6	232.1	230.3	230.3	231.0	210.0	210.0
Total electric industry	30,538.0	30,140.7	29,602.8	29,456.9	29,720.0	29,634.7	29,083.1	30,062.5	30,434.9	30,128.2	30,330.8	29,901.9	29,825.3	30,302.3	30,413.0	30,305.0	30,189.0	30,422.0
Battery	1.3	1.3	1.0	1.0	1.0	.	.	.	.	.	.	.	.	.	.	.	.	.
Coal	6,291.1	8,034.9	8,329.3	8,590.3	9,190.4	9,216.7	9,414.2	10,837.5	10,948.4	10,946.5	11,261.8	11,346.6	11,531.2	11,793.5	11,920.6	11,910.0	11,860.0	11,982.0
Hydroelectric	264.1	263.5	264.4	273.4	269.9	266.9	263.0	330.9	333.1	331.4	236.0	237.8	236.7	251.1	250.0	249.0	257.0	253.0
Natural gas	13,301.1	10,821.5	10,563.3	10,716.9	10,663.1	10,785.8	10,394.1	10,190.8	10,899.7	10,941.6	11,075.6	11,027.6	11,027.4	11,200.4	11,211.6	11,235.0	10,322.0	10,286.0
..Natural gas - CC	6,864.8	4,442.6	4,453.6	4,451.9	4,413.6	4,421.0	4,294.5	4,296.5	4,291.6	4,210.1	4,777.0	4,762.3	4,759.4	4,749.9	4,911.7	.	.	.
..Natural gas - GT	3,896.0	3,848.4	3,846.9	3,852.9	3,874.0	3,970.8	3,964.9	3,428.5	3,556.8	3,614.4	3,319.3	3,313.9	3,316.6	3,442.7	3,292.3	.	.	.
..Natural gas - IC	386.6	358.4	354.6	348.4	165.6	184.1	132.0	138.3	122.6	122.6	129.6	135.9	135.9	135.3	135.1	.	.	.
..Natural gas - ST	2,153.7	2,172.1	1,908.2	2,063.7	2,209.9	2,209.9	2,002.7	2,327.5	2,928.7	2,994.5	2,849.7	2,815.5	2,815.5	2,872.5	2,872.5	.	.	.
Nuclear	3,318.0	4,113.8	4,086.5	4,089.6	4,122.2	4,119.8	4,105.4	3,976.5	3,982.0	3,929.1	3,936.2	3,957.4	3,947.0	3,953.0	3,969.0	3,969.0	4,006.0	3,982.0
Other	3.8	.	.	.	.	.	.	.	0.9	.	.	.	.	7.6	.	8.0	.	.
Other biomass	168.4	162.0	170.0	166.0	224.0	221.1	222.5	222.5	215.5	198.8	195.7	182.9	175.9	168.0	168.8	156.0	149.0	157.0
Other gas	250.0	250.0	250.0	250.0	250.0	250.0	250.0	250.0	.	.	.	.	.	.	.	.	12.0	5.0
Petroleum	487.0	490.8	506.0	512.0	510.7	537.6	545.6	590.2	585.2	589.5	616.1	639.4	640.4	683.8	667.1	673.0	1,499.0	1,675.0
..Petroleum - GT	214.3	214.3	231.7	231.7	231.7	262.7	262.7	300.2	312.2	314.5	315.9	319.8	320.9	341.4	340.1	.	.	.
..Petroleum - IC	225.5	229.3	227.1	233.1	231.8	227.7	235.7	242.8	225.8	227.8	253.0	272.4	272.3	295.2	295.0	.	.	.
..Petroleum - ST	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	47.2	32.0	.	.	.
Pumped storage	2,185.6	2,143.8	2,235.0	2,232.0	2,152.0	2,134.0	2,103.0	1,964.0	1,872.0	1,872.0	1,871.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0
Solar	707.7	353.3	225.0	102.0	98.2	73.0	12.5	2.0	.	.	.	.	.	.	.	.	.	.
..Solar- PV	707.7	353.3	225.0	102.0	98.2	73.0	12.5	2.0	.	.	.	.	.	.	.	.	.	.
Wind	3,239.0	3,167.8	2,634.3	2,185.7	1,900.5	1,691.8	1,434.8	1,360.1	1,360.1	1,080.3	874.8	374.6	162.6	142.6	123.6	2.0	2.0	1.0
..Wind - Onshore	3,239.0	3,167.8	2,634.3	2,185.7	1,900.5	1,691.8	.	.	.	.	.	.	.	.	.	.	.	.
Wood	320.9	338.0	338.0	338.0	338.0	338.0	338.0	338.0	238.0	239.0	263.6	263.6	232.1	230.3	230.3	231.0	210.0	210.0

Other biomass includes agricultural byproducts, landfill gas, biogenic municipal solid waste, other biomass (solid, liquid and gas) and sludge waste.
Other gases includes blast furnace gas, and other manufactured and waste gases derived from fossil fuels.
Other includes non-biogenic municipal solid waste, batteries, chemicals, hydrogen, pitch, purchased steam, sulfur, tire-derived fuels, waste heat and miscellaneous technologies.
Source: U.S. Energy Information Administration, Form EIA-860, Annual Electric Generator Report.

Year 2004	Year 2003	Year 2002	Year 2001	Year 2000	Year 1999	Year 1998	Year 1997	Year 1996	Year 1995	Year 1994	Year 1993	Year 1992	Year 1991	Year 1990	Percent share 2000	Percent share 2010	Percent share 2020	Percent share 2022
23,310.0	23,345.0	23,575.0	22,833.0	22,757.0	22,378.0	21,948.0	21,916.0	21,990.0	21,986.0	22,396.0	22,395.0	22,347.0	22,258.0	22,298.0	88.3	72.6	75.5	73.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0
11,623.0	11,636.0	11,627.0	11,638.0	11,636.0	11,574.0	11,840.0	11,796.0	11,794.0	11,795.0	11,908.0	11,909.0	11,909.0	11,940.0	11,912.0	45.1	37.6	27.9	20.4
217.0	218.0	231.0	229.0	239.0	243.0	243.0	260.0	267.0	265.0	330.0	330.0	330.0	330.0	333.0	0.9	0.7	0.8	0.8
3,982.0	3,964.0	4,253.0	3,302.0	3,245.0	2,131.0	1,440.0	1,435.0	1,437.0	1,435.0	800.0	800.0	800.0	727.0	703.0	12.6	15.5	22.1	26.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	4.4	8.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	5.5	10.5	10.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.5	1.2	1.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	9.4	6.0	6.6
3,971.0	3,971.0	3,938.0	3,931.0	3,930.0	3,921.0	3,918.0	3,922.0	3,987.0	3,989.0	3,967.0	3,967.0	3,967.0	3,942.0	4,007.0	15.2	10.6	11.2	10.9
.	.	.	.	.	.	.	.	.	.	272.0	272.0	265.0	265.0	.	.	.	.	.
1,646.0	1,685.0	1,654.0	1,860.0	1,834.0	2,636.0	2,635.0	2,630.0	2,634.0	2,632.0	3,246.0	3,246.0	3,204.0	3,182.0	3,471.0	7.1	1.9	1.5	1.4
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1.1	0.8	0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	0.7	0.7
1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	7.3	6.3	7.5	7.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.2
.	.	.	.	1.0	1.0	1.0	.	.	.	.	.	.	.	.	0.0	.	4.3	6.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	4.3	6.1
7,078.0	7,103.0	6,056.0	4,054.0	3,028.0	3,003.0	2,673.0	2,950.0	2,936.0	2,925.0	2,777.0	2,756.0	2,712.0	2,629.0	2,690.0	11.7	27.4	24.5	26.4
354.0	354.0	354.0	291.0	329.0	362.0	357.0	636.0	661.0	654.0	654.0	643.0	637.0	610.0	677.0	1.3	1.1	0.2	0.2
27.0	27.0	27.0	27.0	28.0	26.0	26.0	26.0	26.0	26.0	26.0	27.0	27.0	20.0	27.0	0.1	0.1	0.1	0.1
6,315.0	6,302.0	5,238.0	2,776.0	2,192.0	2,198.0	1,871.0	1,861.0	1,844.0	1,841.0	1,739.0	1,739.0	1,742.0	1,760.0	1,755.0	8.5	21.5	13.6	16.9
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	15.9	10.7	13.9
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	5.6	2.5	2.4
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.4	0.4
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	2.7	2.6	.
.	.	.	494.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0
157.0	158.0	176.0	166.0	182.0	148.0	153.0	141.0	141.0	122.0	113.0	103.0	99.0	88.0	85.0	0.7	0.6	0.6	0.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	0.8
15.0	52.0	50.0	11.0	13.0	11.0	8.0	2.0	6.0	2.0	2.0	2.0	3.0	5.0	0.0	0.1	0.2	0.2	0.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.1	0.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.2	0.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.5	2.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.5	2.1
1.0	1.0	1.0	1.0	.	.	.	.	.	.	.	.	.	.	.	.	0.5	4.6	4.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	4.6	4.5
210.0	210.0	211.0	288.0	284.0	258.0	258.0	284.0	258.0	279.0	243.0	243.0	206.0	147.0	147.0	1.1	0.8	1.1	1.1
30,388.0	30,449.0	29,631.0	26,887.0	25,785.0	25,381.0	24,621.0	24,866.0	24,926.0	24,911.0	25,173.0	25,151.0	25,059.0	24,887.0	24,988.0	100.0	100.0	100.0	100.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0
11,976.0	11,989.0	11,981.0	11,929.0	11,965.0	11,936.0	12,197.0	12,432.0	12,455.0	12,449.0	12,563.0	12,552.0	12,545.0	12,551.0	12,588.0	46.4	38.7	28.1	20.6
245.0	245.0	258.0	256.0	267.0	269.0	269.0	286.0	293.0	291.0	356.0	356.0	356.0	349.0	360.0	1.0	0.8	0.9	0.9
10,296.0	10,266.0	9,491.0	6,078.0	5,437.0	4,329.0	3,311.0	3,296.0	3,281.0	3,275.0	2,539.0	2,539.0	2,543.0	2,487.0	2,458.0	21.1	37.0	35.7	43.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	16.0	15.0	22.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	11.1	13.0	12.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.5	1.2	1.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	9.4	6.4	7.1
3,971.0	3,971.0	3,938.0	3,931.0	3,930.0	3,921.0	3,918.0	3,922.0	3,987.0	3,989.0	3,967.0	3,967.0	3,967.0	3,942.0	4,007.0	15.2	13.2	13.8	10.9
.	.	.	494.0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0
157.0	158.0	176.0	166.0	182.0	148.0	153.0	141.0	141.0	122.0	113.0	103.0	99.0	88.0	85.0	0.7	0.6	0.6	0.6
.	.	.	.	.	.	.	.	.	.	272.0	272.0	265.0	265.0	.	.	.	0.8	0.8
1,660.0	1,737.0	1,704.0	1,872.0	1,847.0	2,648.0	2,643.0	2,633.0	2,640.0	2,634.0	3,249.0	3,249.0	3,207.0	3,187.0	3,472.0	7.2	2.1	1.7	1.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1.1	0.8	0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.9	0.8	0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.2	0.2
1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	1,872.0	7.3	6.3	7.5	7.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	2.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	2.3
1.0	1.0	1.0	1.0	1.0	1.0	1.0	.	.	.	.	.	.	.	.	0.0	0.5	8.9	10.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	8.9	10.6
210.0	210.0	211.0	288.0	284.0	258.0	258.0	284.0	258.0	279.0	243.0	243.0	206.0	147.0	147.0	1.1	0.8	1.1	1.1

Table 5. Electric power industry generation by primary energy source, 1990 through 2022

Michigan

megawatthours

	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005
Electric utilities	81,577,914	81,451,708	69,820,694	78,881,960	81,450,131	79,938,707	78,006,408	85,370,227	84,075,322	83,171,310	80,474,999	87,609,471	89,666,874	82,787,341	94,503,953	96,785,842	97,373,706	104,830,689
Battery	-57	-83	-79	-24	-3	.	.	.	.	.	.	.	.	.	.	.	.	.
Coal	34,117,671	36,710,359	27,588,907	36,942,257	41,830,492	41,530,832	39,988,445	52,296,557	52,275,272	55,616,170	52,470,940	58,182,906	64,766,712	65,867,455	68,421,489	69,406,550	66,654,737	69,158,736
Hydroelectric	1,318,287	1,262,346	1,614,106	1,525,746	1,440,799	1,540,019	1,432,762	1,386,571	1,467,606	1,292,863	1,102,691	1,230,678	1,142,977	1,234,066	1,247,863	1,146,768	1,381,242	1,355,963
Natural gas	17,154,284	11,771,750	13,147,485	11,750,643	10,492,640	8,250,504	10,049,701	6,320,409	3,325,070	2,657,548	4,400,766	2,688,135	1,173,481	563,510	784,967	1,079,596	982,534	1,717,091
..Natural gas - CC	12,306,937	6,683,175	6,906,242	7,359,746	6,279,003	5,780,593	6,347,543	4,818,918	2,321,357	1,210,791	2,545,517	1,662,900	4,445	1,454	1,322	.	.	.
..Natural gas - GT	3,334,619	3,166,924	4,278,168	2,512,407	3,256,011	1,741,575	3,046,724	1,132,733	601,163	942,292	874,312	423,897	339,065	179,543	158,634	.	.	.
..Natural gas - IC	901,826	964,748	933,140	796,233	83,608	31,361	13,114	3,351	447	2,108	4,114	3,538	2,245	514	1,729	.	.	.
..Natural gas - ST	610,903	956,903	1,029,935	1,082,256	874,018	696,976	642,320	365,407	402,103	502,357	976,823	597,799	827,726	382,000	623,283	.	.	.
Nuclear	23,283,131	27,323,520	24,337,423	26,044,108	25,022,754	26,283,696	24,506,529	23,015,266	25,422,922	22,879,127	22,841,501	26,248,447	23,383,919	15,732,299	24,649,692	25,690,938	29,066,165	32,871,574
Other	0	0	0	0	0	0	11,051	31,920	32,156	14,117	24,546	25,634	27,165	31,676	33,777	40,131	37,278	45,003
Other biomass	.	.	.	.	.	.	.	.	0	.	0	0	0	11	63	54	.	.
Other gas	.	11,678	45,232	153,596	151,018	148,559	144,627	178,326	91,997	68,492	.	.	.	.	.	105,130	18,854	0
Petroleum	1,400,737	994,737	767,319	762,664	1,095,421	960,399	668,813	645,811	834,048	323,561	133,951	173,662	195,180	215,189	281,604	445,915	272,106	788,563
..Petroleum - GT	1,924	5,027	790	-295	10,777	5,516	8,897	2,508	1,638	674	1,790	5,528	6,010	7,447	7,669	.	.	.
..Petroleum - IC	5,525	9,238	2,957	3,114	1,033	2,386	1,046	-2,420	148	58	4,025	4,575	-12,940	5,777	104	.	.	.
..Petroleum - ST	1,393,287	980,473	763,572	759,845	1,083,611	952,496	658,870	645,724	832,262	322,829	128,137	163,560	202,109	201,965	273,831	.	.	.
Pumped storage	-868,131	-715,146	-845,480	-696,488	-698,455	-674,759	-751,650	-480,821	-700,889	-870,822	-773,280	-945,017	-1,022,559	-856,864	-915,502	-1,129,241	-1,039,210	-1,106,241
Solar	77,910	85,312	89,007	86,608	86,796	62,992	9,235	1,190	.	.	.	.	.	.	.	.	.	.
..Solar- PV	77,910	85,312	89,007	86,608	86,796	62,992	9,235	1,190	.	.	.	.	.	.	.	.	.	.
Wind	5,094,082	4,007,235	3,076,774	2,312,849	2,028,669	1,836,465	1,946,895	1,974,993	1,327,129	1,190,254	273,884	2,818	.	.	.	.	.	.
..Wind - Onshore	5,094,082	4,007,235	3,076,774	2,312,849	2,028,669	1,836,465	.	.	.	.	.	.	.	.	.	.	.	.
Wood	.	.	.	0	0	0	0	4	11	0	0	2,208	.	.	.	.	.	.
IPP, commercial and industrial	35,919,138	34,061,422	36,804,027	37,819,529	34,386,963	32,374,793	34,115,382	27,637,823	22,741,669	22,246,490	27,683,051	21,560,036	21,884,497	18,415,264	20,485,853	22,524,095	15,183,032	16,789,082
Coal	364,516	343,544	372,123	399,232	500,372	489,716	538,427	587,475	624,573	675,283	665,492	765,363	837,663	980,229	1,433,947	1,404,048	1,125,424	1,164,240
Hydroelectric	67,637	77,418	99,235	124,043	128,400	138,938	131,593	112,652	132,416	126,186	104,135	126,630	107,576	137,860	116,515	123,221	139,111	105,745
Natural gas	24,029,500	18,740,968	23,286,354	22,678,883	20,494,251	17,880,154	19,245,452	13,724,388	9,197,767	9,683,844	17,347,592	10,293,919	11,075,781	7,856,040	8,817,069	12,061,388	10,427,421	12,046,801
..Natural gas - CC	19,411,127	14,632,505	18,102,075	17,620,212	16,107,488	14,002,035	15,022,766	10,644,941	6,878,399	7,521,940	16,060,408	9,650,771	10,097,487	7,307,601	8,183,459	.	.	.
..Natural gas - GT	3,622,802	3,085,076	3,949,196	4,107,624	3,651,605	3,185,597	3,592,612	2,567,327	1,941,091	1,723,860	1,011,172	489,175	860,768	460,258	562,408	.	.	.
..Natural gas - IC	50,543	13,195	8,190	8,575	9,987	10,002	10,650	11,326	715	1,191	1,806	356	212	137	323	.	.	.
..Natural gas - ST	945,027	1,010,193	1,226,893	942,472	725,171	682,520	619,425	500,794	377,561	436,853	274,207	153,617	117,315	88,044	70,879	.	.	.
Nuclear	2,730,230	7,014,799	5,995,123	6,865,167	5,455,940	6,097,496	7,045,181	6,318,520	5,822,926	6,041,696	5,178,213	6,641,020	6,240,661	6,118,710	6,834,736	5,826,015	.	.
Other	147,050	143,091	135,400	173,126	252,315	259,533	290,594	372,882	371,645	298,258	370,117	337,522	304,511	312,682	252,165	262,835	525,244	516,858
Other biomass	784,317	907,355	982,225	915,104	957,467	985,855	972,596	1,038,263	1,055,106	987,688	956,227	827,244	802,376	834,001	739,474	721,767	736,823	716,561
Other gas	1,329,565	1,190,076	923,417	1,542,941	1,446,619	1,503,607	1,469,995	1,034,452	1,027,849	888,173	314,755	269,175	299,005	202,510	264,407	177,284	393,493	372,119
Petroleum	154,150	154,785	166,353	152,524	118,091	156,112	150,166	180,681	217,282	208,920	191,192	169,107	186,849	184,060	175,935	252,610	129,781	88,996
..Petroleum - GT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	.	.	.
..Petroleum - IC	67	85	77	215	65	67	127	123	142	109	302	179	287	217	195	.	.	.
..Petroleum - OTH	356	2,234	1,319	126	344	27	0	51	110	0	0	936	30	85	0	.	.	.
..Petroleum - ST	153,727	152,465	164,956	152,184	117,682	156,018	150,039	180,506	217,030	208,811	190,890	167,992	186,532	183,758	175,733	.	.	.
Solar	781,469	338,493	66,161	56,353	31,357	312	.	.	.	.	.	.	.	.	.	.	.	.
..Solar- PV	781,469	338,493	66,161	56,353	31,357	312	.	.	.	.	.	.	.	.	.	.	.	.
Wind	4,057,097	3,689,652	3,658,318	3,512,856	3,428,583	3,354,808	2,748,888	2,821,905	2,540,989	1,609,370	857,804	453,656	360,340	300,172	141,182	2,723	2,212	1,848
..Wind - Onshore	4,057,097	3,689,652	3,658,318	3,512,856	3,428,583	3,354,808	.	.	.	.	.	.	.	.	.	.	.	.
Wood	1,473,609	1,461,241	1,119,318	1,399,299	1,573,568	1,508,262	1,522,489	1,446,604	1,751,118	1,727,072	1,697,524	1,676,399	1,669,736	1,489,001	1,710,423	1,692,202	1,703,524	1,775,914
Total electric industry	117,497,052	115,513,130	106,624,721	116,701,488	115,837,095	112,313,501	112,121,790	113,008,050	106,816,991	105,417,801	108,158,050	109,169,507	111,551,371	101,202,605	114,989,806	119,309,936	112,556,739	121,619,771
Battery	-57	-83	-79	-24	-3	.	.	.	.	.	.	.	.	.	.	.	.	.
Coal	34,482,187	37,053,903	27,961,029	37,341,489	42,330,864	42,020,548	40,526,872	52,884,033	52,899,844	56,291,453	53,136,432	58,948,269	65,604,374	66,847,683	69,855,436	70,810,599	67,780,161	70,322,976
Hydroelectric	1,385,924	1,339,764	1,713,341	1,649,789	1,569,199	1,678,957	1,564,355	1,499,223	1,600,022	1,419,049	1,206,826	1,357,308	1,250,553	1,371,926	1,364,378	1,269,989	1,520,353	1,461,708
Natural gas	41,183,784	30,512,718	36,433,839	34,429,525	30,986,892	26,130,658	29,295,154	20,044,798	12,522,837	12,341,392	21,748,358	12,982,054	12,249,262	8,419,551	9,602,037	13,140,984	11,409,955	13,763,892
..Natural gas - CC	31,718,064	21,315,680	25,008,317	24,979,958	22,386,491	19,782,628	21,370,309	15,463,859	9,199,756	8,732,731	18,605,925	11,313,671	10,101,932	7,309,055	8,184,781	.	.	.
..Natural gas - GT	6,957,421	6,252,000	8,227,364	6,620,031	6,907,616	4,927,171	6,639,336	3,700,060	2,542,254	2,666,151	1,885,484	913,073	1,199,832	639,801	721,042	.	.	.
..Natural gas - IC	952,369	977,942	941,330	804,808	93,596	41,363	23,764	14,678	1,163	3,299	5,920	3,894	2,457	651	2,052	.	.	.
..Natural gas - ST	1,555,930	1,967,095	2,256,828	2,024,728	1,599,189	1,379,496	1,261,744	866,201	779,664	939,211	1,251,029	751,416	945,041	470,044	694,162	.	.	.
Nuclear	26,013,361	34,338,319	30,332,546	32,909,275	30,478,694	32,381,192	31,551,710	29,333,786	31,245,848	28,920,823	28,019,714	32,889,467	29,624,580	21,851,009	31,484,428	31,516,953	29,066,165	32,871,574
Other	147,050	143,091	135,400	173,126	252,315	259,533	301,645	404,802	403,801	312,375	394,663	363,156	331,677	344,358	285,942	302,966	562,522	561,861
Other biomass	784,317	907,355	982,225	915,104	957,467	985,855	972,596	1,038,263	1,055,106	987,688	956,227	827,244	802,376	834,012	739,537	721,822	736,823	716,561
Other gas	1,329,565	1,201,754	968,649	1,696,538	1,597,637	1,652,167	1,614,622	1,212,778	1,119,846	956,665	314,755	269,175	299,005	202,510	264,407	282,414	412,347	372,119
Petroleum	1,554,886	1,149,522	933,672	915,188	1,213,512	1,116,511	818,979	826,492	1,051,330	532,481	325,143	342,769	382,028	399,249	457,538	698,525	401,887	877,559
..Petroleum - GT	1,924	5,027	790	-295	10,777	5,516	8,897	2,508	1,638	674	1,790	5,528	6,010	7,447	7,676	.	.	.
..Petroleum - IC	5,592	9,323	3,034	3,329	1,098	2,453	1,174	-2,298	290	167	4,327	4,754	-12,653	5,994	299	.	.	.
..Petroleum - OTH	356	2,234	1,319	126	344	27	0	51	110	0	0	936	30	85	0	.	.	.
..Petroleum - ST	1,547,014	1,132,937	928,528	912,029	1,201,294	1,108,514	808,908	826,231	1,049,292	531,640	319,026	331,552	388,641	385,722	449,564	.	.	.
Pumped storage	-868,131	-715,146	-845,480	-696,488	-698,455	-674,759	-751,650	-480,821	-700,889	-870,822	-773,280	-945,017	-1,022,559	-856,864	-915,502	-1,129,241	-1,039,210	-1,106,241
Solar	859,379	423,805	155,168	142,961	118,153	63,304	9,235	1,190	.	.	.	.	.	.	.	.	.	.
..Solar- PV	859,379	423,805	155,168	142,961	118,153	63,304	9,235	1,190	.	.	.	.	.	.	.	.	.	.
Wind	9,151,179	7,696,887	6,735,092	5,825,705	5,457,252	5,191,273	4,695,783	4,796,898	3,868,118	2,799,624	1,131,688	456,474	360,340	300,172	141,182	2,723	2,212	1,848
..Wind - Onshore	9,151,179	7,696,887	6,735,092	5,825,705	5,457,252	5,191,273	.	.	.	.	.	.	.	.	.	.	.	.
Wood	1,473,609	1,461,241	1,119,318	1,399,299	1,573,568	1,508,262	1,522,489	1,446,608	1,751,129	1,727,072	1,697,524	1,678,607	1,669,736	1,489,001	1,710,423	1,692,202	1,703,524	1,775,914

Other biomass includes agricultural byproducts, landfill gas, biogenic municipal solid waste, other biomass (solid, liquid and gas) and sludge waste.
Other gases includes blast furnace gas, and other manufactured and waste gases derived from fossil fuels.
Other includes non-biogenic municipal solid waste, batteries, chemicals, hydrogen, pitch, purchased steam, sulfur, tire-derived fuels, waste heat and miscellaneous technologies.
Note: Totals may not equal sum of components because of independent rounding.
Source: U.S. Energy Information Administration, Form EIA-923, Power Plant Operations Report and predecessor forms.

Year 2004	Year 2003	Year 2002	Year 2001	Year 2000	Year 1999	Year 1998	Year 1997	Year 1996	Year 1995	Year 1994	Year 1993	Year 1992	Year 1991	Year 1990	Percent share 2000	Percent share 2010	Percent share 2020	Percent share 2022
99,608,512	96,634,055	100,451,718	97,067,330	89,572,141	87,874,695	85,146,307	89,564,616	95,155,261	92,478,772	83,720,636	92,250,107	82,679,444	94,567,383	89,058,681	86.0	80.4	65.5	69.4
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0
67,253,690	66,448,916	65,389,899	66,931,691	66,980,252	69,118,017	69,142,807	65,552,021	66,097,259	65,425,002	67,538,611	61,558,991	61,434,530	65,138,291	65,295,742	64.3	58.1	25.9	29.0
1,420,178	1,242,987	1,557,942	1,450,093	1,328,083	1,367,296	1,282,471	1,592,707	1,660,109	1,486,539	1,536,190	1,639,359	1,647,175	1,651,742	1,492,822	1.3	1.0	1.5	1.1
735,011	1,098,627	2,336,031	2,362,038	2,441,140	2,448,449	2,152,055	838,412	737,006	1,163,390	656,757	680,194	1,021,751	998,058	665,142	2.3	1.1	12.3	14.6
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	6.5	10.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.3	4.0	2.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.9	0.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.7	1.0	0.5
30,561,961	27,953,563	31,087,454	26,710,782	18,882,432	14,590,711	12,494,153	21,913,808	26,829,363	24,448,397	14,144,281	28,525,000	18,848,731	27,021,214	21,610,500	18.1	21.0	22.8	19.8
34,693	23,361	25,185	15,250	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	0	.	.	.	.	.	.	.	.	.	.	0.0	0.0	.	.
1,082	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	.
714,881	883,847	1,090,767	724,313	993,932	1,282,696	1,005,170	602,053	651,860	687,264	655,860	619,777	498,159	553,863	689,461	1.0	0.2	0.7	1.2
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.7	1.2
-1,112,984	-1,017,246	-1,035,560	-1,126,837	-1,053,698	-932,474	-930,349	-934,385	-820,336	-731,820	-811,063	-773,214	-770,902	-795,785	-694,986	-1.0	-0.9	-0.8	-0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.1
.	.	.	.	0	0	0	.	.	.	.	.	.	.	.	0.0	.	2.9	4.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	2.9	4.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
18,878,757	14,713,005	17,437,370	14,778,282	14,637,455	15,365,020	15,331,086	17,406,144	17,363,047	14,965,841	14,586,751	14,118,445	12,642,494	11,410,740	11,001,054	14.0	19.6	34.5	30.6
1,352,329	1,328,567	1,309,609	1,331,477	1,286,747	1,286,976	1,329,849	1,892,829	1,774,893	1,775,644	2,233,003	2,400,090	1,912,171	1,739,932	1,771,127	1.2	0.8	0.3	0.3
119,406	142,836	111,310	111,825	99,596	91,037	114,646	119,758	123,421	110,648	124,078	122,483	135,096	99,926	135,096	0.1	0.1	0.1	0.1
13,812,692	10,275,917	13,517,387	10,811,475	10,166,125	11,065,307	10,933,126	12,549,899	12,277,609	10,411,464	9,779,791	9,340,020	8,506,888	7,501,019	7,172,814	9.8	9.9	21.8	20.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	9.1	17.0	16.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	3.7	3.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	1.2	0.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	5.6	5.6	2.3
256,688	285,751	256,232	130,653	64,276	90,414	62,903	41,037	31,390	25,394	23,986	47,857	32,283	28,222	.	0.1	0.3	0.1	0.1
689,936	727,314	745,124	661,120	1,034,570	888,984	958,814	918,717	891,240	671,429	534,523	476,658	329,409	504,978	310,842	1.0	0.7	0.9	0.7
597,665	2,193	10,108	5,614	.	.	.	579	238,393	582	595	898	243,754	217,824	340,949	.	0.3	0.9	1.1
181,528	180,046	12,718	25,577	195,332	201,810	171,785	155,980	180,913	168,838	173,702	144,271	130,608	104,709	172,263	0.2	0.2	0.2	0.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.2	0.2	0.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.7
1,875	2,660	329	280	.	.	.	.	.	.	.	.	.	.	.	.	0.3	3.4	3.5
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	3.4	3.5
1,866,638	1,767,721	1,474,552	1,700,261	1,790,809	1,740,491	1,759,962	1,727,344	1,845,188	1,801,843	1,717,073	1,586,167	1,352,286	1,214,131	1,097,962	1.7	1.5	1.0	1.3
118,487,269	111,347,060	117,889,087	111,845,612	104,209,597	103,239,715	100,477,393	106,970,760	112,518,309	107,444,613	98,307,387	106,368,552	95,321,938	105,978,123	100,059,735	100.0	100.0	100.0	100.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0
68,606,019	67,777,483	66,699,508	68,263,168	68,266,999	70,404,993	70,472,656	67,444,850	67,872,152	67,200,646	69,771,614	63,959,081	63,346,701	66,878,223	67,066,869	65.5	58.8	26.2	29.3
1,539,584	1,385,823	1,669,252	1,561,918	1,427,679	1,458,333	1,397,117	1,712,465	1,783,530	1,597,187	1,660,268	1,761,842	1,782,271	1,751,668	1,627,918	1.4	1.1	1.6	1.2
14,547,703	11,374,544	15,853,418	13,173,513	12,607,265	13,513,756	13,085,181	13,388,311	13,014,615	11,574,854	10,436,548	10,020,214	9,528,639	8,499,077	7,837,956	12.1	11.0	34.2	35.1
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	9.1	23.5	27.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1.1	7.7	5.9
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.9	0.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.8	2.1	1.3
30,561,961	27,953,563	31,087,454	26,710,782	18,882,432	14,590,711	12,494,153	21,913,808	26,829,363	24,448,397	14,144,281	28,525,000	18,848,731	27,021,214	21,610,500	18.1	26.6	28.4	22.1
291,381	309,112	281,417	145,903	64,276	90,414	62,903	41,037	31,390	25,394	23,986	47,857	32,283	28,222	.	0.1	0.3	0.1	0.1
689,936	727,314	745,124	661,120	1,034,570	888,984	958,814	918,717	891,240	671,429	534,523	476,658	329,409	504,978	310,842	1.0	0.7	0.9	0.7
598,747	2,193	10,108	5,614	.	.	.	579	238,393	582	595	898	243,754	217,824	340,949	.	0.3	0.9	1.1
896,409	1,063,893	1,103,485	749,890	1,189,264	1,484,506	1,176,955	758,033	832,773	856,102	829,562	764,048	628,767	658,572	861,724	1.1	0.3	0.9	1.3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.0	0.0	0.0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.3	0.9	1.3
-1,112,984	-1,017,246	-1,035,560	-1,126,837	-1,053,698	-932,474	-930,349	-934,385	-820,336	-731,820	-811,063	-773,214	-770,902	-795,785	-694,986	-1.0	-0.9	-0.8	-0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.7
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.1	0.7
1,875	2,660	329	280	0	0	0	.	.	.	.	.	.	.	.	0.0	0.3	6.3	7.8
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	6.3	7.8
1,866,638	1,767,721	1,474,552	1,700,261	1,790,809	1,740,491	1,759,962	1,727,344	1,845,188	1,801,843	1,717,073	1,586,167	1,352,286	1,214,131	1,097,962	1.7	1.5	1.0	1.3

Table 6. Electric power delivered fuel prices and quality for coal, petroleum, natural gas, 1990 through 2022

Michigan

	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014
Coal (dollars per million Btu)	**2.39**	**2.07**	**2.05**	**2.11**	**2.14**	**2.19**	**2.26**	**2.40**	**2.62**
Average heat value (Btu per pound)	9,427	9,465	9,496	9,379	9,343	9,303	9,419	9,412	9,528
Average sulfur content (percent)	0.53	0.56	0.57	0.50	0.48	0.47	0.55	0.49	0.52
Petroleum (dollars per million Btu)	**2.43**	**2.44**	**2.04**	**2.81**	**2.31**	**2.16**	**2.41**	**3.03**	**3.44**
Average heat value (Btu per gallon)	131,743	131,434	130,623	132,606	130,524	128,654	129,371	128,482	132,396
Average sulfur content (percent)	5.57	5.53	5.50	5.53	5.61	5.58	5.72	5.62	4.77
Natural gas (dollars per million Btu)	**6.52**	**4.01**	**2.07**	**2.63**	**3.27**	**3.21**	**2.75**	**3.16**	**6.51**
Average heat value (Btu per cubic foot)	1,049	1,052	1,052	1,055	1,045	1,035	1,034	1,027	1,023

Petroleum includes petroleum liquids and petroleum coke.

Note: Due to different reporting requirements between the Form EIA-923 and historical FERC Form 423, the receipts data from 2008 and on are not directly comparable to prior years. There may be a notable ir

Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005	Year 2004	Year 2003	Year 2002	Year 2001
2.68	**2.79**	**2.68**	**2.12**	**2.07**	**1.97**	**1.72**	**1.68**	**1.58**	**1.39**	**1.34**	**1.32**	**1.27**
9,387	9,513	9,731	9,753	9,751	9,902	9,920	9,975	10,021	9,967	10,123	10,255	10,235
0.46	0.52	0.57	0.57	0.49	0.54	0.54	0.56	0.56	0.53	0.57	0.57	0.57
6.67	**13.17**	**8.28**	**5.90**	**5.31**	**10.57**	**8.15**	**7.96**	**6.91**	**4.75**	**4.13**	**2.74**	**3.98**
132,355	138,138	134,962	135,158	138,974	138,423	144,798	144,829	145,714	146,540	146,845	144,917	148,810
5.64	5.03	4.05	4.04	3.38	3.28	1.84	1.74	1.74	1.45	1.67	1.88	1.37
4.48	**3.18**	**4.70**	**4.92**	**4.53**	**8.61**	**6.56**	**6.01**	**5.56**	**4.36**	**3.86**	**3.52**	**3.83**
1,020	1,016	1,014	1,014	1,015	1,013	1,014	1,009	1,013	1,018	1,015	1,007	990

ıcrease in fuel receipts beginning with 2008. For more information, please see the Technical Notes in the Electric Power Annual.

Year 2000	**Year 1999**	**Year 1998**	**Year 1997**	**Year 1996**	**Year 1995**	**Year 1994**	**Year 1993**	**Year 1992**	**Year 1991**	**Year 1990**
1.30	**1.31**	**1.33**	**1.37**	**1.40**	**1.45**	**1.51**	**1.53**	**1.56**	**1.59**	**1.60**
10,425	10,487	10,563	10,566	10,504	10,677	10,925	10,853	10,995	11,052	11,131
0.59	0.62	0.67	0.67	0.63	0.63	0.68	0.68	0.69	0.70	0.70
3.68	**2.57**	**2.41**	**3.09**	**3.13**	**2.88**	**2.93**	**3.06**	**2.97**	**2.86**	**3.20**
136,583	136,595	130,455	135,205	138,114	146,081	145,440	147,226	147,079	146,467	146,012
1.49	1.44	1.56	1.32	1.15	0.81	0.74	0.72	0.73	0.70	0.72
3.90	**2.52**	**2.32**	**2.56**	**2.69**	**2.00**	**2.40**	**2.42**	**1.95**	**1.96**	**2.11**
710	608	542	310	274	365	403	379	414	389	224

Table 7. Electric power industry emissions estimates, 1990 through 2022

Michigan

Emission type	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014
Sulfur dioxide (short tons)									
Coal	43,019	53,193	34,075	51,156	66,017	65,244	84,667	135,577	156,939
Natural gas	368	329	422	307	285	304	254	134	104
Other	6,390	6,728	6,609	7,359	7,417	8,120	7,385	7,316	7,667
Petroleum	4,001	4,051	3,725	23,088	8,202	9,998	9,644	7,579	8,809
Total	53,778	64,301	44,831	81,910	81,921	83,666	101,950	150,606	173,519
Nitrogen oxide (short tons)									
Coal	19,566	23,849	16,346	23,269	31,350	31,168	32,408	44,293	52,728
Natural gas	20,818	20,695	33,729	19,838	11,633	9,340	10,617	7,682	7,798
Other	11,707	11,833	13,193	12,207	13,119	13,657	13,653	14,484	14,701
Petroleum	1,695	1,907	1,172	1,213	1,300	1,339	1,141	1,236	1,929
Total	53,786	58,284	64,440	56,527	57,402	55,504	57,819	67,695	77,156
Carbon dioxide (thousand metric tons)									
Coal	36,426	37,095	28,760	37,865	43,155	42,524	41,425	54,415	54,456
Natural gas	19,439	15,760	22,511	17,419	15,968	13,499	15,041	10,593	7,425
Other	233	227	203	320	578	617	690	701	681
Petroleum	2,412	1,963	1,709	1,628	1,734	1,775	1,488	1,411	1,701
Total	58,510	55,045	53,183	57,232	61,435	58,414	58,644	67,119	64,264
Total emission rate (lbs/MWh)									
Sulfur dioxide	0.9	1.1	0.8	1.4	1.4	1.5	1.8	2.7	3.2
Nitrogen oxide	0.9	1.0	1.2	1.0	1.0	1.0	1.0	1.2	1.4
Carbon dioxide	1,096	1,048	1,097	1,079	1,167	1,144	1,151	1,307	1,324

Source: Calculations made by the Electric Power Systems and Reliability Team; Office of Electricity, Renewables, and Uranium Statistics; U.S. Energy Information Administration.

Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005	Year 2004	Year 2003	Year 2002
200,702	203,862	230,553	252,711	294,301	362,918	358,465	346,823	362,690	354,593	369,039	358,670
96	140	64	71	48	24	47	32	31	35	28	35
7,893	7,950	8,395	7,910	6,996	6,172	6,112	6,388	6,382	6,386	6,378	8,907
28,397	25,022	20,403	19,098	16,583	13,950	24,934	6,684	28,171	25,957	26,455	25,947
237,088	236,974	259,415	279,790	317,928	383,064	389,508	359,912	397,265	386,930	401,785	393,513
62,657	63,718	70,387	79,144	82,646	107,692	108,816	106,182	114,271	116,307	126,560	134,922
5,830	8,474	5,040	4,943	3,890	4,831	5,462	5,040	5,745	5,050	6,228	17,264
14,920	14,088	12,502	11,348	11,748	12,213	12,560	13,126	12,641	12,765	12,366	13,159
1,848	2,814	2,436	2,523	2,324	2,173	3,939	1,475	4,470	4,189	3,997	3,732
85,255	89,094	90,365	97,958	100,608	126,909	129,473	124,658	136,048	136,977	147,710	167,605
58,267	55,291	61,137	66,569	67,345	70,823	71,516	68,456	70,913	68,971	66,103	65,258
7,134	10,973	6,669	6,454	4,789	5,275	6,919	7,212	7,488	7,613	6,004	8,306
631	725	699	612	651	578	559	559	548	555	592	584
1,160	887	797	845	803	791	1,234	490	908	1,433	1,494	1,078
67,193	67,877	69,301	74,480	73,589	77,468	80,228	76,718	79,856	78,572	74,192	75,225
4.5	4.4	4.8	5.0	6.3	6.7	6.5	6.4	6.5	6.5	7.2	6.7
1.6	1.6	1.7	1.8	2.0	2.2	2.2	2.2	2.2	2.3	2.7	2.8
1,402	1,381	1,397	1,469	1,600	1,482	1,479	1,500	1,445	1,459	1,466	1,404

Year 2001	Year 2000	Year 1999	Year 1998	Year 1997	Year 1996	Year 1995	Year 1994	Year 1993	Year 1992	Year 1991	Year 1990
370,730	396,468	406,682	453,444	439,598	409,709	388,720	425,868	392,676	374,114	405,484	400,043
35	31	31	34	41	39	36	35	33	28	31	30
6,886	8,282	8,008	6,800	6,539	6,317	5,650	4,569	4,971	5,002	4,689	4,476
28,399	23,543	27,181	25,915	20,669	22,188	24,068	16,517	14,407	11,402	15,781	17,348
406,006	428,323	441,905	486,196	466,848	438,252	418,478	446,989	412,086	390,546	425,983	421,898
149,430	166,900	184,280	215,592	190,508	185,874	164,027	333,094	325,794	308,452	327,211	325,650
18,942	16,874	18,834	18,964	21,133	20,265	21,076	13,493	11,761	11,645	11,287	11,681
11,621	12,360	11,547	11,576	11,327	11,788	10,623	4,163	3,892	3,191	2,845	2,647
3,957	4,243	6,264	7,534	4,109	4,200	4,069	2,297	2,050	1,779	1,866	2,366
182,584	200,376	220,927	253,678	227,081	222,119	199,795	353,048	343,496	325,067	343,210	342,342
69,374	68,743	70,221	71,428	67,418	67,704	66,146	67,614	62,561	61,525	65,335	65,193
7,540	7,822	8,713	8,559	8,247	8,141	7,292	6,011	5,812	5,830	5,417	5,278
252	526	527	475	503	463	389	387	395	387	373	263
798	1,767	2,010	1,672	1,240	1,352	1,347	1,220	1,007	866	899	1,022
77,964	78,857	81,471	82,135	77,409	77,660	75,173	75,232	69,775	68,609	72,024	71,755
7.3	8.2	8.6	9.7	8.7	7.8	7.8	9.1	7.7	8.2	8.0	8.4
3.3	3.8	4.3	5.0	4.2	3.9	3.7	7.2	6.5	6.8	6.5	6.8
1,534	1,665	1,736	1,798	1,592	1,518	1,539	1,684	1,443	1,583	1,495	1,578

Table 8. Sales to ultimate customers, revenue, and average price by sector, 1990 through 2022

Michigan

Sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016
Sales (megawatthours)							
Residential	35,034,971	35,868,100	35,862,912	33,495,725	35,131,422	32,977,374	34,543,262
Commercial	37,114,401	36,860,868	35,490,797	37,860,783	38,925,268	38,325,322	38,985,906
Industrial	28,485,570	27,081,082	25,654,081	29,886,432	30,806,023	30,590,574	30,934,422
Other	NA	NA	NA	NA	NA	NA	NA
Transportation	4,320	3,231	4,116	6,353	6,783	5,823	4,223
Total	100,639,262	99,813,281	97,011,906	101,249,293	104,869,496	101,899,093	104,467,813
Revenue (thousand dollars)							
Residential	6,255,971	6,289,783	5,831,461	5,273,119	5,426,835	5,078,011	5,258,083
Commercial	4,657,585	4,537,108	4,156,478	4,313,039	4,339,291	4,217,018	4,146,763
Industrial	2,372,266	2,082,727	1,858,134	2,114,082	2,187,188	2,200,758	2,137,716
Other	NA	NA	NA	NA	NA	NA	NA
Transportation	534	398	469	671	730	698	491
Total	13,286,355	12,910,015	11,846,542	11,700,911	11,954,044	11,496,486	11,543,053
Customers							
Residential	4,475,317	4,458,038	4,423,595	4,384,305	4,365,529	4,344,321	4,311,008
Commercial	554,487	550,701	546,115	544,690	543,261	542,959	538,677
Industrial	5,689	5,706	5,580	5,726	5,972	6,196	6,191
Other	NA	NA	NA	NA	NA	NA	NA
Transportation	2	2	2	2	2	2	1
Total	5,035,495	5,014,447	4,975,292	4,934,723	4,914,764	4,893,478	4,855,877
Average price to ultimate customers (cents/kWh)							
Residential	17.86	17.54	16.26	15.74	15.45	15.40	15.22
Commercial	12.55	12.31	11.71	11.39	11.15	11.00	10.64
Industrial	8.33	7.69	7.24	7.07	7.10	7.19	6.91
Other	NA	NA	NA	NA	NA	NA	NA
Transportation	12.35	12.30	11.39	10.56	10.76	11.99	11.63
Total	13.20	12.93	12.21	11.56	11.40	11.28	11.05

U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005
33,357,876	33,514,991	34,013,168	34,461,140	34,811,337	34,680,715	32,854,122	34,297,438	35,366,081	34,622,099	36,094,954
38,440,734	37,348,927	37,697,520	38,514,266	38,612,718	38,123,171	37,870,363	38,974,426	40,046,871	39,298,995	39,599,845
30,677,019	32,445,935	31,321,534	31,835,905	31,624,220	30,840,513	27,391,101	32,504,511	33,878,817	34,092,935	34,744,739
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
4,292	4,245	6,083	6,880	5,283	4,820	5,428	4,896	4,980	3,668	5,025
102,479,921	103,314,098	103,038,305	104,818,191	105,053,558	103,649,219	98,121,014	105,781,271	109,296,749	108,017,697	110,444,563
4,810,815	4,846,496	4,962,369	4,871,034	4,621,167	4,320,775	3,812,658	3,685,390	3,611,793	3,381,935	3,032,824
4,057,255	4,060,031	4,170,783	4,211,356	3,988,981	3,740,718	3,500,740	3,575,202	3,513,901	3,344,517	3,104,565
2,154,662	2,491,113	2,416,682	2,427,143	2,315,040	2,183,317	1,912,766	2,186,015	2,192,100	2,061,249	1,849,998
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
491	400	533	556	451	513	586	579	486	369	657
11,023,223	11,398,040	11,550,367	11,510,089	10,925,638	10,245,323	9,226,749	9,447,186	9,318,280	8,788,070	7,988,044
4,282,858	4,273,126	4,265,264	4,250,620	4,249,136	4,245,158	4,253,786	4,290,313	4,298,455	4,299,273	4,284,083
532,858	522,422	520,327	521,091	521,322	520,233	520,551	518,776	518,058	514,049	509,964
6,041	13,289	13,419	13,074	12,961	12,827	13,065	12,776	13,227	13,317	13,390
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
1	2	1	1	1	1	1	1	1	1	1
4,821,758	4,808,839	4,799,011	4,784,786	4,783,420	4,778,219	4,787,403	4,821,866	4,829,741	4,826,640	4,807,438
14.42	14.46	14.59	14.13	13.27	12.46	11.60	10.75	10.21	9.77	8.40
10.55	10.87	11.06	10.93	10.33	9.81	9.24	9.17	8.77	8.51	7.84
7.02	7.68	7.72	7.62	7.32	7.08	6.98	6.73	6.47	6.05	5.32
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
11.44	9.43	8.77	8.08	8.53	10.65	10.79	11.83	9.76	10.06	13.07
10.76	11.03	11.21	10.98	10.40	9.88	9.40	8.93	8.53	8.14	7.23

Year 2004	Year 2003	Year 2002	Year 2001	Year 2000	Year 1999	Year 1998	Year 1997	Year 1996	Year 1995	Year 1994
33,103,586	33,669,474	34,336,161	32,304,798	30,707,267	30,661,187	29,807,978	28,726,279	28,901,473	28,622,895	27,174,208
38,632,100	35,391,365	35,880,320	35,025,499	35,867,003	35,095,922	33,839,513	32,410,931	32,037,663	31,305,837	30,411,630
34,867,337	39,812,955	33,537,474	34,174,112	37,267,697	37,275,750	35,983,417	35,429,624	34,499,412	33,920,578	32,716,794
NA	NA	959,565	904,938	930,249	948,147	875,287	823,826	863,018	851,824	857,355
3,017	3,399	NA	NA	NA	NA	NA	NA	NA	NA	NA
106,606,040	108,877,193	104,713,520	102,409,347	104,772,216	103,981,006	100,506,195	97,390,660	96,301,566	94,701,134	91,159,987
2,758,552	2,813,077	2,844,554	2,667,172	2,617,706	2,676,360	2,584,189	2,461,915	2,448,299	2,387,301	2,249,213
2,925,172	2,671,529	2,794,428	2,640,082	2,832,471	2,755,186	2,641,974	2,539,696	2,543,091	2,462,154	2,410,662
1,716,747	1,975,944	1,684,308	1,737,746	1,898,271	1,873,483	1,809,150	1,760,605	1,750,987	1,738,782	1,716,262
NA	NA	100,088	93,912	100,192	96,410	93,997	89,653	93,570	91,230	90,379
238	279	NA	NA	NA	NA	NA	NA	NA	NA	NA
7,400,709	7,460,829	7,423,378	7,138,912	7,448,640	7,401,439	7,129,310	6,851,869	6,835,947	6,679,467	6,466,516
4,248,920	4,216,573	4,188,117	4,147,897	4,099,153	4,058,091	4,024,218	3,975,175	3,914,312	3,867,468	3,817,961
504,754	483,168	471,509	465,622	461,175	450,754	440,794	432,196	423,876	417,807	410,810
14,322	14,224	13,442	13,805	13,670	13,531	13,214	13,137	13,186	13,085	12,560
NA	NA	9,410	9,002	9,856	11,873	8,421	7,721	16,814	17,771	16,442
1	1	NA	NA	NA	NA	NA	NA	NA	NA	NA
4,767,997	4,713,966	4,682,478	4,636,326	4,583,854	4,534,249	4,486,647	4,428,229	4,368,188	4,316,131	4,257,773
8.33	8.35	8.28	8.26	8.52	8.73	8.67	8.57	8.47	8.34	8.28
7.57	7.55	7.79	7.54	7.90	7.85	7.81	7.84	7.94	7.86	7.93
4.92	4.96	5.02	5.08	5.09	5.03	5.03	4.97	5.08	5.13	5.25
NA	NA	10.43	10.38	10.77	10.17	10.74	10.88	10.84	10.71	10.54
7.89	8.21	NA	NA	NA	NA	NA	NA	NA	NA	NA
6.94	6.85	7.09	6.97	7.11	7.12	7.09	7.04	7.10	7.05	7.09

Year 1993	Year 1992	Year 1991	Year 1990	Percent share 2000	Percent share 2010	Percent share 2020	Percent share 2022
26,770,174	25,670,669	26,759,510	25,318,849	29.3	33.5	37.0	34.8
28,930,387	21,208,468	21,454,734	20,609,561	34.2	36.8	36.6	36.9
30,571,544	35,656,772	35,006,636	35,062,022	35.6	29.8	26.4	28.3
1,316,497	1,304,316	1,297,663	1,376,437	0.9	0.0	0.0	0.0
NA	NA	NA	NA	0.0	0.0	0.0	0.0
87,588,602	83,840,225	84,518,543	82,366,869	100.0	100.0	100.0	100.0
2,184,506	2,081,705	2,157,926	1,982,483	35.1	42.2	49.2	47.1
2,319,009	1,755,746	1,756,557	1,678,553	38.0	36.5	35.1	35.1
1,632,454	2,103,854	2,061,464	2,051,268	25.5	21.3	15.7	17.9
120,411	121,257	118,905	137,348	1.3	0.0	0.0	0.0
NA	NA	NA	NA	0.0	0.0	0.0	0.0
6,256,380	6,062,562	6,094,852	5,849,652	100.0	100.0	100.0	100.0
3,781,048	3,745,401	3,715,552	3,661,732	89.4	88.8	88.9	88.9
404,806	397,213	392,114	384,526	10.1	10.9	11.0	11.0
12,397	14,513	14,367	14,653	0.3	0.3	0.1	0.1
17,506	18,128	17,684	17,310	0.2	0.0	0.0	0.0
NA	NA	NA	NA	0.0	0.0	0.0	0.0
4,215,757	4,175,255	4,139,717	4,078,221	100.0	100.0	100.0	100.0
8.16	8.11	8.06	7.83				
8.02	8.28	8.19	8.14				
5.34	5.90	5.89	5.85				
9.15	9.30	9.16	9.98				
NA	NA	NA	NA				
7.14	7.23	7.21	7.10				

Table 9. Sales to ultimate customers statistics, 2022

Michigan

	Full service providers					Other providers		
Item	**Investor owned**	**Public**	**Federal**	**Cooperative**	**Non-utility**	**Energy**	**Delivery**	**Total**
Number of entities	7	40	NA	10	2	10	5	
Number of customers	4,379,686	314,788	NA	335,375	3	5,643	NA	5,035,495
Retail (megawatthours)	79,668,552	7,358,821	NA	4,323,883	414,854	8,873,152	NA	100,639,262
Percentage of sales	79.2	7.3	NA	4.3	0.4	8.8	NA	100.0
Revenue from sales (thousand dollars)	10,997,439.4	869,138.8	NA	624,941.8	24,590.0	638,574.4	131,670.6	13,286,355.0
Percentage of revenue	82.8	6.5	NA	4.7	0.2	4.8	1.0	100.0
Average price to ultimate customers (cents/kWh)	13.80	11.81	NA	14.45	5.93	7.20	1.48	13.20

Notes: Data are shown for All Sectors. Full Service Providers sell bundled electricity services (e.g., both energy and delivery) to end users. Full Service Providers may purchase electricity from others (such as independent Power Producers or other full service providers) prior to delivery. Other Providers sell either the energy or the delivery services, but not both. Sales volumes and customer counts shown for Other Providers refer to delivered electricity, which is a joint activity of both energy and delivery providers; for clarity, they are reported only in the Energy column in this table.The revenue shown under Other Providers represents the revenue realized from the sale of the energy and the delivery services distinctly. "Public" entities include municipalities, State power agencies, and municipal marketing authorities. Federal entities are either owned or financed by the Federal Government. "Cooperatives" are electric utilities legally established to be owned by and operated for the benefit of those using its services. The cooperative will generate, transmit and/or distribute supplies of electric energy to a specified area not being serviced by another utility. "Non-utility" sales represent direct electricity transactions from independent generators to end use consumers. Totals may not equal sum of components because of independent rounding.
Total number of entities are not summed for the state to prevent possible duplication.
Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Table 10. Supply and disposition of electricity, 1990 through 2022

Michigan

megawatthours

Category	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014
Supply									
Generation									
..Electric utilities	81,577,914	81,451,708	69,820,694	78,881,960	81,450,131	79,938,707	78,006,408	85,370,227	84,075,322
..Independent power producers	19,758,870	19,924,161	18,626,790	19,735,665	17,612,759	17,593,600	17,619,977	14,418,920	12,787,845
..Combined heat and power, electric	14,048,436	12,062,068	16,361,003	15,951,611	14,582,738	12,629,847	14,326,924	10,925,817	7,631,138
Electric power sector generation subtotal	**115,385,220**	**113,437,937**	**104,808,487**	**114,569,235**	**113,645,628**	**110,162,154**	**109,953,309**	**110,714,964**	**104,494,305**
..Combined heat and power, commercial	749,820	676,502	662,180	728,986	867,486	831,057	881,083	1,012,742	971,778
..Combined heat and power, industrial	1,362,012	1,398,691	1,154,054	1,403,267	1,323,981	1,320,290	1,287,397	1,280,344	1,350,907
Industrial and commercial generation subtotal	**2,111,832**	**2,075,193**	**1,816,234**	**2,132,253**	**2,191,467**	**2,151,347**	**2,168,481**	**2,293,086**	**2,322,686**
Total net generation	**117,497,052**	**115,513,130**	**106,624,721**	**116,701,488**	**115,837,095**	**112,313,501**	**112,121,790**	**113,008,050**	**106,816,991**
Total international imports	**5,237,898**	**5,282,204**	**5,790,141**	**6,047,749**	**6,540,049**	**5,734,967**	**7,837,006**	**8,481,253**	**6,175,525**
Net interstate imports	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Total supply	**122,734,950**	**120,795,334**	**112,414,862**	**122,749,237**	**122,377,144**	**118,048,468**	**119,958,796**	**121,489,303**	**112,992,516**
Disposition									
Sales to ultimate customers									
..Full service providers	91,351,256	90,795,892	88,672,937	91,921,848	95,568,004	92,588,972	94,935,158	92,569,534	91,446,084
..Energy-only providers	8,873,152	8,639,559	7,945,332	8,911,569	8,870,771	8,906,962	9,116,127	9,305,012	11,451,880
..Facility direct sales	414,854	377,830	393,637	415,876	430,721	403,159	416,528	605,375	416,134
Total electric industry sales	**100,639,262**	**99,813,281**	**97,011,906**	**101,249,293**	**104,869,496**	**101,899,093**	**104,467,813**	**102,479,921**	**103,314,098**
Direct use	**2,536,443**	**2,380,982**	**2,142,041**	**2,340,308**	**2,528,022**	**2,399,105**	**2,412,215**	**2,090,106**	**2,333,108**
Total international exports	**3,492,772**	**3,093,884**	**4,083,510**	**3,402,327**	**53,295**	**29,468**	**30,268**	**190,098**	**331,263**
Estimated losses	**5,443,725**	**4,695,863**	**5,403,007**	**5,490,130**	**5,408,922**	**5,543,151**	**5,452,288**	**5,112,277**	**5,379,559**
Unaccounted	**-181,850**	**637,479**	**-145,736**	**252,773**	**655,603**	**710,136**	**1,296,279**	**1,597,213**	**1,335,822**
Net interstate exports	**10,804,598**	**10,173,844**	**3,920,134**	**10,014,406**	**8,861,806**	**7,467,515**	**6,299,933**	**10,019,688**	**298,666**
Total disposition	**122,734,950**	**120,795,334**	**112,414,862**	**122,749,237**	**122,377,144**	**118,048,468**	**119,958,796**	**121,489,303**	**112,992,516**
Net interstate trade	**10,804,598**	**10,173,844**	**3,920,134**	**10,014,406**	**8,861,806**	**7,467,515**	**6,299,933**	**10,019,688**	**298,666**
Net trade index (ratio)	**1.1**	**1.1**	**1.0**	**1.1**	**1.1**	**1.1**	**1.1**	**1.1**	**1.0**

Net Interstate Trade = Total Supply - (Total Electric Industry Sales + Direct Use + Total International Exports (if applies) + Estimated Losses).
Net Trade Index is the sum of Total Supply / (Total Disposition - Net Interstate Trade).
A negative Net Interstate Trade value indicates a net import of electric power.
Notes: Totals may not equal sum of components because of independent rounding. Estimated Losses are reported at the utility level, and then allocated to States based on the utility`s salesto ultimate customers by State. Repor
Beginning with publication year 2010, Total disposition has been reorganized to include Net Interstate Trade. Therefore, Total Disposition equals Total Supply.
Sources: U.S. Energy Information Administration, Form EIA-923, Power Plant Operations Report and predecessor forms. U.S. Energy Information Administration,Form EIA-860, Annual Electric Generator Report. U.S. Energy Inforn

Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007	Year 2006	Year 2005	Year 2004	Year 2003	Year 2002	Year 2001
83,171,310	80,474,999	87,609,471	89,666,874	82,787,341	94,503,953	96,785,842	97,373,706	104,830,689	99,608,512	96,634,055	100,451,718	97,067,330
12,560,766	14,300,177	12,184,173	12,569,865	10,449,447	10,953,505	11,027,611	3,859,411	4,337,023	2,560,189	2,302,109	5,030,864	2,399,126
7,312,667	11,051,885	7,347,404	7,474,970	6,203,600	7,349,933	9,327,166	9,077,221	10,161,162	13,904,316	9,917,144	10,137,521	10,501,594
103,044,743	**105,827,061**	**107,141,047**	**109,711,709**	**99,440,389**	**112,807,391**	**117,140,618**	**110,310,338**	**119,328,874**	**116,073,017**	**108,853,308**	**115,620,103**	**109,968,049**
861,283	967,956	788,951	624,181	603,624	535,131	627,216	515,407	534,676	536,342	503,966	477,004	239,307
1,511,775	1,363,033	1,239,509	1,215,481	1,158,593	1,647,284	1,542,101	1,730,994	1,756,221	1,877,911	1,989,785	1,791,980	1,638,255
2,373,058	**2,330,989**	**2,028,459**	**1,839,663**	**1,762,216**	**2,182,415**	**2,169,318**	**2,246,400**	**2,290,897**	**2,414,252**	**2,493,752**	**2,268,984**	**1,877,562**
105,417,801	**108,158,050**	**109,169,507**	**111,551,371**	**101,202,605**	**114,989,806**	**119,309,936**	**112,556,738**	**121,619,771**	**118,487,269**	**111,347,060**	**117,889,087**	**111,845,612**
6,032,954	**4,572,066**	**4,525,243**	**6,117,627**	**7,576,434**	**6,305,172**	**1,681,860**	**357,046**	**1,681,055**	**2,054,387**	**1,253,352**	**240,232**	**74,012**
1,251,369	**2,227,684**	**899,647**	**0**	**204,074**	**0**	**1,857,500**	**9,749,351**	**4,207,616**	**4,401,794**	**13,442,948**	**2,644,718**	**3,595,157**
112,702,124	**114,957,800**	**114,594,397**	**117,668,998**	**108,983,113**	**121,294,978**	**122,849,296**	**122,663,135**	**127,508,442**	**124,943,450**	**126,043,360**	**120,774,037**	**115,514,781**
92,605,231	95,173,582	95,230,803	94,564,763	93,654,152	102,320,575	104,526,113	101,899,292	98,602,601	92,097,202	96,659,455	100,213,318	101,776,743
9,992,639	9,198,981	9,361,428	9,083,972	4,046,710	2,999,260	4,292,693	5,619,061	11,333,864	13,991,287	10,112,012	4,500,202	632,604
440,435	445,628	461,327	484	420,152	461,436	477,943	499,344	508,098	517,551	2,105,726	1,565,547	0
103,038,305	**104,818,191**	**105,053,558**	**103,649,219**	**98,121,014**	**105,781,271**	**109,296,749**	**108,017,697**	**110,444,563**	**106,606,040**	**108,877,193**	**106,279,067**	**102,409,347**
2,359,430	**2,368,855**	**1,927,006**	**1,899,233**	**1,792,173**	**2,144,060**	**2,005,136**	**2,353,796**	**2,584,479**	**2,922,287**	**2,919,243**	**2,882,639**	**2,821,309**
214,848	**302,005**	**456,671**	**2,553,774**	**1,939,287**	**4,000,591**	**2,887,818**	**2,473,613**	**4,411,246**	**5,258,329**	**4,817,768**	**2,474,343**	**2,175,612**
5,535,180	**5,676,320**	**6,491,641**	**6,403,217**	**6,246,131**	**6,738,319**	**6,917,662**	**7,003,745**	**7,381,644**	**7,811,664**	**7,994,648**	**7,971,953**	**8,008,765**
1,554,360	**1,792,429**	**665,520**	**909,497**	**884,508**	**1,381,430**	**1,741,932**	**.**	**.**	**.**	**.**	**.**	**.**
0	**0**	**0**	**2,254,058**	**0**	**1,249,307**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
112,702,124	**114,957,800**	**114,594,397**	**117,668,998**	**108,983,113**	**121,294,978**	**122,849,296**	**122,663,135**	**127,508,442**	**124,943,450**	**126,043,360**	**120,774,037**	**115,514,781**
-1,251,369	**-2,227,684**	**-899,647**	**2,254,058**	**-204,074**	**1,249,307**	**-1,857,500**	**-9,749,351**	**-4,207,616**	**-4,401,794**	**-13,442,948**	**-2,644,718**	**-3,595,157**
1.0	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**	**0.9**	**1.0**	**1.0**	**0.9**	**1.0**	**1.0**

ted losses may include electricity unaccounted for by the utility.   Direct use is commercial or industrial use of electricity that (1) is self-generated (2) is produced by either the same entity that consumes the power or an affiliate,ar

nation Administration, Form EIA-861, Annual Electric Power Industry Report. Form EIA-111, Quarterly Imports and Exports Report.

Year 2000	Year 1999	Year 1998	Year 1997	Year 1996	Year 1995	Year 1994	Year 1993	Year 1992	Year 1991	Year 1990
89,572,141	87,874,695	85,146,307	89,564,616	95,155,261	92,478,772	83,720,636	92,250,107	82,679,444	94,567,383	89,058,681
1,751,367	1,723,457	1,746,821	1,679,487	1,777,210	1,456,350	1,343,056	1,185,746	868,192	693,687	638,996
10,476,171	11,079,892	11,014,262	12,287,614	12,044,779	9,611,129	9,221,499	8,905,594	7,907,290	6,702,210	6,353,648
101,799,678	**100,678,044**	**97,907,390**	**103,531,717**	**108,977,250**	**103,546,251**	**94,285,190**	**102,341,447**	**91,454,926**	**101,963,280**	**96,051,325**
622,156	683,703	638,193	635,704	625,592	562,902	471,502	452,436	331,497	578,313	411,321
1,787,762	1,877,968	1,931,810	2,803,340	2,915,466	3,335,459	3,550,695	3,574,668	3,535,515	3,436,529	3,597,089
2,409,918	**2,561,671**	**2,570,003**	**3,439,043**	**3,541,058**	**3,898,362**	**4,022,196**	**4,027,104**	**3,867,012**	**4,014,843**	**4,008,411**
104,209,596	**103,239,715**	**100,477,393**	**106,970,760**	**112,518,308**	**107,444,613**	**98,307,387**	**106,368,552**	**95,321,938**	**105,978,123**	**100,059,735**
1,328,760	**889,216**	**2,027,472**	**3,384,292**	**2,125,829**	**5,800,588**	**6,910,227**	**2,419,866**	**83,476**	**107,629**	**39,599**
13,581,288	**13,892,710**	**13,319,056**	**806,667**	**0**	**0**	**0**	**0**	**0**	**0**	**3,135,880**
119,119,644	**118,021,641**	**115,823,921**	**111,161,719**	**114,644,137**	**113,245,201**	**105,217,614**	**108,788,418**	**95,405,414**	**106,085,752**	**103,235,214**
104,370,569	103,479,677	100,506,195	97,390,660	96,301,566	94,701,134	91,159,987	87,588,602	83,840,225	84,518,543	82,366,869
401,647	501,329	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
104,772,216	**103,981,006**	**100,506,195**	**97,390,660**	**96,301,566**	**94,701,134**	**91,159,987**	**87,588,602**	**83,840,225**	**84,518,543**	**82,366,869**
2,887,280	**2,973,171**	**2,872,197**	**4,098,164**	**4,026,079**	**4,436,534**	**4,541,485**	**4,557,801**	**4,466,876**	**4,371,282**	**4,347,354**
1,656,102	**1,108,301**	**3,561,049**	**2,004,494**	**219,123**	**40,982**	**1,172**	**28,736**	**314,833**	**553,719**	**10,957,882**
8,149,525	**8,157,531**	**7,146,765**	**7,342,958**	**7,475,091**	**7,228,086**	**6,925,090**	**7,010,035**	**6,627,887**	**6,489,739**	**6,253,358**
.	.	.	.	.	.	.	.	.	.	.
0	**0**	**0**	**0**	**6,249,131**	**6,602,996**	**2,971,852**	**10,072,794**	**740,387**	**10,864,462**	**0**
119,119,644	**118,021,641**	**115,823,921**	**111,161,719**	**114,644,137**	**113,245,201**	**105,217,614**	**108,788,418**	**95,405,414**	**106,085,752**	**103,235,214**
-13,581,288	**-13,892,710**	**-13,319,056**	**-806,667**	**6,249,131**	**6,602,996**	**2,971,852**	**10,072,794**	**740,387**	**10,864,462**	**-3,135,880**
0.9	**0.9**	**0.9**	**1.0**	**1.1**	**1.1**	**1.0**	**1.1**	**1.0**	**1.1**	**1.0**

ıd (3) is used in direct support of a service or industrial process located within the same facility or group of facilities that houses the generating equipment. Direct use is exclusive of station use.

Table 11. Net metering, 2010 through 2022

Michigan

Technology by sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010
Photovoltaic													
Capacity (MW)	**152.685**	**119.795**	**94.225**	**66.458**	**44.215**	**28.544**	**22.256**	**16.972**	**13.915**	**11.493**	**8.690**	**5.540**	**3.420**
Residential	112.645	84.950	65.447	46.870	28.192	17.144	12.545	9.715	7.853	6.351	4.860	3.581	2.837
Commercial	38.658	33.361	27.414	18.507	15.006	10.778	9.199	6.745	5.551	4.630	3.724	1.913	0.540
Industrial	1.382	1.484	1.365	1.081	1.017	0.622	0.512	0.512	0.511	0.512	0.103	0.047	0.033
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customers	**18,441**	**14,451**	**11,554**	**8,387**	**4,937**	**3,246**	**2,375**	**1,958**	**1,612**	**1,299**	**996**	**769**	**383**
Residential	17,237	13,372	10,598	7,643	4,342	2,738	1,944	1,589	1,299	1,032	807	624	331
Commercial	1,163	1,036	912	705	565	486	418	356	300	254	184	142	48
Industrial	41	43	44	39	30	22	13	13	13	13	5	3	4
Transportation	0	0	0	0	0	0	0	0	0	0	0	0	0
Storage													
Capacity (MW)	**8.452**	**5.013**	**0.072**	**0.044**	**0.014**	**0.014**	**0.014**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	8.097	4.897	0.042	0.014	0.014	0.014	0.014	.	.	.	.	.	.
Commercial	0.355	0.092	0.030	0.030	0.000	0.000	0.000	.	.	.	.	.	.
Industrial	0.000	0.024	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Customers	**1,258**	**917**	**11**	**3**	**2**	**2**	**2**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	1,245	902	10	2	2	2	2	.	.	.	.	.	.
Commercial	13	11	1	1	0	0	0	.	.	.	.	.	.
Industrial	0	4	0	0	0	0	0	.	.	.	.	.	.
Transportation	0	0	0	0	0	0	0	.	.	.	.	.	.
Virtual PV (1MW and over)													
Capacity (MW)	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Commercial	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Industrial	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Customers	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	0	0	0	0	0	0	0	.	.	.	.	.	.
Commercial	0	0	0	0	0	0	0	.	.	.	.	.	.
Industrial	0	0	0	0	0	0	0	.	.	.	.	.	.
Transportation	0	0	0	0	0	0	0	.	.	.	.	.	.
Virtual PV (under 1MW)													
Capacity (MW)	**0.469**	**0.442**	**0.408**	**0.391**	**0.196**	**0.153**	**0.0**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	0.433	0.414	0.381	0.363	0.127	0.104	0.000	.	.	.	.	.	.
Commercial	0.036	0.028	0.027	0.028	0.069	0.049	0.000	.	.	.	.	.	.
Industrial	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	.	.	.	.	.	.
Customers	**424**	**378**	**379**	**369**	**135**	**115**	**0**	**.**	**.**	**.**	**.**	**.**	**.**
Residential	418	371	372	362	126	108	0	.	.	.	.	.	.
Commercial	6	7	7	7	9	7	0	.	.	.	.	.	.
Industrial	0	0	0	0	0	0	0	.	.	.	.	.	.
Transportation	0	0	0	0	0	0	0	.	.	.	.	.	.
Wind													
Capacity (MW)	**1.535**	**1.684**	**1.70**	**1.767**	**1.805**	**1.775**	**2.029**	**1.980**	**2.115**	**1.811**	**2.461**	**1.385**	**40.585**
Residential	1.056	1.087	1.101	1.164	1.189	1.157	1.190	1.139	1.048	0.997	1.677	0.892	40.523
Commercial	0.474	0.592	0.594	0.598	0.611	0.613	0.826	0.828	1.054	0.802	0.772	0.486	0.052
Industrial	0.005	0.005	0.005	0.005	0.005	0.005	0.013	0.013	0.013	0.012	0.012	0.007	0.010
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customers	**308**	**318**	**321**	**340**	**344**	**343**	**344**	**345**	**336**	**327**	**318**	**284**	**219**
Residential	244	253	255	273	274	271	269	270	265	257	258	238	204
Commercial	63	64	65	66	69	71	73	73	69	68	58	45	14

Table 11. Net metering, 2010 through 2022
Michigan

Technology by sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010
Industrial	1	1	1	1	1	1	2	2	2	2	2	1	1
Transportation	0	0	0	0	0	0	0	0	0	0	0	0	0
Other													
Capacity (MW)	**2.052**	**2.042**	**2.040**	**2.041**	**1.482**	**1.462**	**1.368**	**1.188**	**1.176**	**1.176**	**0.613**	**0.602**	**0.031**
Residential	0.037	0.027	0.025	0.026	0.025	0.022	0.003	0.013	0.003	0.003	0.007	0.006	0.026
Commercial	1.365	1.365	1.365	1.365	0.807	0.790	0.775	0.775	0.773	0.773	0.606	0.596	0.005
Industrial	0.650	0.650	0.650	0.650	0.650	0.650	0.590	0.400	0.400	0.400	0.000	0.000	0.000
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customers	**20**	**19**	**18**	**19**	**15**	**13**	**8**	**8**	**7**	**7**	**10**	**9**	**3**
Residential	6	5	4	5	4	3	1	2	1	1	2	2	1
Commercial	11	11	11	11	8	7	5	5	5	5	8	7	2
Industrial	3	3	3	3	3	3	2	1	1	1	0	0	0
Transportation	0	0	0	0	0	0	0	0	0	0	0	0	0
All technologies													
Capacity (MW)	**156.741**	**123.963**	**98.373**	**70.657**	**47.698**	**31.934**	**25.653**	**20.140**	**17.206**	**14.480**	**11.761**	**7.528**	**44.026**
Residential	114.171	86.478	66.954	48.423	29.533	18.427	13.738	10.867	8.904	7.351	6.544	4.479	43.386
Commercial	40.533	35.346	29.400	20.498	16.493	12.230	10.800	8.348	7.378	6.205	5.102	2.995	0.597
Industrial	2.037	2.139	2.020	1.736	1.672	1.277	1.115	0.925	0.924	0.924	0.115	0.054	0.043
Transportation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customers	**19,193**	**15,166**	**12,272**	**9,115**	**5,431**	**3,717**	**2,727**	**2,311**	**1,955**	**1,633**	**1,324**	**1,062**	**605**
Residential	17,905	14,001	11,229	8,283	4,746	3,120	2,214	1,861	1,565	1,290	1,067	864	536
Commercial	1,243	1,118	995	789	651	571	496	434	374	327	250	194	64
Industrial	45	47	48	43	34	26	17	16	16	16	7	4	5
Transportation	0	0	0	0	0	0	0	0	0	0	0	0	0

Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Table 12. Advanced metering, 2007 through 2022
Michigan

Technology by sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016
AMR meters	**151,851**	**274,777**	**303,756**	**322,578**	**316,951**	**322,771**	**324,508**
Residential	124,257	232,969	259,288	274,155	271,079	276,627	277,454
Commercial	27,385	40,872	43,317	47,134	44,718	44,879	45,759
Industrial	209	936	1,151	1,289	1,154	1,265	1,295
Transportation	0	0	0	0	0	0	0
AMI meters	**5,174,298**	**4,988,939**	**4,912,650**	**4,807,606**	**4,671,367**	**4,647,128**	**3,977,236**
Residential	4,638,043	4,489,617	4,427,343	4,336,436	4,213,368	4,192,689	3,628,725
Commercial	531,422	497,170	483,791	469,854	456,725	453,209	347,417
Industrial	4,827	2,146	1,510	1,310	1,272	1,228	1,092
Transportation	6	6	6	6	2	2	2
Standard meters	**61,633**	**101,719**	**124,662**	**186,992**	**264,535**	**266,845**	**813,671**
Residential	48,758	79,989	98,792	153,543	222,900	224,353	671,188
Commercial	11,057	17,908	22,057	29,409	37,457	38,197	138,612
Industrial	1,818	3,822	3,813	4,040	4,178	4,295	3,871
Transportation	0	0	0	0	0	0	0
All meters	**5,387,782**	**5,365,435**	**5,341,068**	**5,317,176**	**5,252,853**	**5,236,744**	**5,115,415**
Residential	4,811,058	4,802,575	4,785,423	4,764,134	4,707,347	4,693,669	4,577,367
Commercial	569,864	555,950	549,165	546,397	538,900	536,285	531,788
Industrial	6,854	6,904	6,474	6,639	6,604	6,788	6,258
Transportation	6	6	6	6	2	2	2

AMI- Advanced Meter Infrastructure.
Prior to 2010, the count was the number of customers, not number of meters.
Starting in 2013 Standard (Non-AMR/AMI) meter data was collected on the EIA-861. This data is not collected on the EIA-861S.

Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008	Year 2007
358,438	**354,444**	**337,976**	**324,455**	**314,211**	**359,361**	**333,902**	**272,851**	**189,606**
308,879	306,626	292,051	283,561	272,718	318,011	299,426	246,630	174,020
48,007	46,331	44,463	41,134	40,083	38,141	32,779	24,761	14,476
1,552	1,487	1,462	1,390	1,410	3,209	1,697	1,460	1,110
0	0	0	0	0	0	0	0	0
3,196,371	**2,217,307**	**1,351,082**	**947,546**	**735,450**	**334,065**	**198,442**	**200,415**	**187,349**
2,958,495	2,055,628	1,248,046	872,991	683,314	309,329	179,593	178,219	165,862
237,180	160,837	102,433	74,392	51,983	24,588	18,709	21,914	21,284
694	842	603	163	153	148	140	282	203
2	0	0	0	0	0	0	0	0
1,336,889	**1,602,535**	**1,674,628**						
1,085,191	1,381,688	1,462,693						
247,970	211,749	202,522						
3,728	9,097	9,381						
0	1	32						
4,891,698	**4,174,286**	**3,363,686**						
4,352,565	3,743,942	3,002,790						
533,157	418,917	349,418						
5,974	11,426	11,446						
2	1	32						

Table 13. Energy efficiency, 2013 through 2022
Michigan

Technology by sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013
Reporting year incremental										
Savings - energy (MWh)	**1,564,184**	**1,643,381**	**1,478,825**	**1,393,370**	**1,409,038**	**1,415,547**	**1,116,333**	**1,073,961**	**1,267,525**	**1,189,290**
Residential	469,232	503,957	508,835	546,444	540,411	626,410	491,442	481,975	576,137	580,319
Commercial	964,825	998,548	799,036	739,803	754,568	684,720	557,073	527,060	611,866	529,368
Industrial	130,126	140,876	170,954	107,124	114,059	104,416	67,818	64,926	79,522	79,603
Transportation	0	0	0	0	0	0	0	0	0	0
Savings - peak demand (MW)	**282.7**	**304.9**	**280.3**	**292.1**	**259.5**	**163.6**	**125.2**	**144.4**	**160.4**	**153.5**
Residential	78.3	92.8	131.5	104.0	74.7	59.6	47.6	55.4	55.5	62.9
Commercial	183.8	189.1	125.3	171.0	155.1	89.6	71.5	80.0	94.9	80.6
Industrial	20.7	22.9	23.5	17.1	29.7	14.5	6.1	9.0	10.0	10.0
Transportation	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Costs - customer incentive (thousand dollars)	**100,731**	**92,765**	**80,511**	**72,620**	**72,223**	**69,034**	**46,686**	**41,692**	**42,461**	**40,771**
Residential	34,463	28,060	24,939	21,745	20,856	20,753	21,419	17,264	16,676	14,620
Commercial	50,379	48,157	35,495	38,780	38,924	36,556	19,237	18,486	19,402	19,974
Industrial	15,889	16,549	20,077	12,094	12,444	11,724	6,030	5,942	6,383	6,177
Transportation	0	0	0	0	0	0	0	0	0	0
Costs - all other costs (thousand dollars)	**241,452**	**243,839**	**179,230**	**173,623**	**173,575**	**157,089**	**137,746**	**138,745**	**132,075**	**117,440**
Residential	114,492	109,533	91,395	84,338	87,973	79,298	74,596	73,098	78,099	57,259
Commercial	117,984	125,873	78,738	78,809	75,807	68,667	57,353	59,742	51,040	55,226
Industrial	8,976	8,432	9,096	10,476	9,795	9,124	5,797	5,905	2,936	4,955
Transportation	0	0	0	0	0	0	0	0	0	0
Incremental life cycle										
Savings - energy (MWh)	**16,022,225**	**18,191,355**	**56,664,033**	**56,483,779**	**55,772,616**	**47,258,192**	**39,797,196**	**10,249,004**	**23,928,770**	**7,501,796**
Residential	2,899,258	3,025,314	23,134,367	22,880,439	22,255,390	18,846,063	16,923,563	4,332,044	11,103,189	3,190,024
Commercial	11,577,447	13,340,599	31,980,628	32,101,777	32,034,234	26,950,129	21,407,154	4,930,332	11,746,598	3,529,233
Industrial	1,545,520	1,825,442	1,549,037	1,501,562	1,482,993	1,462,000	1,466,479	986,628	1,078,983	782,539
Transportation	0	0	0	0	0	0	0	0	0	0
Savings - peak demand (MW)	**261.7**	**287.4**	**263.5**	**262.6**	**239.9**	**162.4**	**147.9**	**152.0**	**156.3**	**10.2**
Residential	65.9	86.3	125.2	112.4	77.5	55.5	56.7	56.5	57.7	4.4
Commercial	175.0	178.1	114.8	133.1	146.0	92.4	82.7	86.5	88.6	5.8
Industrial	20.8	23.0	23.6	17.1	16.3	14.5	8.5	9.0	10.0	0.0
Transportation	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Costs - customer incentive (thousand dollars)	**100,731**	**92,765**	**80,511**	**72,620**	**72,223**	**69,034**	**46,686**	**42,990**	**55,302**	**58,771**
Residential	34,463	28,060	24,939	21,745	20,856	20,753	21,419	17,801	24,277	21,972
Commercial	50,379	48,157	35,495	38,780	38,924	36,556	19,237	19,247	24,647	30,173
Industrial	15,889	16,549	20,077	12,094	12,444	11,724	6,030	5,942	6,378	6,626
Transportation	0	0	0	0	0	0	0	0	0	0
Costs - all other costs (thousand dollars)	**241,452**	**243,839**	**1,010,980**	**896,229**	**789,552**	**679,833**	**571,799**	**487,511**	**411,053**	**323,615**
Residential	114,492	109,533	551,626	481,238	423,463	361,246	306,280	258,355	228,506	174,070
Commercial	117,984	125,873	450,258	404,515	356,294	309,463	259,707	223,252	179,577	143,808
Industrial	8,976	8,432	9,096	10,476	9,795	9,124	5,812	5,905	2,972	5,737
Transportation	0	0	0	0	0	0	0	0	0	0

NOTE 1- Data withheld pending EIA review.
Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Table 14. Capacity and usage factors by month, 2022

Michigan

Technology	Year end capacity (MW)	Time adjusted capacity (MW)	Annual	January	February	March	April	May
Capacity Factors								
Nuclear	3,318.0	3,635.9	81.7	91.0	78.4	75.3	49.8	56.3
Other, Gas	250.0	250.0	74.3	71.8	65.0	66.3	63.1	78.1
Hydroelectric	264.1	264.1	59.9	60.2	55.1	62.4	62.8	64.9
Wood	320.9	326.7	59.6	55.6	54.5	58.1	59.0	62.5
Natural Gas - CC	6,864.8	5,620.7	58.7	74.3	68.0	62.1	55.4	48.4
Other, Biomass	168.4	168.4	56.7	57.1	67.5	62.9	60.0	59.9
Coal	6,291.1	7,847.3	52.5	55.1	45.9	38.6	42.9	61.7
Other, not Biomass or Gas	3.8	3.8	45.8	44.5	40.2	37.2	33.8	30.9
Petroleum - ST	47.2	47.2	40.5	35.6	43.0	27.7	35.5	45.8
Wind - Onshore	3,239.0	3,232.8	32.2	36.6	43.0	38.0	34.8	30.4
Natural Gas - IC	386.6	382.0	28.3	28.4	25.7	22.8	21.1	19.2
Solar - PV	472.7	455.3	21.2	9.0	13.1	19.2	21.9	27.7
Natural Gas - GT	3,896.0	3,884.6	20.4	25.9	16.4	12.1	12.8	19.1
Natural Gas - ST	2,153.7	2,153.7	4.3	3.7	4.9	2.1	2.8	3.1
Petroleum - IC	225.5	228.0	0.3	0.2	0.3	0.2	0.5	0.4
Petroleum - GT	214.3	214.3	0.2	0.2	0.2	0.2	0.2	0.2
Usage Factors								
Pumped Storage	2,185.6	2,175.6	12.6	8.3	7.7	9.8	6.8	7.8
Battery	1.3	1.3	0.6	0.5	0.6	0.5	0.4	0.5
All Sources	30,303.0	30,891.8						

Time adjusted capacity for the month is the summer capacity of generators in operation for the entire month; units that began operation during the month or that retired during the month a
period covered by the capacity factor calculation.
Sources: U.S. Energy Information Administration, Form EIA-860, Annual Electric Generator Report. and U.S. Energy Information Administration, Form EIA-923, Power Plant Operations Repor

June	July	August	September	October	November	December
96.1	98.5	95.5	93.3	66.7	88.3	103.8
76.4	87.8	67.4	84.8	75.9	75.1	79.4
67.5	51.8	58.4	59.1	47.8	66.2	62.7
64.7	57.9	59.7	56.6	60.6	60.4	66.1
60.7	65.0	69.3	58.0	55.7	45.8	49.1
57.2	46.7	45.1	56.9	58.5	64.9	45.2
55.5	61.8	54.3	55.6	58.6	39.5	61.6
50.1	64.8	59.2	54.0	50.8	35.7	47.1
30.4	41.8	44.7	44.8	48.3	48.8	39.5
25.4	21.3	17.6	21.1	36.5	43.7	39.3
30.7	39.4	36.5	32.9	31.7	22.3	28.4
35.8	32.8	30.1	23.3	20.1	12.8	5.3
25.8	29.4	22.9	21.2	17.0	18.4	23.5
8.4	8.9	5.8	3.9	2.0	2.0	4.2
0.5	0.1	0.2	0.1	0.2	0.3	0.3
0.4	0.2	0.3	0.2	0.2	0.2	0.3
16.7	20.3	21.8	16.9	8.1	13.9	12.6
0.7	0.5	0.5	0.5	0.5	0.6	0.6

are excluded. Time adjusted capacity is the capacity of all the generators that were included in the time

rt

Table 15. Capacity and usage factors, 2008 through 2022
Michigan

Generation technology	2022 Time adjusted capacity (MW)	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016
Capacity Factors								
Nuclear	3,635.9	81.7	95.3	84.6	91.9	84.4	89.7	87.5
Other, Gas	250.0	74.3	66.5	71.5	80.7	75.0	77.3	74.6
Hydroelectric	264.1	59.9	58.0	73.1	68.9	66.4	71.8	66.9
Wood	326.7	59.6	57.2	48.3	56.2	62.4	59.8	60.9
Natural Gas - CC	5,620.7	58.7	54.8	63.9	64.3	57.9	51.6	56.7
Other, Biomass	168.4	56.7	65.4	69.7	63.1	55.1	57.4	57.0
Coal	7,847.3	52.5	53.8	39.1	50.5	54.4	52.9	48.2
Other, not Biomass or Gas	3.8	45.8						
Petroleum - ST	47.2	40.5	39.8	42.8	41.3	38.0	40.4	44.3
Wind - Onshore	3,232.8	32.2	29.5	32.6	32.5	32.7	37.3	
Natural Gas - IC	382.0	28.3	31.4	30.1	28.3	6.5	3.0	2.0
Solar - PV	455.3	21.2	19.8	17.0	16.3	15.3	16.3	14.7
Natural Gas - GT	3,884.6	20.4	18.5	24.3	19.5	19.8	14.2	20.1
Natural Gas - ST	2,153.7	4.3	6.5	7.9	7.8	5.9	5.0	4.3
Petroleum - IC	228.0	0.3	0.3	0.1	0.1	0.1	0.1	0.1
Petroleum - GT	214.3	0.2	0.3	0.1	0.0	0.6	0.3	0.4
Wind								39.1
Usage Factors								
Pumped Storage	2,175.6	12.6	10.3	12.2	9.8	9.5	9.3	10.3
Battery	1.3	0.6	0.8	1.0	1.2	0.5		
All Sources	30,891.8							

Note: Time adjusted capacity for the year is the capacity of all the generators that were included in the capacity factor calculation.
Sources: U.S. Energy Information Administration, Form EIA-860, Annual Electric Generator Report. and U.S. Energy Information Administration, Form EIA-923, Power Pla

Year 2015	Year 2014	Year 2013	Year 2012	Year 2011	Year 2010	Year 2009	Year 2008
84.2	89.6	84.0	81.1	94.9	85.7	63.2	90.3
53.6							
51.7	54.8	48.9	57.8	64.7	59.9	61.9	61.7
58.0	68.3	67.3	66.7	71.4	71.5	65.0	71.7
41.1	24.5	23.7	45.1	27.8	24.9	18.1	19.6
63.0	65.6	64.2	66.5	61.4	59.3	66.1	59.8
56.9	56.4	59.4	55.1	60.2	65.9	64.9	67.6
	52.5						
47.1	42.9	45.3	48.7	46.2	42.3	40.9	51.5
1.3	0.1	0.4	0.5	0.4	0.2	0.1	0.2
12.1							
12.3	8.2	8.4	6.5	3.1	4.1	2.1	2.5
2.3	8.8	8.0	3.8	1.8	2.7	1.1	2.1
0.0	0.1	0.1	0.3	0.3	0.2	0.4	0.2
0.1	0.2	0.1	0.1	0.2	0.2	0.3	0.3
40.3	37.4	34.4	30.5	27.7	25.3	26.6	26.2
6.8	10.1	12.8					

ant Operations Report

Table 16. Distributed generators, capacity, 2016 through 2022
Michigan

megawatts

Technology by sector	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016
Photoelectric	**37.993**	**32.508**	**28.488**	**27.730**	**27.689**	**22.639**	**27.252**
Residential	4.656	2.717	2.715	2.715	3.174	3.152	9.153
Commercial	15.446	13.018	11.007	10.910	9.958	7.028	4.854
Industrial	2.444	2.703	1.544	1.544	1.870	0.995	0.055
Transportation	0.000						
Direct Connected	15.447	14.069	13.222	12.561	12.687	11.464	13.190
Storage	**1.850**	**1.850**	**0.000**	**0.000**			**1.000**
Residential	0.000						
Commercial	0.600	0.600					
Industrial	0.250	0.250					
Transportation	0.000						
Direct Connected	1.000	1.000					1.000
Wind	**0.394**	**0.371**	**0.371**	**0.371**	**0.362**	**0.365**	**0.803**
Residential	0.108	0.088	0.088	0.088	0.076	0.079	0.067
Commercial	0.285	0.283	0.283	0.283	0.286	0.286	0.736
Industrial	0.000						
Transportation	0.000						
Direct Connected	0.001						
Hydroelectric	**4.144**	**4.159**	**4.089**	**4.594**	**3.978**	**3.978**	**3.978**
Residential	0.000			0.400			
Commercial	0.050	0.050	0.050	0.050	0.050	0.050	0.050
Industrial	0.000						
Transportation	0.000						
Direct Connected	4.094	4.109	4.039	4.144	3.928	3.928	3.928
Fuel Cell	**0.250**	**0.250**	**0.250**	**0.250**	**0.250**	**0.250**	**0.250**
Residential	0.000						
Commercial	0.250	0.250	0.250	0.250	0.250	0.250	0.250
Industrial	0.000						
Transportation	0.000						
Direct Connected	0.000						
Internal Combustion	**12.461**	**11.821**	**11.821**	**12.821**	**8.421**	**8.061**	**7.935**
Residential	0.000						

Table 16. Distributed generators, capacity, 2016 through 2022
Michigan

megawatts

Commercial	2.540	1.900	1.900	1.900	1.900	1.540	0.590
Industrial	2.906	2.906	2.906	2.906	2.906	2.906	3.730
Transportation	0.000						
Direct Connected	7.015	7.015	7.015	8.015	3.615	3.615	3.615
Gas Turbine	**0.000**	**0.000**	**0.000**	**0.000**			**0.600**
Residential	0.000						
Commercial	0.000						
Industrial	0.000						0.600
Transportation	0.000						
Direct Connected	0.000						
Steam	**0.672**	**0.000**	**0.000**	**0.000**			
Residential	0.000						
Commercial	0.672						
Industrial	0.000						
Transportation	0.000						
Direct Connected	0.000						
Other	**4.060**	**4.060**	**2.145**	**2.145**	**2.145**	**2.145**	**0.945**
Residential	0.000						
Commercial	1.600	1.600	0.945	0.945	0.945	0.945	0.045
Industrial	2.460	2.460	1.200	1.200	1.200	1.200	0.900
Transportation	0.000						
Direct Connected	0.000						
Total	**61.824**	**55.019**	**47.164**	**47.911**	**42.845**	**37.438**	**42.763**
Residential	4.764	2.805	2.803	3.203	3.250	3.231	9.220
Commercial	21.443	17.701	14.435	14.338	13.389	10.099	6.525
Industrial	8.060	8.319	5.650	5.650	5.976	5.101	5.285
Transportation	0.000	0.000	0.000	0.000			
Direct Connected	27.557	26.193	24.276	24.720	20.230	19.007	21.733

Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.

Table 17. Reliability, 2013 through 2022
Michigan

Metric	Year 2022	Year 2021	Year 2020	Year 2019	Year 2018	Year 2017	Year 2016	Year 2015	Year 2014	Year 2013
IEEE only										
Reporting statistics										
Total utilities	57	57	57	58	58	58	58	58	59	59
Utilities reported	19	21	21	21	18	17	17	16	15	14
Percent reporting	94	93	93	94	93	93	93	93	94	94
All events										
SAIDI	520.7	890.9	416.7	570.2	450.2	802.2	268.4	374.5	592.5	791.0
SAIFI	1.340	1.647	1.375	1.542	1.374	1.413	1.130	1.151	1.230	1.531
CAIDI	388.7	540.8	303.1	369.7	327.6	567.8	237.5	325.4	481.9	516.5
Without major event days										
SAIDI	166.8	178.6	168.3	213.9	186.4	180.1	194.2	183.4	183.3	199.1
SAIFI	1.016	1.017	1.069	1.162	1.054	0.984	1.004	0.979	0.898	0.913
CAIDI	164.2	175.6	157.5	184.1	176.8	183.0	193.5	187.3	204.2	218.0
Loss of supply removed										
SAIDI	519.9	882.1	414.3	565.5	448.0	798.2	262.6	363.7	589.0	793.9
SAIFI	1.326	1.615	1.339	1.505	1.346	1.388	1.105	1.119	1.199	1.504
CAIDI	391.9	546.2	309.5	375.8	332.7	574.9	237.7	324.9	491.4	527.9
Any method										
Reporting statistics										
Total utilities	57	57	57	58	58	58	58	58	59	59
Utilities reported	24	29	29	29	25	25	25	23	21	19
Percent reporting	97	97	97	98	98	98	98	98	97	96
All events										
SAIDI	513.1	873.3	410.7	554.9	442.9	778.8	267.8	363.4	574.7	782.3
SAIFI	1.339	1.656	1.384	1.535	1.373	1.414	1.146	1.141	1.213	1.523
CAIDI	383.2	527.5	296.8	361.5	322.6	550.9	233.6	318.5	473.8	513.6
Without major events										
SAIDI	166.0	178.4	167.2	211.1	185.0	179.4	193.1	178.8	180.0	198.6
SAIFI	1.015	1.033	1.082	1.162	1.055	0.989	1.012	0.967	0.893	0.915
CAIDI	163.6	172.6	154.6	181.7	175.4	181.5	190.8	184.8	201.5	217.1

Source: U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report.
Any method equals IEEE plus Other.
Percent Reporting is an approximate estimate of how many customers are covered by these metrics. The numerator is reported number of meters used on the reliability schedule, while the denominator is the number of customers reported on the sales to ultimate customers schedule.

UNITED STATES SECURITIES AND EXCHANGE COMMISSION

Washington, D.C. 20549

FORM 10-K

☒ **ANNUAL REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934**

For the Fiscal Year Ended December 31, 2023

Or

☐ **TRANSITION REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934**

For the transition period from _____ to _____

Commission File Number: 1-11607

DTE Energy Company

Michigan	**38-3217752**
(State or other jurisdiction of incorporation or organization)	(I.R.S Employer Identification No.)

Commission File Number: 1-2198

DTE Electric Company

Michigan	**38-0478650**
(State or other jurisdiction of incorporation or organization)	(I.R.S Employer Identification No.)

Registrants address of principal executive offices: One Energy Plaza, Detroit, Michigan 48226-1279

Registrants telephone number, including area code: (313) 235-4000

Securities registered pursuant to Section 12(b) of the Act:

Registrant	Title of Each Class	Trading Symbol(s)	Name of Exchange on which Registered
DTE Energy Company (DTE Energy)	Common stock, without par value	DTE	New York Stock Exchange
DTE Energy	2017 Series E 5.25% Junior Subordinated Debentures due 2077	DTW	New York Stock Exchange
DTE Energy	2020 Series G 4.375% Junior Subordinated Debentures due 2080	DTB	New York Stock Exchange
DTE Energy	2021 Series E 4.375% Junior Subordinated Debentures due 2081	DTG	New York Stock Exchange
DTE Electric Company (DTE Electric)	None		None

Securities registered pursuant to Section 12(g) of the Act:

DTE Energy	**None**	**DTE Electric**	**None**

Indicate by check mark if the registrant is a well-known seasoned issuer, as defined in Rule 405 of the Securities Act.

DTE Energy **Yes** ☒ **No** ☐ **DTE Electric** **Yes** ☒ **No** ☐

Indicate by check mark if the registrant is not required to file reports pursuant to Section 13 or Section 15(d) of the Act.

DTE Energy **Yes** ☐ **No** ☒ **DTE Electric** **Yes** ☐ **No** ☒

Indicate by check mark whether the registrant (1) has filed all reports required to be filed by Section 13 or 15(d) of the Securities Exchange Act of 1934 during the preceding 12 months (or for such shorter period that the registrant was required to file such reports), and (2) has been subject to such filing requirements for the past 90 days.

DTE Energy **Yes** ☒ **No** ☐ **DTE Electric** **Yes** ☒ **No** ☐

Indicate by check mark whether the registrant has submitted electronically every Interactive Data File required to be submitted pursuant to Rule 405 of Regulation S-T during the preceding 12 months (or for such shorter period that the registrant was required to submit such files).

DTE Energy **Yes** ☒ **No** ☐ **DTE Electric** **Yes** ☒ **No** ☐

Indicate by check mark whether the registrant is a large accelerated filer, an accelerated filer, a non-accelerated filer, a smaller reporting company, or an emerging growth company. See the definitions of "large accelerated filer," "accelerated filer," "smaller reporting company," and "emerging growth company" in Rule 12b-2 of the Exchange Act.

	Large accelerated filer	Accelerated filer	Non-accelerated filer	Smaller reporting company	Emerging growth company
DTE Energy	☒	☐	☐	☐	☐
DTE Electric	☐	☐	☒	☐	☐

If an emerging growth company, indicate by check mark if the registrant has elected not to use the extended transition period for complying with any new or revised financial accounting standards provided pursuant to Section 13(a) of the Exchange Act. ☐

Indicate by check mark whether the registrant has filed a report on and attestation to its management’s assessment of the effectiveness of its internal control over financial reporting under Section 404(b) of the Sarbanes-Oxley Act (15 U.S.C. 7262(b)) by the registered public accounting firm that prepared or issued its audit report.

DTE Energy **Yes** ☒ **No** ☐ **DTE Electric** **Yes** ☐ **No** ☒

If securities are registered pursuant to Section 12(b) of the Act, indicate by check mark whether the financial statements of the registrant included in the filing reflects the correction of an error to previously issued financial statements.

DTE Energy ☐ **DTE Electric** ☐

Indicate by check mark whether any of those error corrections are restatements that required a recovery analysis of incentive based compensation received by any of the registrants' executive officers during the relevant recovery period pursuant to §240.10D-1(b).

DTE Energy ☐ **DTE Electric** ☐

Indicate by check mark whether the registrant is a shell company (as defined in Rule 12b-2 of the Act).

DTE Energy **Yes** ☐ **No** ☒ **DTE Electric** **Yes** ☐ **No** ☒

On June 30, 2023, the aggregate market value of DTE Energy's voting and non voting common equity held by non-affiliates was approximately $22.6 billion (based on the New York Stock Exchange closing price on such date).

Number of shares of Common Stock outstanding at January 31, 2024:

Registrant	Description	Shares
DTE Energy	Common Stock, without par value	206,452,985
DTE Electric	Common Stock, $10 par value, indirectly-owned by DTE Energy	138,632,324

DOCUMENTS INCORPORATED BY REFERENCE

Certain information in DTE Energy's definitive Proxy Statement for its 2024 Annual Meeting of Common Shareholders to be held May 2, 2024, which will be filed with the Securities and Exchange Commission pursuant to Regulation 14A, not later than 120 days after the end of the Registrants' fiscal year covered by this report on Form 10-K, is incorporated herein by reference to Part III (Items 10, 11, 12, 13, and 14) of this Form 10-K.

This combined Form 10-K is filed separately by two registrants: DTE Energy and DTE Electric. Information contained herein relating to any individual registrant is filed by such registrant solely on its own behalf. DTE Electric makes no representation as to information relating exclusively to DTE Energy.

DTE Electric, an indirect wholly-owned subsidiary of DTE Energy, meets the conditions set forth in General Instructions I(1)(a) and (b) of Form 10-K and is therefore filing this form with the reduced disclosure format specified in General Instruction I(2) of Form 10-K.

TABLE OF CONTENTS

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Part I

Items 1. and 2. ***Business and Properties***

General

In 1995, DTE Energy incorporated in the State of Michigan. DTE Energy's utility operations consist primarily of DTE Electric and DTE Gas. DTE Energy also has two other segments that are engaged in a variety of energy-related businesses.

DTE Electric is a Michigan corporation organized in 1903 and is an indirect wholly-owned subsidiary of DTE Energy. DTE Electric is a public utility engaged in the generation, purchase, distribution, and sale of electricity to approximately 2.3 million customers in southeastern Michigan.

DTE Gas is a Michigan corporation organized in 1898 and is an indirect wholly-owned subsidiary of DTE Energy. DTE Gas is a public utility engaged in the purchase, storage, transportation, distribution, and sale of natural gas to approximately 1.3 million customers throughout Michigan and the sale of storage and transportation capacity.

DTE Energy's other businesses include 1) DTE Vantage which is primarily involved in renewable natural gas projects and providing custom energy solutions to industrial, commercial, and institutional customers, and 2) energy marketing and trading operations.

DTE Electric and DTE Gas are regulated by the MPSC. Certain activities of DTE Electric and DTE Gas, as well as various other aspects of businesses under DTE Energy, are regulated by the FERC. In addition, the Registrants are regulated by other federal and state regulatory agencies including the NRC, the EPA, EGLE, and for DTE Energy, the CFTC and CARB.

The Registrants' annual reports on Form 10-K, quarterly reports on Form 10-Q, current reports on Form 8-K, proxy statements, and all amendments to such reports are available free of charge through the Investor Relations SEC Filings page of DTE Energy's website: *www.dteenergy.com*, as soon as reasonably practicable after they are filed with or furnished to the SEC.

The DTE Energy Code of Ethics and Standards of Behavior, Board of Directors' Mission and Guidelines, Board Committee Charters, and Categorical Standards for Director Independence are also posted on the DTE Energy website. The information on DTE Energy's website is not part of this report or any other report that DTE Energy files with, or furnishes to, the SEC.

Additionally, the public may read and copy any materials the Registrants file electronically with the SEC at *www.sec.gov*.

Corporate Structure

DTE Energy sets strategic goals, allocates resources, and evaluates performance based on the following structure. For financial information by segment for the last three years, see Note 22 to the Consolidated Financial Statements, "Segment and Related Information."

Electric

- The Electric segment consists principally of DTE Electric, which is engaged in the generation, purchase, distribution, and sale of electricity to approximately 2.3 million residential, commercial, and industrial customers in southeastern Michigan.

Gas

- The Gas segment consists principally of DTE Gas, which is engaged in the purchase, storage, transportation, distribution, and sale of natural gas to approximately 1.3 million residential, commercial, and industrial customers throughout Michigan and the sale of storage and transportation capacity.

Non-utility Operations

- DTE Vantage is comprised primarily of renewable energy projects that sell electricity and pipeline-quality gas and projects that deliver custom energy solutions to industrial, commercial, and institutional customers.

- Energy Trading consists of energy marketing and trading operations.

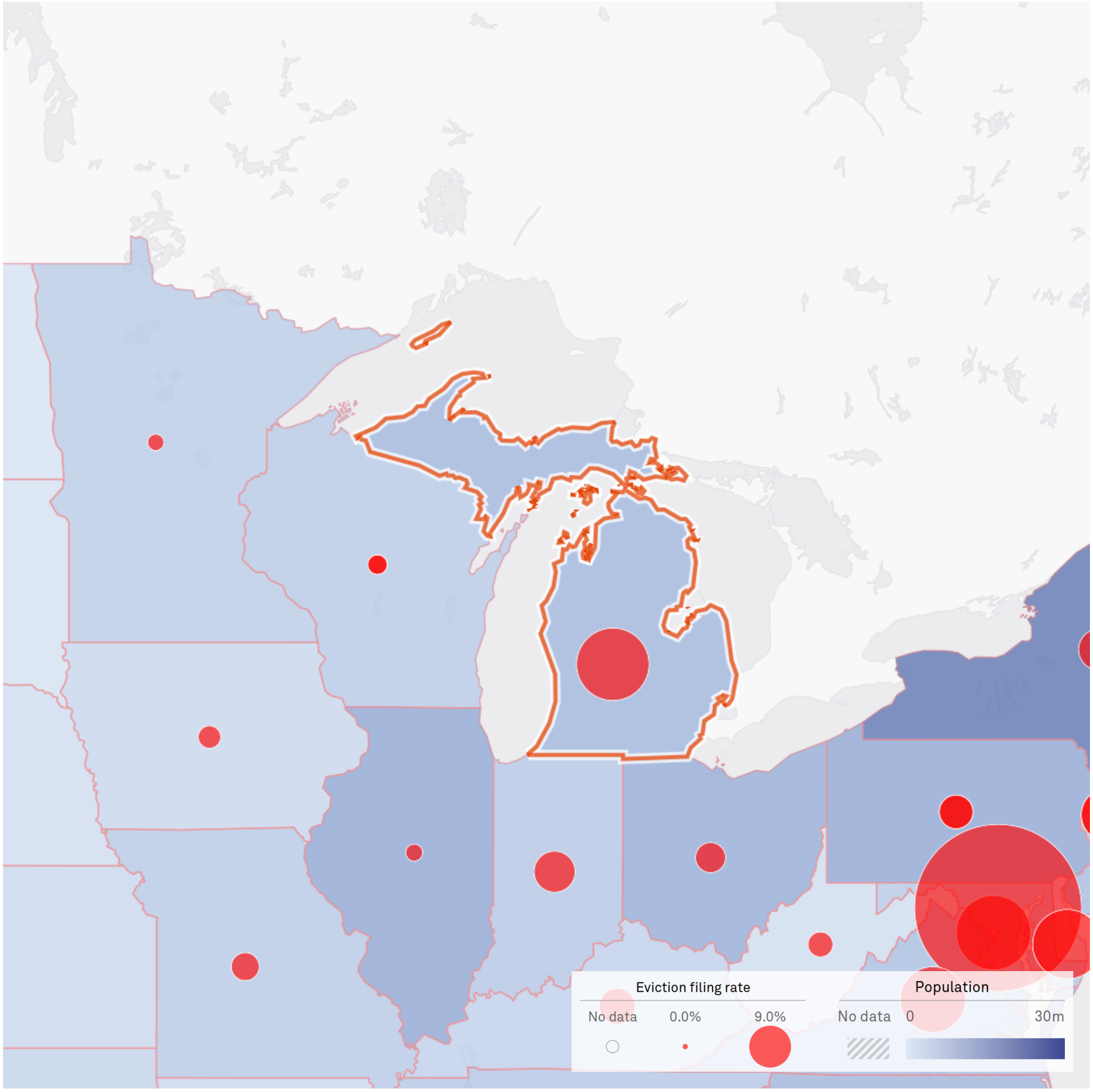
UNDERSTANDING EVICTION IN

MICHIGAN

A presentation generated by The Eviction Lab at Princeton University

Data extracted on 2024-07-20

For further information, visit evictionlab.org

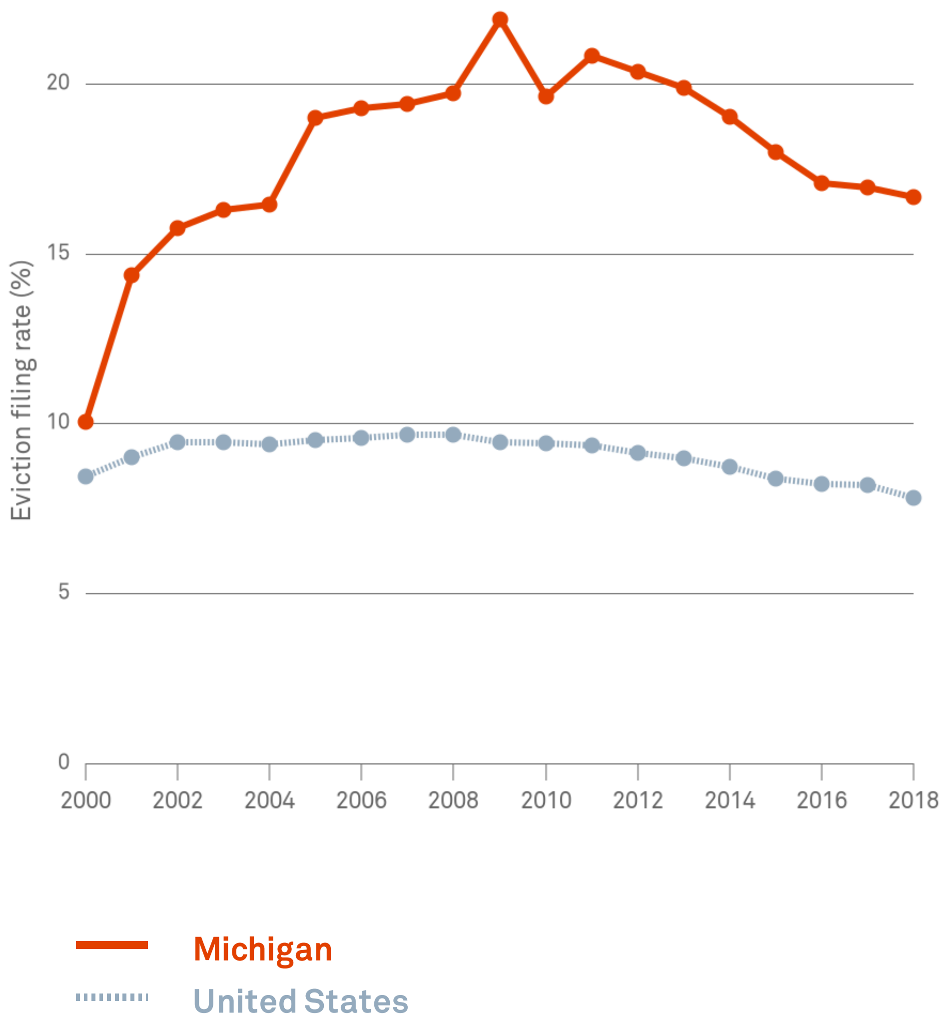


MICHIGAN HAD 191,957 EVICTION FILINGS IN 2018

- Eviction filings per day: **525.91**
- Eviction filing rate: **16.65%** (min: 16.45%, max: 16.86%)
- Households threatened rate: **12.61%** (min: 11.02%, max: 13.93%)
- Population: **9,957,488**

* The eviction filing rate is the number of eviction filings per 100 renter-occupied households.
* The households threatened rate is the number of unique households that received an eviction filing. This measure is the same regardless of how many evictions were filed in a year against the same household.
Please see our FAQ section to better understand these issues https://evictionlab.org/help-faq/

COMPARISON OF EVICTION FILING RATES OVER TIME



Michigan

2018

525.91
Filings per Day

16.65% [1]
Est. Filing Rate

Eviction Filings	191,957 [2]
Households Threatened	145,337 [3]
Households Threatened Rate	12.61% [4]

Census Demographics

Population	9,957,488
% Renter-Occupied Households	24.73%
Poverty Rate	10.37%
Median Gross Rent	$850
Median Household Income	$54,938
Median Property Value	$146,200
Rent Burden	29.8%
Black	13.66%
White	75.21%
Hispanic/Latinx	5%
Asian	3.04%
American Indian/Alaska Native	0.46%
Native Hawaiian/Pacific Islander	0.02%
Multiple Races	2.45%
Other Races	0.14%

[1] min: 16.45%, max: 16.86%
[2] min: 189,625, max: 194,339
[3] min: 126,997, max: 160,614
[4] min: 11.02%, max: 13.93%

UNDERSTANDING EVICTION IN

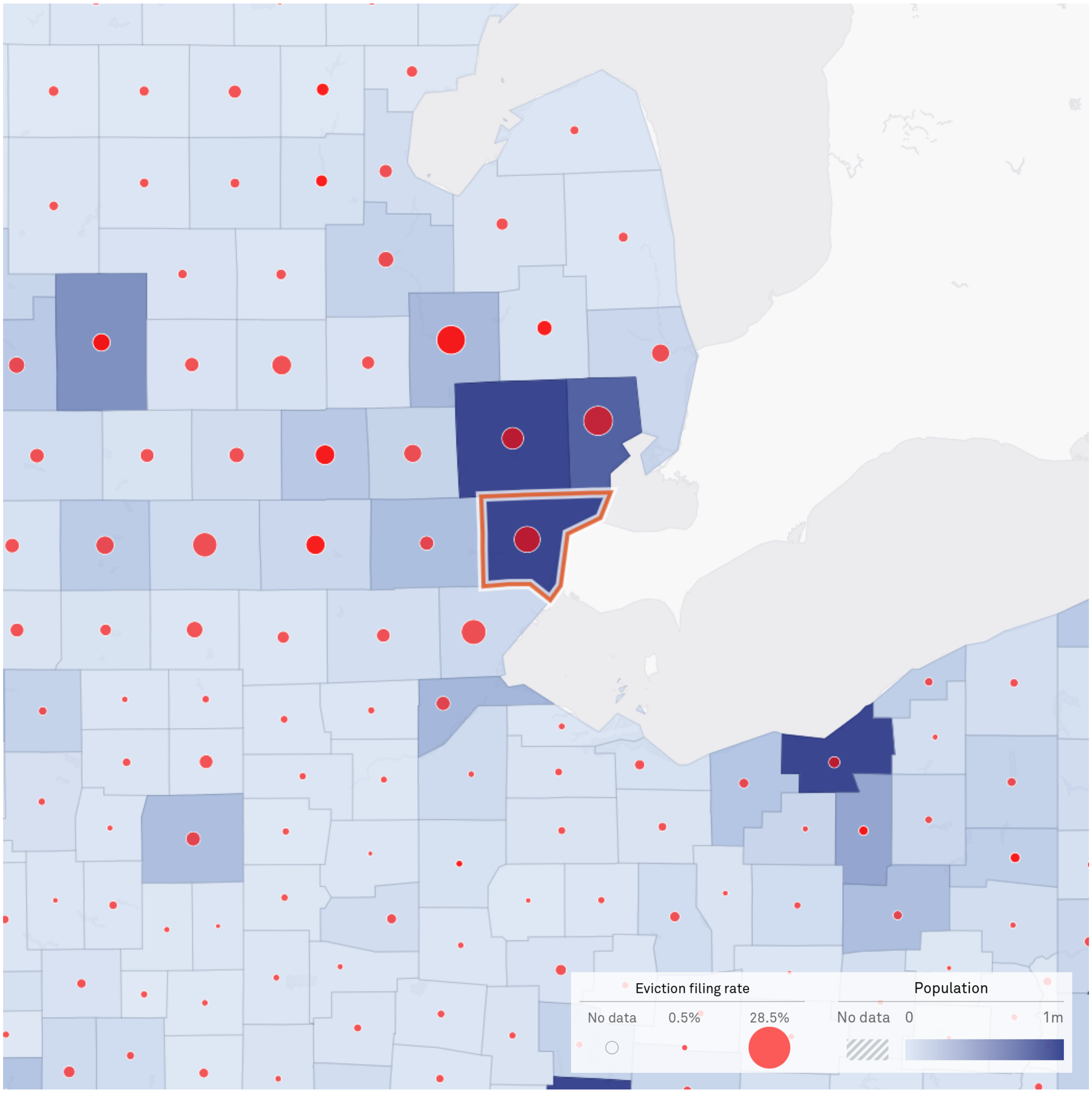
WAYNE COUNTY, MICHIGAN

A presentation generated by The Eviction Lab at Princeton University

Data extracted on 2024-07-20

For further information, visit evictionlab.org

EVICTION LAB

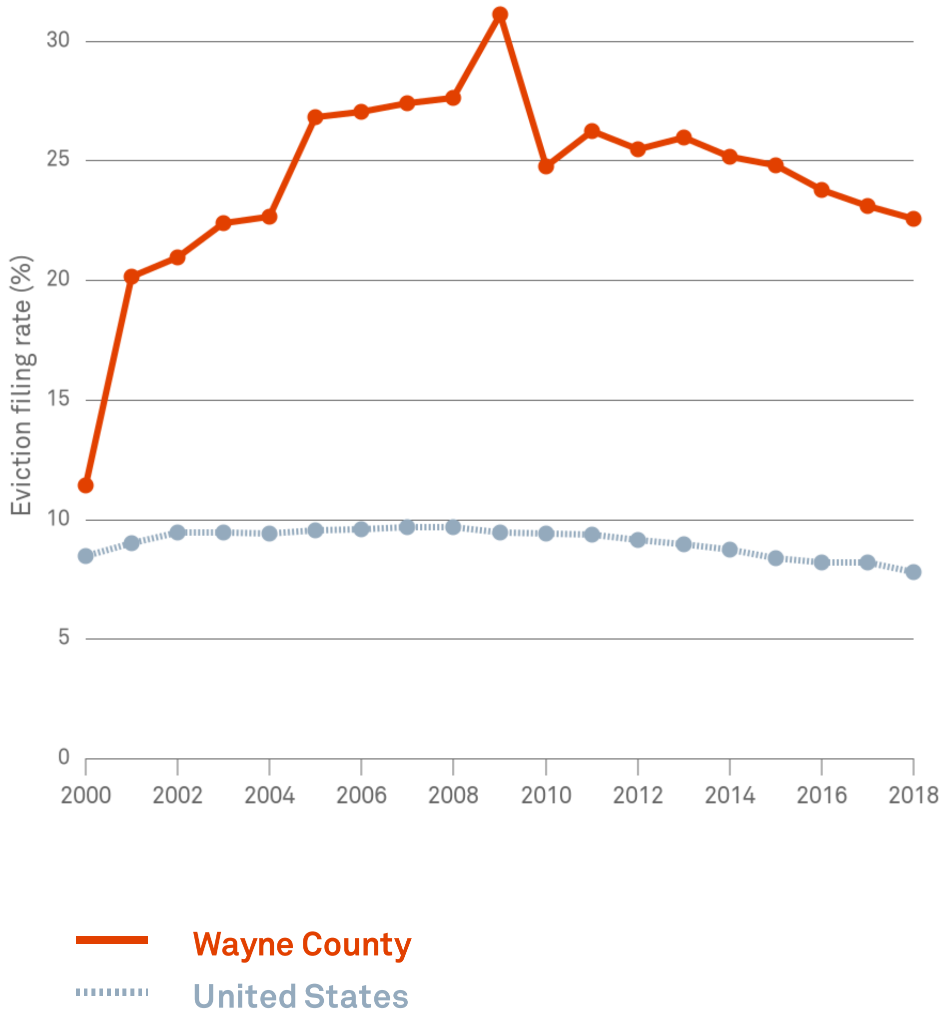


WAYNE COUNTY HAD 56,323 EVICTION FILINGS IN 2018

- Eviction filings per day: **154.31**
- Eviction filing rate: **22.55%** (min: 22.28%, max: 22.83%)
- Households threatened rate: **17.53%** (min: 14.94%, max: 19.64%)
- Population: **1,761,382**

* The eviction filing rate is the number of eviction filings per 100 renter-occupied households.
* The households threatened rate is the number of unique households that received an eviction filing. This measure is the same regardless of how many evictions were filed in a year against the same household.
Please see our FAQ section to better understand these issues https://evictionlab.org/help-faq/

COMPARISON OF EVICTION FILING RATES OVER TIME



Wayne County

2018

154.31
Filings per Day

22.55% [1]
Est. Filing Rate

Eviction Filings	56,323 [2]
Households Threatened	43,791 [3]
Households Threatened Rate	17.53% [4]

Census Demographics

Population	1,761,382
% Renter-Occupied Households	30.4%
Poverty Rate	17.84%
Median Gross Rent	$850
Median Household Income	$45,321
Median Property Value	$102,700
Rent Burden	33.1%
Black	38.71%
White	49.58%
Hispanic/Latinx	5.86%
Asian	3.24%
American Indian/Alaska Native	0.26%
Native Hawaiian/Pacific Islander	0.03%
Multiple Races	2.07%
Other Races	0.26%

1 min: 22.28%, max: 22.83%
2 min: 55,642, max: 57,019
3 min: 37,307, max: 49,058
4 min: 14.94%, max: 19.64%

Facts About Eviction

What is an eviction?

An eviction happens when a landlord expels people from property they own. Evictions are landlord-initiated involuntary moves that happen to renters, whereas foreclosures are involuntary moves that happen to homeowners when a bank or other lending agency repossesses a home.

Why do people get evicted?

Most evictions happen because renters cannot or do not pay their rent. Landlords can evict renters for a number of other reasons, too, including taking on boarders, damaging property, causing a disturbance, or breaking the law. In most American cities and towns, landlords can evict renters even if they have not missed a rent payment or otherwise violated their lease agreement; these are called "no fault" evictions.

What is the relationship between the affordable housing crisis and the eviction epidemic?

Today, most poor renting families spend at least half of their income on housing costs, with one in four of those families spending over 70 percent of their income just on rent and utilities. Incomes for Americans of modest means have flatlined while housing costs have soared. Only one in four families who qualifies for affordable housing programs gets any kind of help. Under those conditions, it has become harder for low-income families to keep up with rent and utility costs, and a growing number are living one misstep or emergency away from eviction.

What is the eviction process like?

Landlords initiate the process, and renters are served notice to appear in court. Almost everywhere in the United States, evictions take place in civil court, where renters have no right to an attorney (with the exception of cities that have created right to counsel programs). For this reason and others, most renters do not appear in eviction court. When this happens, they receive a default eviction judgement, provided that the landlord or a representative is present. Renters who do appear in court may also receive an eviction judgement ordering them to vacate their home by a specific date. Eviction cases can be resolved in other ways as well. For one, the case may be dismissed or ruled in favor of defendants, allowing renter to remain in their home. In addition, a mediated agreement can be established between a landlord and a renter, often called a "settlement" or "stipulation," which comes with certain terms. If renters meet the terms, the eviction is dismissed; if they do not, an eviction judgment can be rendered. In the event that evicted renters do not leave their home by the specified date, their landlord may file a "writ of restitution," which permits law enforcement officers to forcibly remove a family and often their belongings.

Who is at most risk of eviction?

Low-income women, especially poor women of color, have a high risk of eviction. Research has shown domestic violence victims and families with children are also at particularly high risk for eviction.

How does an eviction affect someone's life?

Eviction causes a family to lose their home. They often are also expelled from their community and their children have to switch schools. Families regularly lose their possessions, too, which are piled on the sidewalk or placed in storage, only to be reclaimed after paying a fee. A legal eviction comes with a court record, which can prevent families from relocating to decent housing in a safe neighborhood, because many landlords screen for recent evictions. Studies also show that eviction causes job loss, as the stressful and drawn-out process of being forcibly expelled from a home causes people to make mistakes at work and lose their job. Eviction also has been shown to affect people's mental health: one study found that mothers who experienced eviction reported higher rates of depression two years after their move. The evidence strongly indicates that eviction is not just a condition of poverty, it is a cause of it.

What is the households threatened rate and how did you calculate it?

An eviction filing does not necessarily mean that the threatened household leaves its home. A common practice is what is known as "serial filing," where a landlord issues a series of eviction filings against a single household.

We created the households threatened rate so that we can clearly identify how many households annually receive at least one eviction filing. When calculating this rate, we looked at the number of households receiving an eviction filing per 100 renter households. The eviction filing rate (the number of filings per 100 renter households) is still available in our database, and this will measure the total of evictions filed, no matter how many happened to the same tenants.

We can use information in our case records to identify when a household receives multiple eviction filings in a given year. By counting the number of households who ever received a filing in a given year, we can calculate the households threatened rate. The eviction filing rate will always be higher than the households threatened rate.

About The Data

This report uses data from a variety of sources. While our primary eviction data were collected manually from courts across the country, we also collected proprietary data from private vendors. Because some areas are missing data over time in the courts and/or proprietary data, we used statistical models to “fill in the gaps” with modeled estimates. For more details on our data sources and modeled estimates, see our methodological report.

For further information, visit evictionlab.org

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 the U.S. homeless population, including the first national estimates of income, employment, and safety net participation based on administrative data. We link restricted-use microdata identifying those recorded as homeless during the 2010 Census to 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. We find that nearly half of these adults had formal employment in the year they were observed as homeless, one-quarter received disability assistance, and more than 85 percent were reached by at least one safety net program, primarily SNAP. Incomes are persistently 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. As our findings illustrate, most people appear to experience homelessness because they are very poor despite being connected to the labor market and safety net, with persistently low incomes leaving them vulnerable to 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 suggests that people 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 afford temporary lodging, those without the possibility of emergency assistance from friends and family, those with mental health or substance abuse conditions that impair decision-making – to end up 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."

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 U.S. has proved challenging. Without a fixed address, such individuals are largely excluded from the household surveys that typically inform our understanding of poverty and well-being in the United States, and they have consequently been understudied in the extreme poverty literature. The most recent national survey to examine this population's income and program receipt, the National Survey of Homeless Assistance Providers and Clients (NSHAPC), dates back nearly three decades to 1996 (Burt 2001). Recent studies linking administrative homeless shelter and employment records have offered important insights but are limited to a handful of cities and a single income source, earnings (Metraux et al. 2018; Wachter, Schnorr, and Riesch 2020). Numerous ethnographic studies and geographically narrow surveys offer nuanced and detailed information on the material well-being of the individuals they represent, but their results may not generalize beyond those settings and they lack longitudinal information. These surveys also rely on self-reports that even when obtained from rigorously tested surveys of the housed have been shown to be substantially biased (Meyer, Mok, and Sullivan 2015).

Understanding the income 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, indicate 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 and safety net participation for the U.S. homeless population. Our sample consists of 140,000 adults recorded as sheltered and unsheltered homeless in the 2010 Census, by far the largest, most representative sample ever used to study these questions. We link these individuals to administrative tax and program records to provide the first national calculation of formal employment, income, and safety net participation for this population. We compare these outcomes to a demographically comparable sample of the housed poor and examine how pathways to homelessness appear to differ by sheltered status, race, gender, Hispanic ethnicity, and geography. We demonstrate the robustness of our findings to different linkage methods and alternative samples, including samples of the sheltered homeless population from the American Community Survey (ACS) and several cities' Homeless Management Information System (HMIS) shelter-use databases.

Our approach benefits not only from large samples that are designed to represent national homelessness patterns, 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) and 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 the modern-day U.S. homeless population is surprisingly well-connected to formal employment and the safety net, in contrast to earlier years' depictions of individuals "unconnected to the world of work" with "no safety net of entitlements" (Rossi 1989). 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. We also find that a substantial share of the homeless population is 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. Their median annual earnings were about $8,300, however, suggesting low-wage, sporadic work. We find SNAP receipt to be especially high, reaching about 77 percent of all adults in our sample in 2010. Connections to work and the safety net coexist 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 experiencing unsheltered homelessness in 2010. In other words, 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 for the sheltered homeless and $8,000 for the unsheltered homeless 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 employment and earnings shocks 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. Put differently, people experiencing homelessness are not just enduring an exceptionally difficult year – they are enduring an exceptionally difficult decade, and perhaps in many cases, an exceptionally difficult life.

Our analyses reveal a high degree of similarity between the material circumstances of people recorded in homeless shelters during the Census and poor housed individuals who share their demographic profile. This poor housed comparison group consists of unmarried individuals who are predominantly male (70 percent), between the ages of 40 and 59 (69 percent), and disproportionately Black (39 percent) relative to the overall population. These individuals had a median income, including the value of in-kind transfers, of about $9,900 in 2010, only about $2,000 higher than the median of $7,500 among those who were in homeless shelters during the Census. By some measures, the housed poor appear to be somewhat *more* deprived than the sheltered homeless sample: 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 Meyer et al. (2021)'s 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.

Our findings help explain several patterns that have emerged in the recent literature on homelessness prevention. Prior work has emphasized the exceptional difficulty of identifying people who are most likely to become homeless and targeting prevention programs towards them, a finding that is consistent with our observation of substantial overlap between the economic circumstances of people in homeless shelters and the housed poor who share their demographic profile (O'Flaherty 2011; Shinn et al. 2013; Von Wachter et al. 2021). Even detailed and accurate information about someone's long-term trajectory of income and safety net participation are unlikely to yield useful predictors of homelessness.

At the same time, several experimental and quasi-experimental studies have found 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, Sullivan, and Wallskog 2016; Phillips and Sullivan 2023). The effectiveness of such emergency assistance programs 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 emergency assistance 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 persistent deprivation documented in this paper. A small-scale payment may be enough to prevent a singular instance of homelessness, but it is unlikely to make a dent in the long-term deprivation that leaves people vulnerable to the loss of housing.

These analyses shine new light on a highly disadvantaged segment of the U.S. population, those for whom extreme poverty can mean extreme vulnerability to homelessness when met with even modest disruptions to their life circumstances. The rest of the paper proceeds as follows. Section 2 discusses prior work on the income and safety net participation of homeless individuals. Section 3 describes our data, Section 4 describes our methodology, and Section 5 presents our main results, as well as analyses of heterogeneity by demographic characteristics and geography. Section 6 analyzes the robustness of our findings to alternative data sources, sample definitions, and linkage methods and presents extensions, including an analysis of demographic and income misreporting in household surveys. 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 representative of the entire U.S. homeless population (Burt, Martha R 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 many other aspects of their life circumstances. This survey painted a picture of deprivation in the U.S. homeless population that was somewhat less grim than Rossi's but nevertheless dire. 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 from that year. 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 somewhat lower employment than NSHAPC, although their estimates are at the annual and quarterly level and therefore not directly comparable to 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 over rates 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 and 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 outside of homeless shelters, 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, including longitudinal patterns. In Section 7, we compare our results in detail to the studies described in this section and how these findings advance and revise our understanding of the level and persistence of deprivation faced by the U.S. homeless population relative to prior work.

3. Data

3.1 2010 Census Data on the U.S. Homeless Population

Our main sample of analysis consists of people who were recorded as experiencing sheltered and 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 individuals 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] Because people using soup kitchens and food vans were only included in the homeless count if they did not indicate a valid residential or shelter address, we classify people enumerated at those locations as

[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.

"unsheltered homeless" in our study. Our 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 organization, 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. In principle, enumerators aimed to collect names and dates of birth from all interviewees. In practice, given the bustling nature of service locations and the fact that many individuals were sleeping during the outdoor counting operation, many individuals were enumerated by sight without providing this personal information. We discuss the implications of such nonresponse and our methods of accounting for the resulting non-linkage in Section 4.

Meyer, Wyse, and Corinth (2023)establish 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 differences in the sources' methodologies – suggests that the Census covered this population reasonably well.

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[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.

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

We use additional data on the sheltered homeless population 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. (B. D. Meyer, Wyse, et al. 2021)provide a detailed description of these outcomes 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 underused 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 confer several advantages for examining heterogeneity and checking the robustness of results based on homeless samples from the Census and ACS. Unlike the Census and ACS, the HMIS data classify individuals into families and can thus be used to examine heterogeneity 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 individuals' first observed shelter enrollment. This 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 the HMIS, these data 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 or not 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 1040s, W-2s, and 1099-Rs.[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' compensation. We also emphasize that our data are limited to formal income and do not include income from informal employment or private transfers. Transfers from family, friends, and private

[3] IRS 1040 records are available for 2003-2015, W2s for 2005-2016, and 1099-Rs for 2003-2015.
[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).

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 population 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 2012).[5] As documented in Meyer, Wyse, and Corinth (2023), 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, as housing units 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 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.,

[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.

Browning, Chiappori, and Weiss 2014). The data requirements needed to identify those individuals for whom shared or low-quality housing represents hardship as extreme as literal homelessness also far exceed the information available in household surveys and administrative data. Meyer et al. (2023) provides 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. 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 align with 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.

While most of our results are calculated for the entire U.S. population (excluding U.S. territories), our SNAP and TANF/General Assistance administrative records cover only a subset of the U.S. As a result, we impose geographic restrictions for analyses of these outcomes or measures that incorporate their values, such as the share of people receiving at least one benefit and the value of income including in-kind transfers. For such outcome measures, we restrict the sample in year *t* to people who in 2010 lived in a state for which we have data in year *t*. In Section 6, we estimate the magnitude of bias in longitudinal SNAP receipt patterns that arises due to migration between states for which we do and do not have administrative data.

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. In the restricted 2010 Census microdata, this software assigns 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 outdoor locations, or TNSOLs. According to the Census's evaluation report on the homeless counting operation, the main proximate reason for this non-linkage is that enumerators did not collect sufficient personal information from these individuals, either because the subjects were sleeping, deemed not "approachable," or because the bustling nature of many service locations prevented them from collecting complete information (Russell and Barrett 2013).

Incomplete linkage could create bias in our income and safety net calculations if the outcomes of unlinked individuals differ systematically from linked individuals. We address this concern by applying inverse probability weights to linked individuals, where these weights are obtained by estimating a probit model of linkage status on age, race, gender, Hispanic origin, state, and homeless location type. The key assumption is that non-linkage no longer biases analyses of outcomes conditional on these observed characteristics. Given low linkage rates and the limited characteristics available in the Census for our probability model, however, we test the robustness of our findings to alternate linkage methods using sheltered homeless samples from ACS and HMIS data. The ACS's rich set of covariates, which include self-reported measures of income and program receipt, allow us to estimate a more detailed inverse probability weighting model on these data and compare our findings to those based on the Census's more limited model. We also compare findings based on the Census homeless samples to those based on HMIS data, where linkage rates are about 90 percent across cities and years because most records contain SSNs.

Despite these robustness checks, we remain concerned that linkage may be non-random with respect to outcomes of interest in the population counted at TNSOLs, even conditional on the covariates in our probability model. The Census's SBE evaluation report indicates that nonresponse appeared to be "most serious" at these locations, where most residents were "asleep and/or covered up" during their overnight counting operation (Russell and Barrett 2013). We therefore exclude people counted at TNSOLs from our main analyses but include them in robustness checks in Section 6.

5. Results

This section contains our main results. We start by providing summary statistics of our homeless samples and comparison groups, before showing how employment, income, and program participation evolve in the years preceding and following an observed period of homelessness during the 2010 Census.[6] We next discuss comparisons in key outcomes between those who are homeless and the demographically comparable sample of the single housed poor population. The last set of results describe differences by gender and family status, race and ethnicity, and geography and discuss potential 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 the distribution of demographic characteristics in the pooled sheltered and unsheltered homeless samples. The characteristics of the single housed poor indicated in Column 3 are therefore equal to a weighted average of the characteristics in Columns 1 and 2 by construction. This reweighting ensures that any subsequent comparisons are not confounded by demographic differences between those experiencing homelessness and single poor housed individuals. Such comparisons should be interpreted as between those experiencing homelessness and a demographically comparable segment of the single housed poor population, i.e., a segment that is 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.

[6] 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.

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.[7]

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. 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 53 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.[8]

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. Nearly half of this population was enrolled in Medicaid, and receipt of TANF and General Assistance was high (58 percent) among homeless shelter users in New York, where we have access to these data. A moderate share received disability benefits in 2010, with a respective 14 and 21 percent of the sheltered and unsheltered homeless receiving SSI, 9 and 14 percent receiving DI, and 3 and 2 percent receiving service-connected disability payments from the VA. 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

[7] Detailed additional results are available in Appendix Tables A1-A7.
[8] For comparison, a full year of work at the federal minimum wage of $7.25 corresponds to about $15,000 of annual earnings.

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 housed comparison samples in 2010 (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 fall 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.[9]

At the same time, we note that material deprivation would be even more extreme in this population without certain safety net programs. For example, median income falls to about $750 for those in shelters and to $0 for the unsheltered homeless population when we deduct 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

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 are *less* connected to formal employment and the safety net, with just 89 percent being 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) falls between that of the sheltered homeless (52 percent) and unsheltered homeless samples (40 percent), with the median value of earnings conditional on

[9] 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.

working being about $12,200, compared to $8,300 among homeless individuals with formal employment. 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 are less likely to receive SNAP, TANF/GA, Medicaid, and VA disability benefits than those experiencing homelessness, but are more likely to receive housing assistance. They receive DI at similar rates to unsheltered homeless individuals, and their receipt of SSI falls (16 percent) falls 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.

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 in 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 administrative SSI records become available to us. 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.[10] 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 this drop is small. Conditional on working, the earnings of sheltered homeless workers are about \$1,500 to \$1,700 lower in 2009 relative to the two surrounding years, and for unsheltered homeless workers it is \$500 to \$1,000 lower. These disruptions are modest relative to the overall trend of declining employment between 2005 and 2016 and are similar in magnitude to the drop in earnings and employment observed among the single housed poor.

Longitudinal Patterns of Safety Net Participation

Looking longitudinally at enrollment in disability programs, we find that receipt of SSI (Figure 4a) and DI (Figure 4b) tends to be increasing for our homeless and housed poor samples in the years surrounding an observed period of homelessness or poverty, but the rate of increase differs across groups, increasing most quickly for the sheltered homeless, followed by the unsheltered, and then the single housed poor. SSI receipt in the sheltered homeless population surpasses that of the single housed poor in 2011 and continues to grow, while SSI receipt in the

[10] 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.

single housed poor population remains nearly level at around 16-17 percent. Accelerating disability program receipt for those experiencing homelessness could either indicate that the onset of disability is associated with the onset of homelessness or that the experience of homelessness causes new disabilities to arise. Alternatively, it could mean that people become connected to disability programs for which they already qualified while they are experiencing homelessness, perhaps due to 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.[11] Medicaid receipt increases steadily through 2013 for both groups, before increasing sharply in 2014 after many states expanded eligibility under the Affordable Care Act (ACA). Receipt of HUD housing benefits appears to dip slightly in 2009 for the sheltered homeless population before increasing through 2016, but the overall level of housing assistance receipt remains low (below 20 percent) for both groups over this entire period.

We find that people who were residing in homeless shelters during the 2010 Census have persistently higher rates of enrollment in non-disability safety net programs than those who were experiencing unsheltered homelessness, despite facing somewhat lower material deprivation overall, as indicated by their higher incomes.[12] 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.

[11] Some of this peak could be due to migration between states for which we do and do not have SNAP data. We examine the potential for such bias in Section 6, with those analyses suggesting that migration is likely only a minimal source of bias.
[12] The unsheltered homeless are more likely than the sheltered homeless to be enrolled in Medicare, but this is largely because eligibility for DI entails Medicare eligibility (in most cases after a two-year qualifying period).

In addition to demographic heterogeneity 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.[13] SNAP enrollment remains steady at about 46 percent over the two years prior to shelter entry, before abruptly increasing to nearly 60 percent in the month of first observed shelter entry. Receipt peaks at 63 percent in the third month after shelter entry, before declining to about 51 percent after a year has passed. While not necessarily indicating a causal relationship, these results are highly suggestive that homeless shelters play a role in connecting their clients to the safety net. They also suggest that connections to the safety net deteriorate in the months following initial shelter entry, perhaps as people leave shelters and maintaining enrollment becomes more difficult.

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 heterogeneity 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.).[14]

Family Status and Gender

We first examine heterogeneity 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 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 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.

[13] See Appendix Table A8.
[14] See Appendix Tables A9-A12.

Differences by gender are likely closely associated with differences in family status, a dimension of heterogeneity emphasized in much of the homelessness literature, including HUD's annual national reports on homelessness. Data from HUD's 2023 report that about 40 percent of sheltered homeless adult women had accompanying children, compared to just 10 percent of sheltered homeless adult men (HUD 2023).[15] Differences in income by gender could reflect higher cost of maintaining housing when children are present, leading women to be unable to afford housing even at higher levels of income. Similarly, higher benefit receipt among homeless women could reflect the greater ease of qualifying in households where children are present.

While Census and ACS data do not report household structure for those experiencing homelessness, we investigate heterogeneity by family status using cross-sections of individuals indicated as being enrolled in HMIS shelters in Los Angeles and Houston on March 30 of 2012 and 2013.[16] Adults in both types of households experience a drop in employment similar in magnitude to the drop among the Census homeless, but employment rates for those without children continue to decline after an observed period of homelessness, while employment among adults with accompanying children recovers almost to its initial level, consistent with 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. These patterns are mirrored in analyses of heterogeneity by family status, with women more likely to be in families with accompanying children.

Race and Hispanic Ethnicity

We next turn to analyzing differences across 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.

[15] 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.
[16] 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. (2023). 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 heterogeneity in shelter enrollment.

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.

Heterogeneity by race is of particular policy interest because people who are Black tend to be 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. Differences in income and program receipt by race may suggest differences in the predominant pathway to homelessness across groups. As suggested by gender-based differences, it is possible that homeless individuals who are Black appear to be somewhat less deprived than those who are white due to differences in the cost of maintaining housing. This cost could be higher, on average, for Black individuals due to housing market discrimination, racial disparities in the criminal justice system, or due to differences in the availability of resources in one's family and social network to help insure against homelessness.

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 examine income and safety net participation in these states separately and compare them to those experiencing homelessness in the rest of the country. As shown in Figure 10a, employment rates are 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) are somewhat higher than those in other states (about $7,500), a difference that could once again reflect differential housing costs by state. We also observe slightly higher rates of disability program receipt in California and New York relative to other states (Figure 11c). In summary, although we find somewhat lower employment and higher disability program receipt in New York and California, these differences are 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. Our next sets of analyses check the robustness of key findings to alternative temporal conceptions of homelessness (i.e., we compare results based on samples of those with a first shelter enrollment in a year to samples of those enrolled in homeless shelters at a point in time) and to different data sources and years (i.e., we compare 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). Our final set of analyses test the robustness of our findings to alternative Census samples designed to address potential bias from non-linkage, misclassification, and the incomplete geographic coverage of our SNAP datasets.

6.1 Misreporting of Income, Benefit Receipt, and Characteristics in the ACS

Household surveys suffer from widespread underreporting of income and safety net benefit receipt, and self-reported measures may be especially inaccurate among those with very low and very high incomes (B. D. Meyer, Mok, and Sullivan 2015; Bollinger et al. 2019). Misreporting of income and program receipt among those experiencing homelessness is of particular interest because nearly all existing work on these outcomes relies on self-reported measures. This section examines the extent to which income, benefit receipt, and demographic characteristics are misreported in the ACS's sheltered homeless samples, as well as housed comparison groups. In doing so, we illustrate the importance of administrative data and provide estimates that may help researchers and service providers to interpret findings in surveys of this population.

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 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 are similar to the misreporting rate 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 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).[17] Among those experiencing homelessness, 43.2 percent of wage earners fail to report any wages in the survey, which is higher than the corresponding false negative rates for the single housed poor (28 percent) and overall housed population (7.7 percent).[18] Among true SNAP recipients, individuals 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) but substantially higher false positive rates (20.4 percent, compared to 13.2 and 3.7 percent).

In summary, 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, the overreporting of program receipt (e.g., SNAP and Medicaid) appears to be a

[17] 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.

[18] 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.

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.

6.2 Income and Program Receipt Relative to First Shelter Enrollment

One limitation of the Census and ACS homeless data is that they do not indicate the start and end dates for spells of homelessness. Assuming these dates are uniformly distributed throughout the year, cross-sectional samples of the homeless population like those in the Census and ACS should, on average, include individuals midway through their spells, but we cannot identify the date of homelessness onset, nor can we examine heterogeneity in income and program receipt by the length of time spent homeless. Knowing the exact date of homelessness onset could help differentiate disruptions to income, employment, and safety net receipt that precede homelessness and those that occur after one becomes homeless. Prior work has also emphasized differences in the life circumstances of people displaying patterns of chronic homelessness (remaining homeless for extended periods of time, typically while struggling with behavioral health or substance abuse conditions), episodic homelessness (frequently cycling in and out of homelessness), and transitional homelessness (having just one or a few short spells) (Kuhn and Culhane 1998). We therefore wish to learn whether income and program receipt in a cross-sectional sample of the homeless population differs from that of samples of people who were ever homeless during a period of time. The former sample will contain a larger share of people who are homeless for extended periods of time than the latter.

Specifically, we leverage shelter entry and exit dates in HMIS data to compare income and program receipt in a cross-section of the homeless population and a sample of people with first shelter enrollments in a year. The first sample, which aligns with the Census's temporal conception of homelessness, consists of people who were enrolled in Los Angeles and Houston shelters on March 30 of 2012 or 2013.[19] The second consists of people with a first observed shelter enrollment in 2012 or 2013 and aligns with HMIS-based samples used in key prior studies, thereby facilitating comparisons with prior work (e.g., Metraux et al. 2018, Von Wachter et al. 2020).

In Los Angeles, both the level and longitudinal patterns of employment (Figure 11a) and disability program receipt (Figure 11b) were similar across the two temporal conceptions of the

[19] 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. (2023) for a discussion of HMIS data quality improvements over time.

homeless population, differing by only about 0 to 4 percentage points across years. In Houston, people in the cross-sectional sample had higher employment rates (by about 3 to 9 percentage points) and lower disability program receipt (by about 5 to 8 percentage points) than those with a first enrollment in the same year. These patterns may be related to gender and family status, which differ substantially across samples: the latter sample has a larger share of women (50 versus 39 percent) and adults with accompanying children (19 versus 14 percent). As in Los Angeles, however, longitudinal patterns in employment and disability program receipt appear similar for the two samples in Houston.

Our findings suggest that using a sample of people with first shelter enrollments in a year rather than a cross-section of those experiencing homelessness at a point in time makes little difference for interpreting longitudinal patterns of income and program receipt, although levels of these outcomes may vary, particularly when characteristics differ substantially between the two temporal conceptions of the homeless population.

6.3 Comparing Census, HMIS, and ACS Sheltered Homeless Samples

We next compare income and program receipt for the Census sheltered homeless samples in Los Angeles and Houston to samples drawn from HMIS records in those cities. Meyer et al. (2023) highlight ambiguities in the definition of a homeless shelter that lead the Census to classify some HMIS facilities as conventional housing or other types of group quarters rather than homeless shelters. For example, the Census appears to have classified many transitional shelters, where people experiencing homelessness can reside for up to two years under a formal tenancy agreement, as conventional housing rather than homelessness shelters. Given these definitional differences, and because HMIS data form the basis for HUD's widely cited point-in-time estimates and are often used in the literature, we compare results based on otherwise comparable samples of the sheltered homeless population drawn from Census and HMIS datasets. These analyses also serve as a check on our methods to account for non-linkage because the majority of HMIS records contain Social Security numbers, leading to much higher linkage rates (about 90 percent in most years in Los Angeles and 96 percent in most years in Houston) than in the Census.[20]

[20] Following Meyer et al. (2023), 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.

Figures 12a and 12b illustrate employment and disability benefit receipt for the Census sheltered homeless from Los Angeles and Houston and for HMIS shelter users with entry and exit dates indicating enrollment during the Census's homeless counting operation in those cities. In Los Angeles, both the levels and longitudinal patterns of employment and disability program receipt were similar for the two samples, with employment differing by at most 4 percentage points and disability program receipt differing by at most 3 percentage points across years. In Houston, the HMIS sample had notably higher employment (by about 7 to 10 percentage points) and lower disability program receipt (by about 9 to 13 percentage points) than the Census sample, although the longitudinal patterns were similar in the two samples.

The prevalence of transitional housing offers one proxy for the degree of misalignment between the Census and HMIS shelter definitions and may help explain the similarity of Census- and HMIS-based results in Los Angeles and their differences in Houston. In Los Angeles, only one-quarter of the HMIS sample was enrolled in transitional housing, compared to about two-thirds of the Houston sample. In other words, the levels of income and program receipt appear to be sensitive to ambiguities in the definition of a homeless shelter, but longitudinal patterns appear robust to these differences. Nationally, the share of all homeless shelter beds that are in transitional housing falls between the shares in Los Angeles and Houston, at about 50 percent in 2010 (U.S. Department of Housing and Urban Development 2010). We might therefore expect our national estimates based on the Census sheltered homeless samples to indicate levels of income and program receipt that are slightly lower than one might obtain if using national HMIS data. Our findings suggest, however, that the Census definition of a homeless shelter identifies a somewhat more deprived segment of the population than the HMIS definition.

6.4 Robustness to Alternative ACS and Census Samples

We describe further checks on our findings' robustness to alternative samples, linkage methods, and years in detail in Appendix A. Our main findings are robust to the use of sheltered homeless samples from the 2010-2014 ACS, suggesting that the patterns we observe generalize beyond those who were homeless in 2010. Comparisons between Census and ACS samples also support the validity of our use of inverse probability weights to adjust for non-linkage in the Census because the ACS has higher linkage rates due to more complete personal information and because the ACS's inverse probability weighting model includes a wealth of additional predictors relative to the Census, including self-reported income and benefit receipt. We also find that key results are robust to the inclusion of those counted during the Census's overnight enumeration at unsheltered locations (a group we excluded from main analyses due to their exceptionally low linkage rate of 17 percent) and to the exclusion of people who were counted at both homeless locations and in housing during the Census (a group which might be thought to include individuals who were misclassified as homeless when they were in fact housed). Finally, we address concerns over potential bias in longitudinal SNAP receipt arising from migration by calculating longitudinal SNAP receipt using a subset of the Census homeless population that we consider less likely to have moved states in the years surrounding 2010. The peak in SNAP receipt in 2010 from our main analyses is somewhat attenuated in this migration-adjusted sample, but remains notable, suggesting that only a small share of this peak reflects bias due to migration between states for which we do and do not have SNAP enrollment data.

7. Comparisons to Past Work

We compare our findings to three key prior studies on 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 nationally representative nature and detailed measures of self-reported income and program receipt, but 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), do not include people who are unsheltered homeless, 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 dollar 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 $7,100 average income reported in NSHAPC.[21] 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.

Comparisons with prior work also suggest a 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

[21] 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.

2010s may reflect well-established patterns of increasing labor supply among single mothers since the 1990s. Prior studies have shown that this trend in the broader low-income population appears to be driven primarily by the Earned Income Tax Credit (EITC) and other tax changes, but also in part by cuts to welfare benefits and similar programs (Meyer and Rosenbaum 2001, Grogger 2003).

Finally, we compare safety net participation in our study to that reported in the NSHAPC.[22] 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 may be driven by the underreporting of benefit receipt in the survey, but our findings in Section 5 suggest that such misreporting – while undoubtedly present – is unlikely to be of sufficient magnitude to explain such large differences. 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.

In summary, our analyses are qualitatively consistent with past studies in demonstrating the dire economic circumstances of people experiencing homelessness. At the same time, we show that these individuals have somewhat greater incomes, employment, and connections to the safety net than previously understood. Differences between our estimates and those in prior work likely reflect some combination of true changes over time – including an apparent rise in employment among homeless mothers and increasing program receipt in recent decades – as well as the improvements to accuracy that come from using administrative data rather than self-reported outcomes, as has been well-established in the broader literature on poverty measurement (e.g.,

[22] 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.

Meyer, Mok, and Sullivan 2015). 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 deprivation, so there can be no doubt that people experiencing homelessness are severely deprived. Rather, these comparisons further underscore that people experience homelessness because they are very poor 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 administrative data. We find that this population is 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). 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. Conversely, 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 suggest that deprivation is highly persistent in this population, with little change in median incomes over the four years prior to and six years after an individual is observed as homeless in 2010. Employment declines steadily between 2005 and 2016, with only a small and transitory drop relative to this long-term trend in the years preceding an observed period of homelessness in 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. Taken together, these 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, our results suggest that extremely low permanent incomes translate into heightened vulnerability to homelessness, leaving individuals 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. 2023), 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 (U.S. Department of Housing and Urban Development 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 just as alarming and deserving of humanitarian 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, Wyse, and Logani 2023), 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).

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.

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.

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.

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*.

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	0.04	0.04	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.

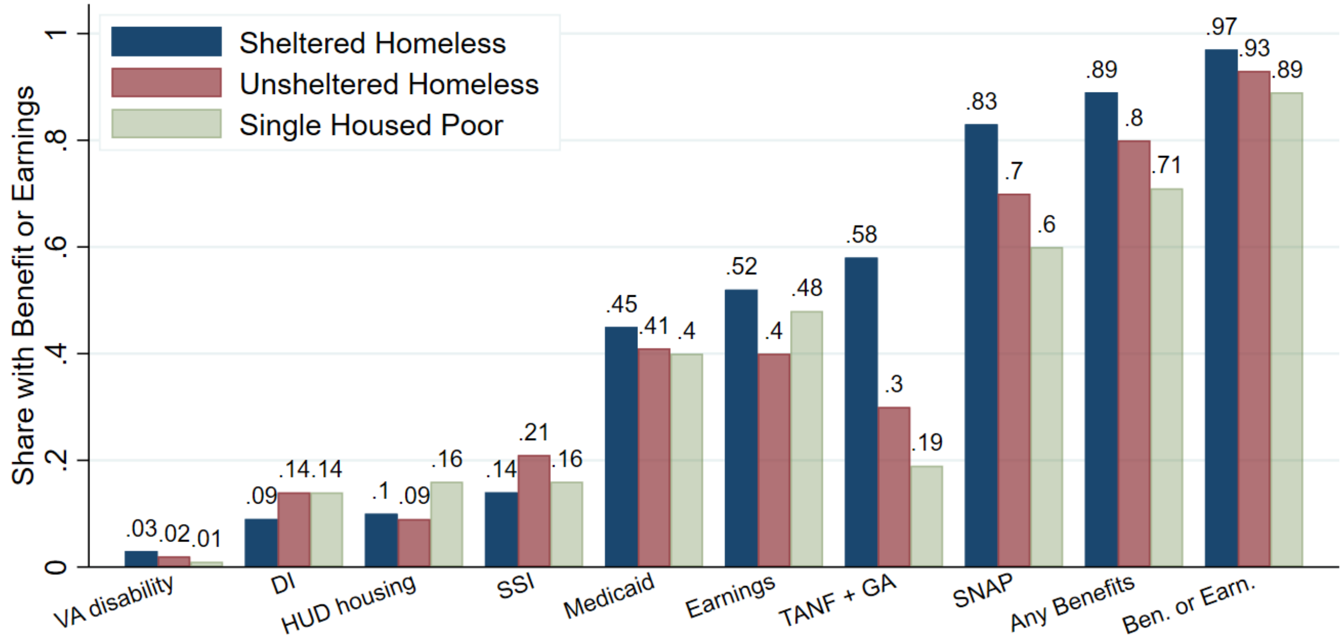
[4]We omit 2009 from the pre-period because we count people as homeless in the beginning of 2010, meaning that many individuals in our sample may have become homeless in 2009 rather than 2010.

[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

Figure 1a: Benefit Receipt and Earnings in 2010

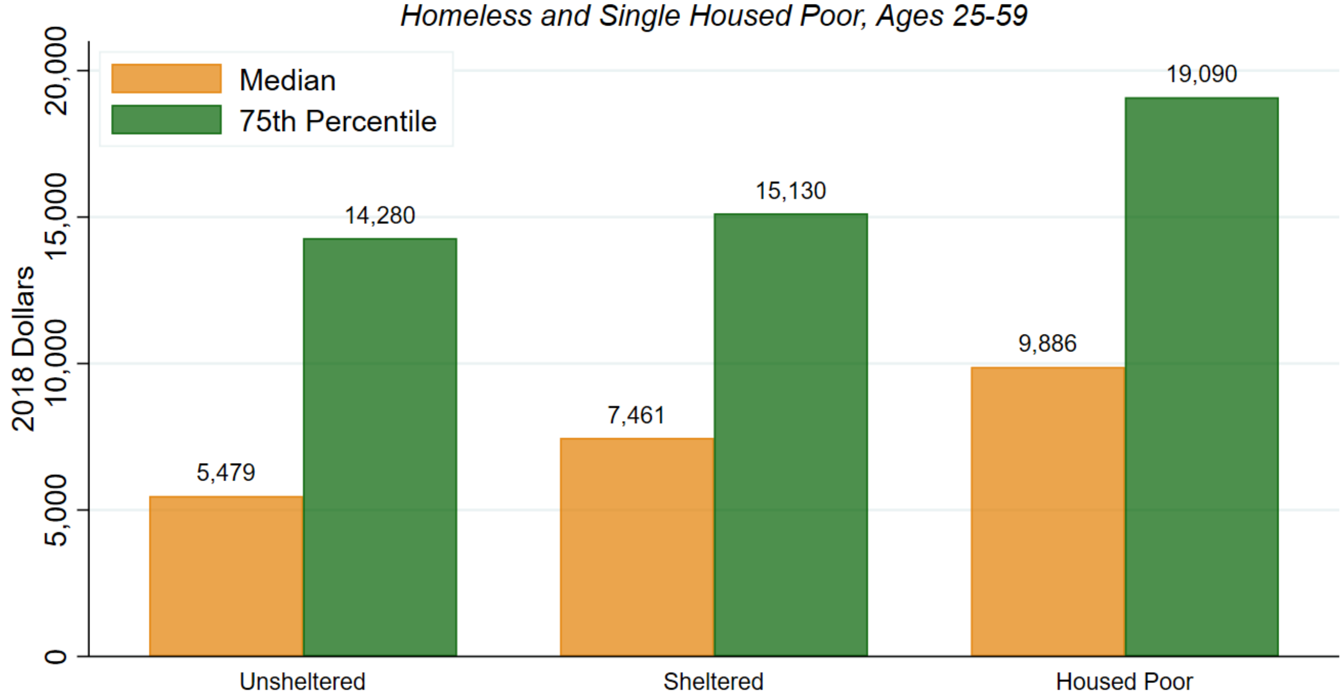
Homeless and Single Housed Poor, Ages 25-59



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.

Figure 1b: Income Including In-Kind Transfers in 2010

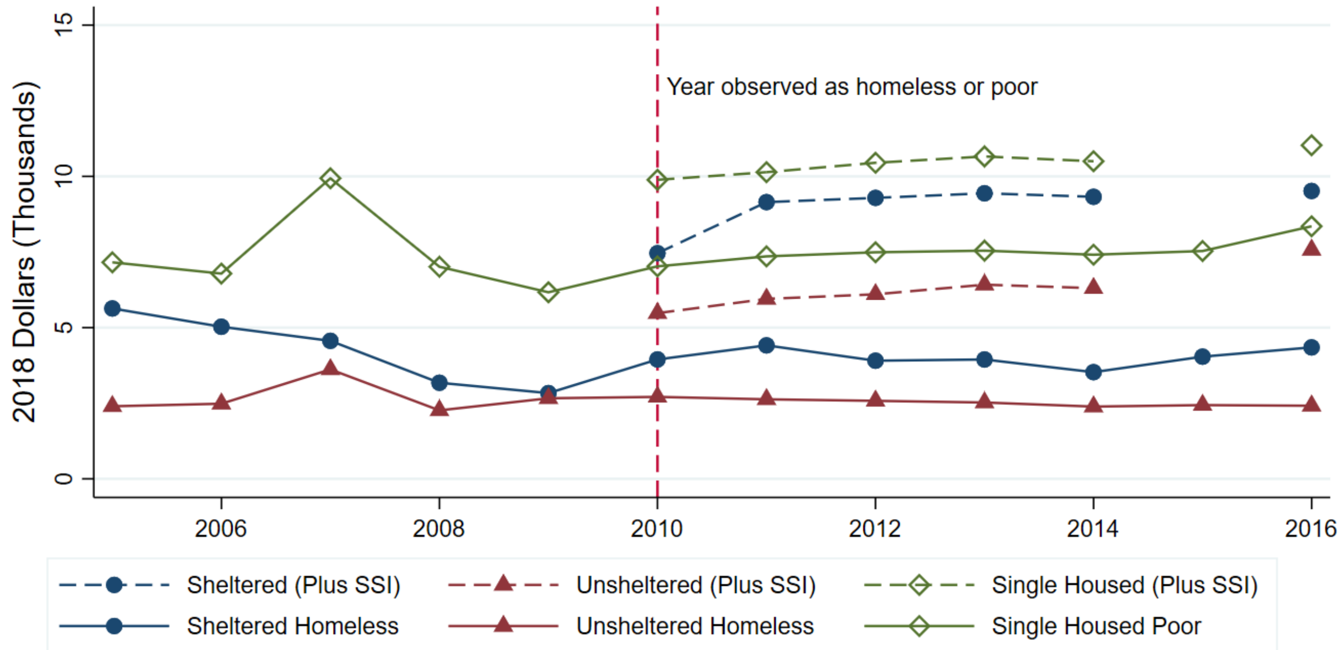
Homeless and Single Housed Poor, Ages 25-59



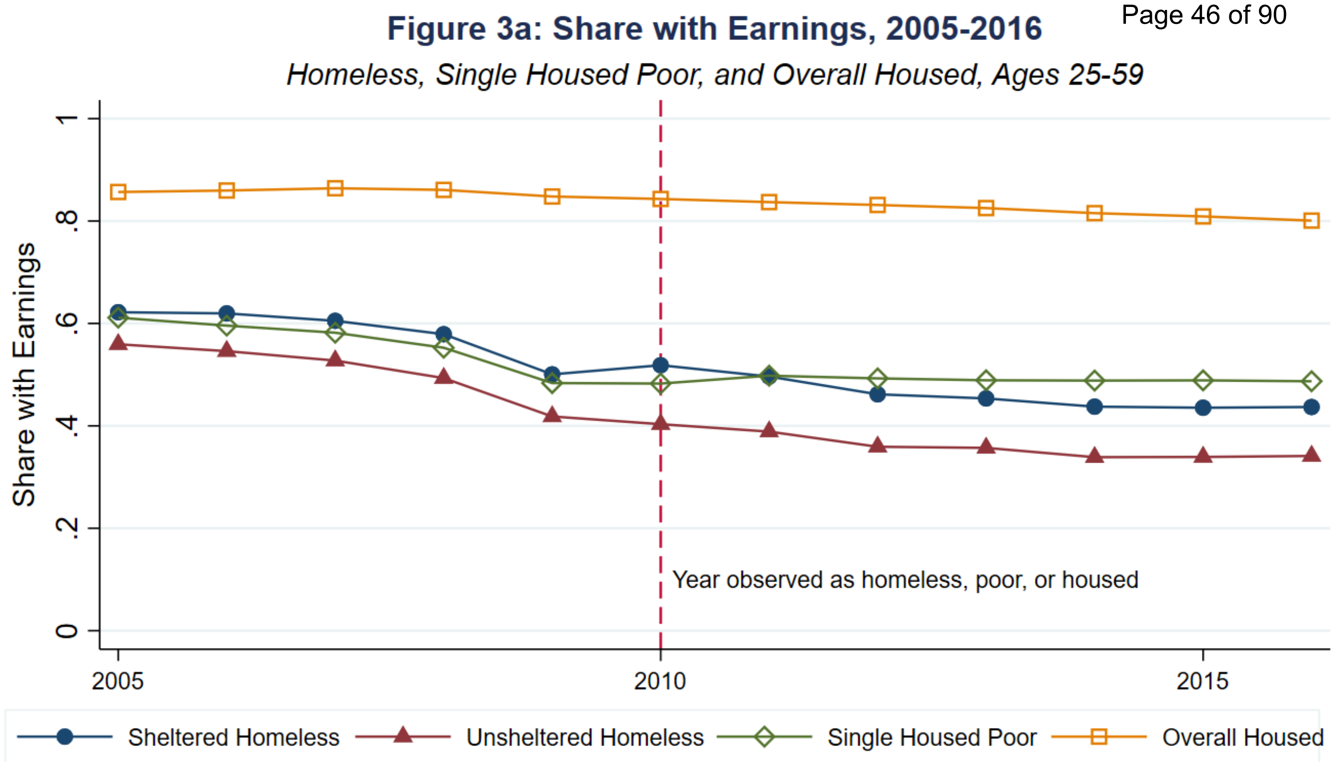
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015) SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010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

Figure 2: Median Income Including In-Kind Transfers in 2005-2016

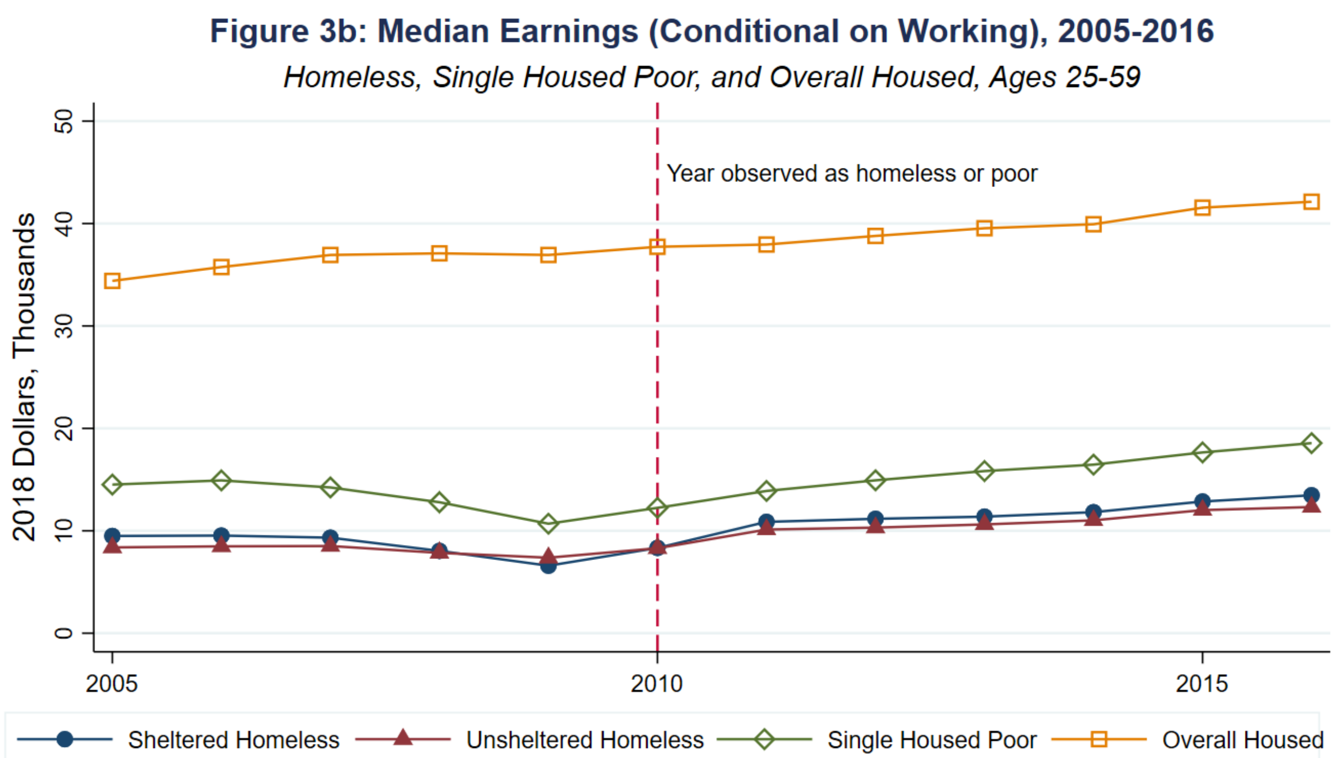
Homeless and Single Housed Poor, Ages 25-59



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.



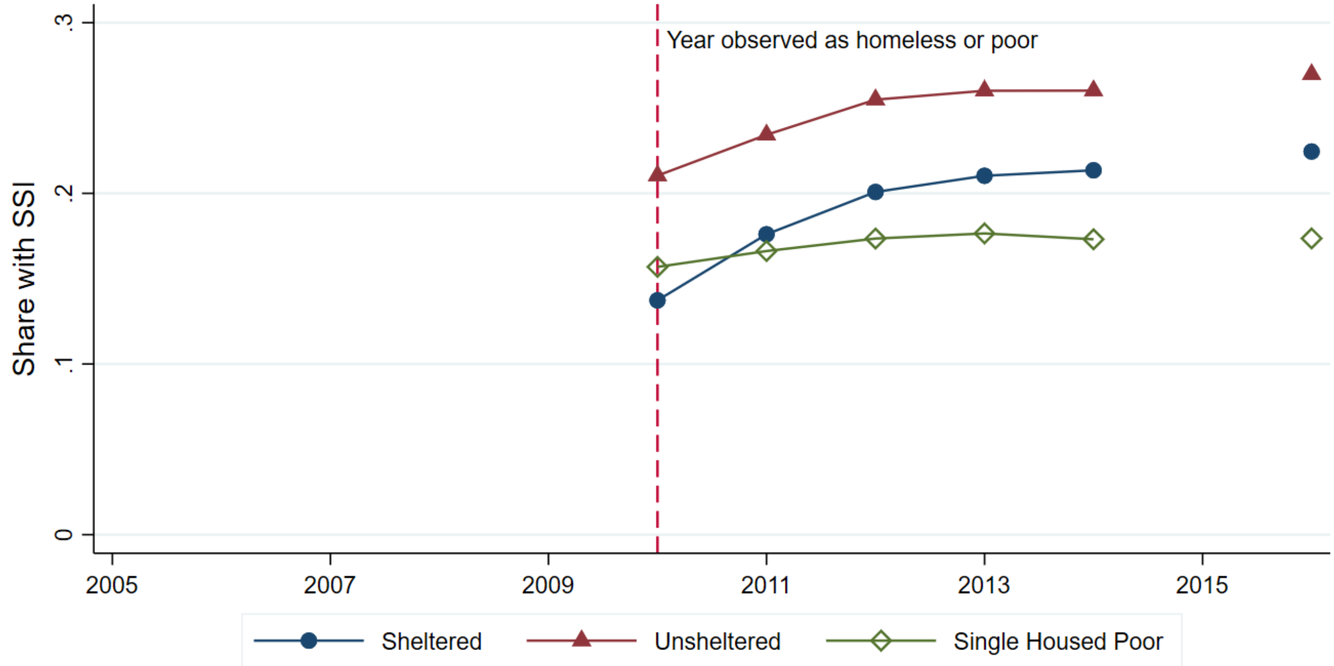
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



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

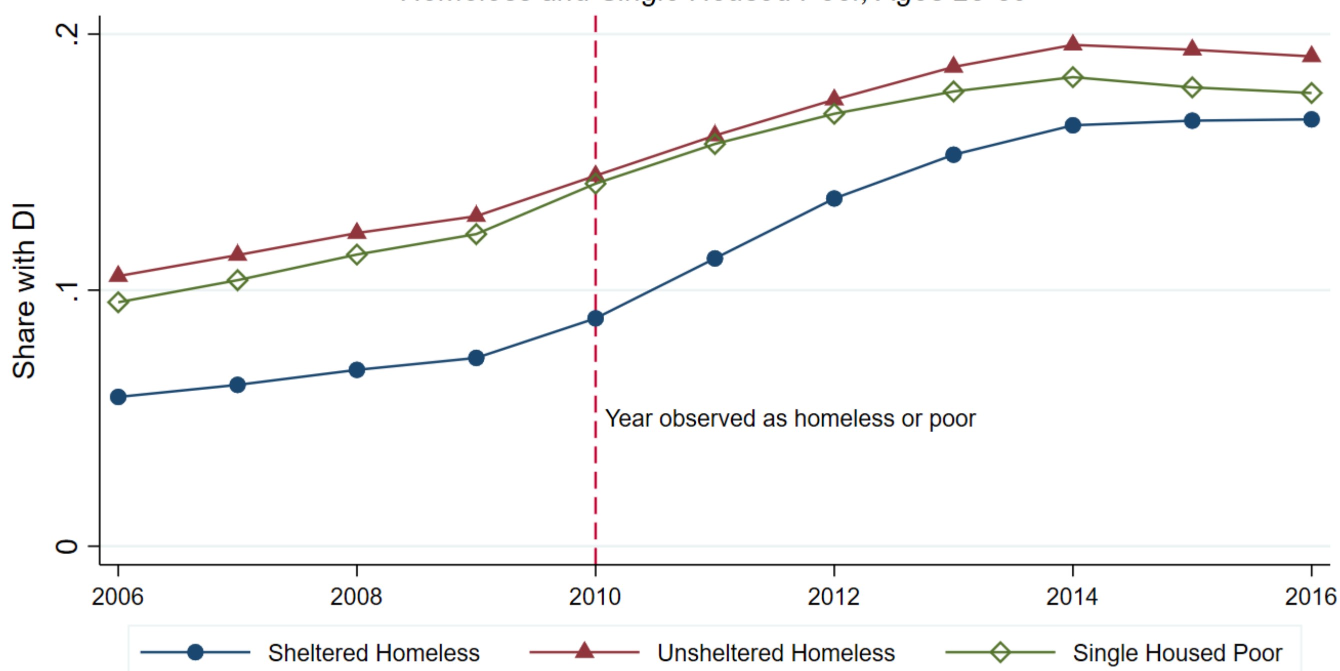
Homeless and Single Housed Poor, Ages 25-59



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.

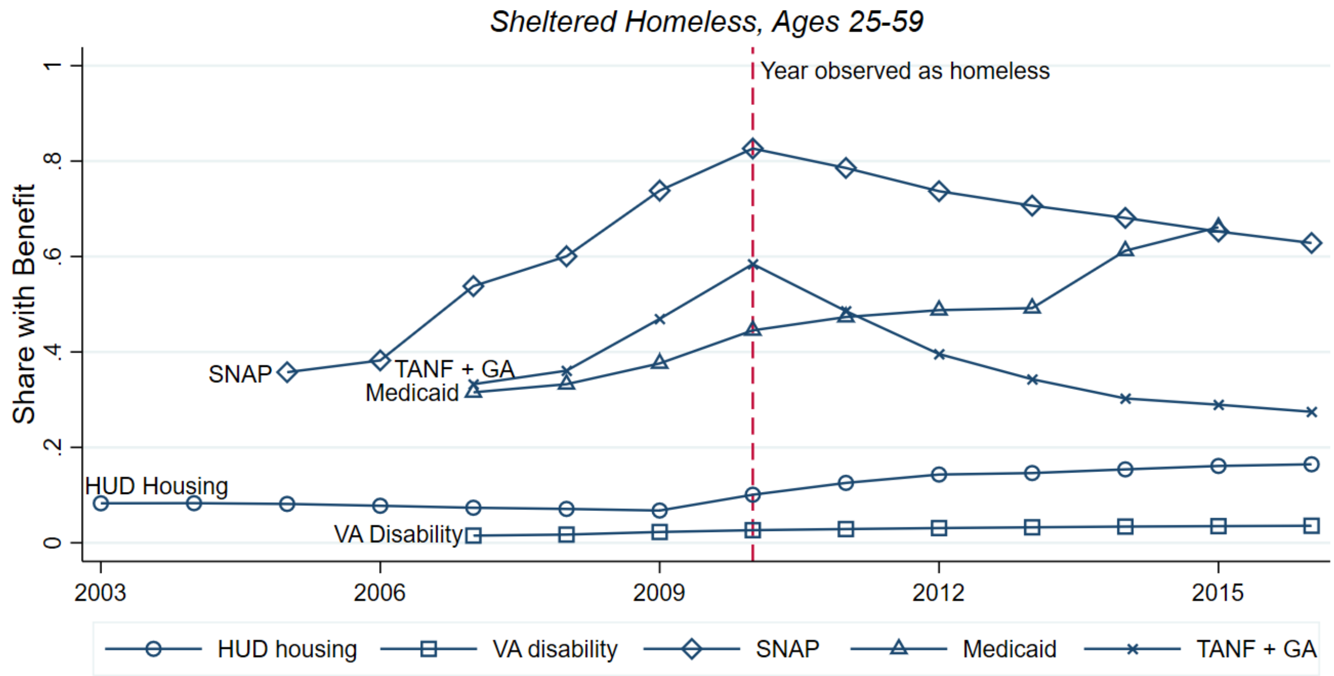
Figure 4b: DI Receipt (According to Medicare Records), 2006-2016

Homeless and Single Housed Poor, Ages 25-59



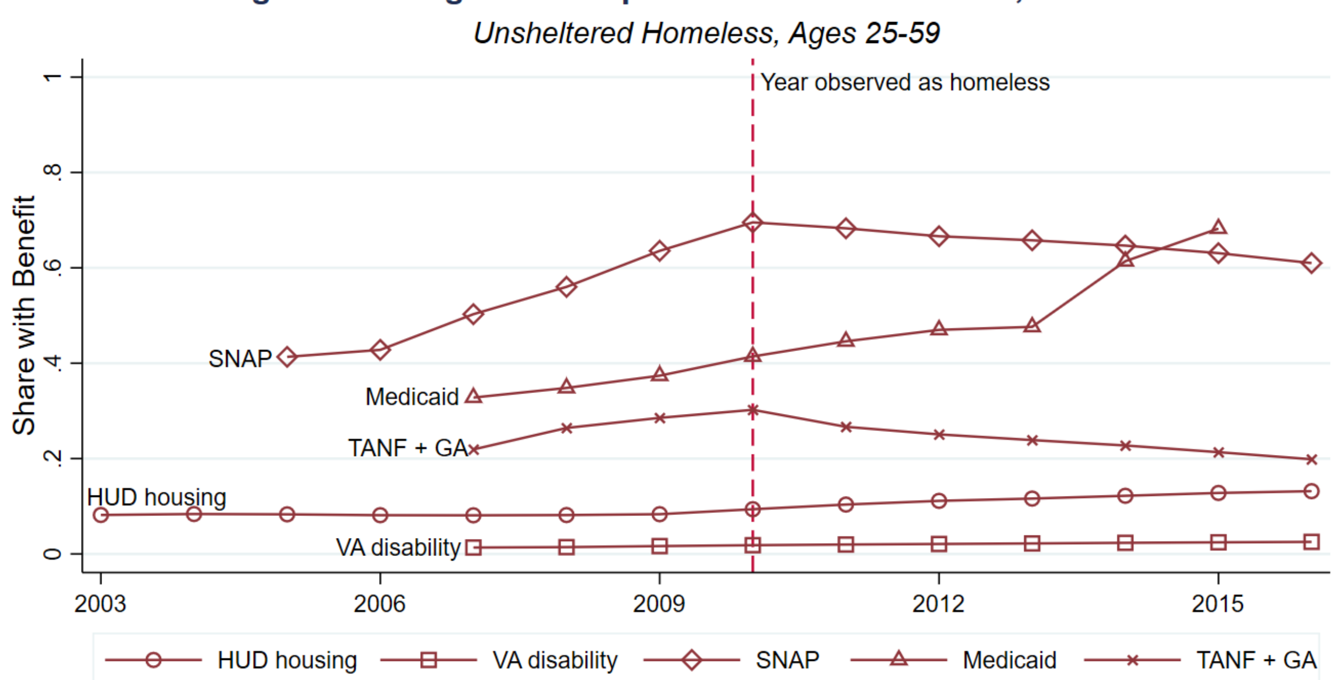
Sources: 2006-2016 Medicare Datasets, 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

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



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.

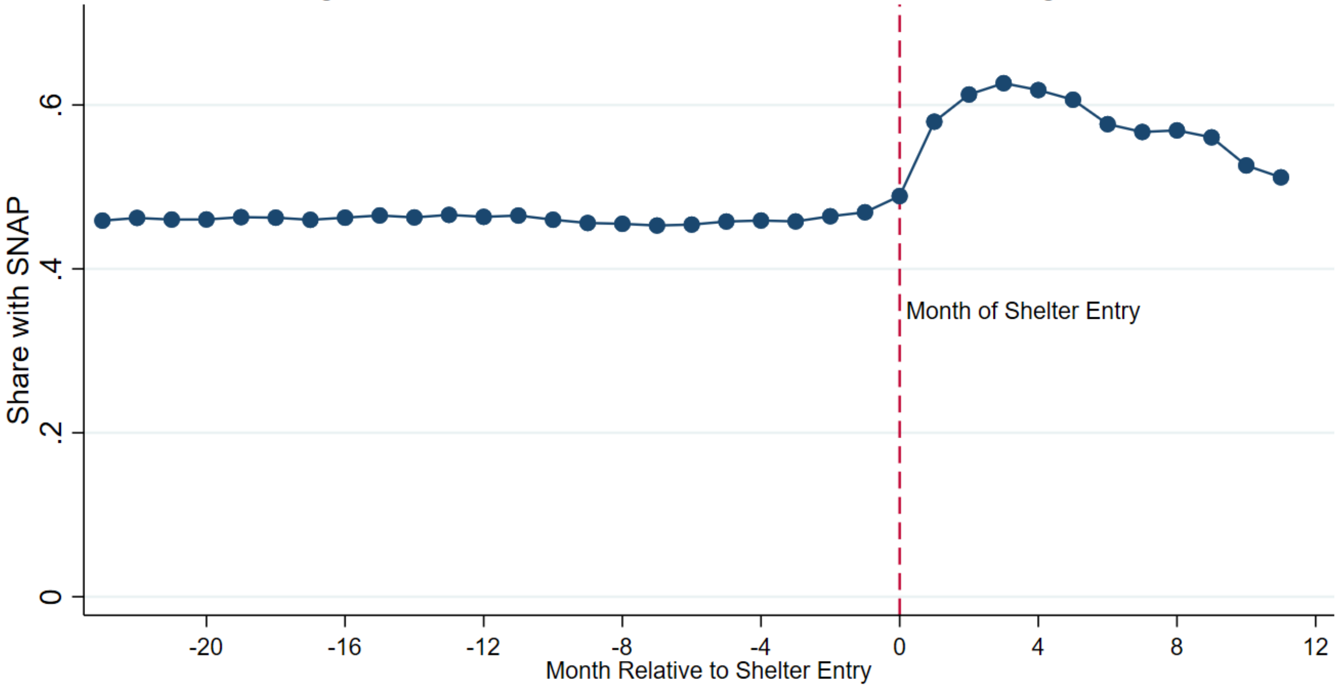
Figure 5b: Program Receipt of Sheltered Homeless, 2003-2016



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

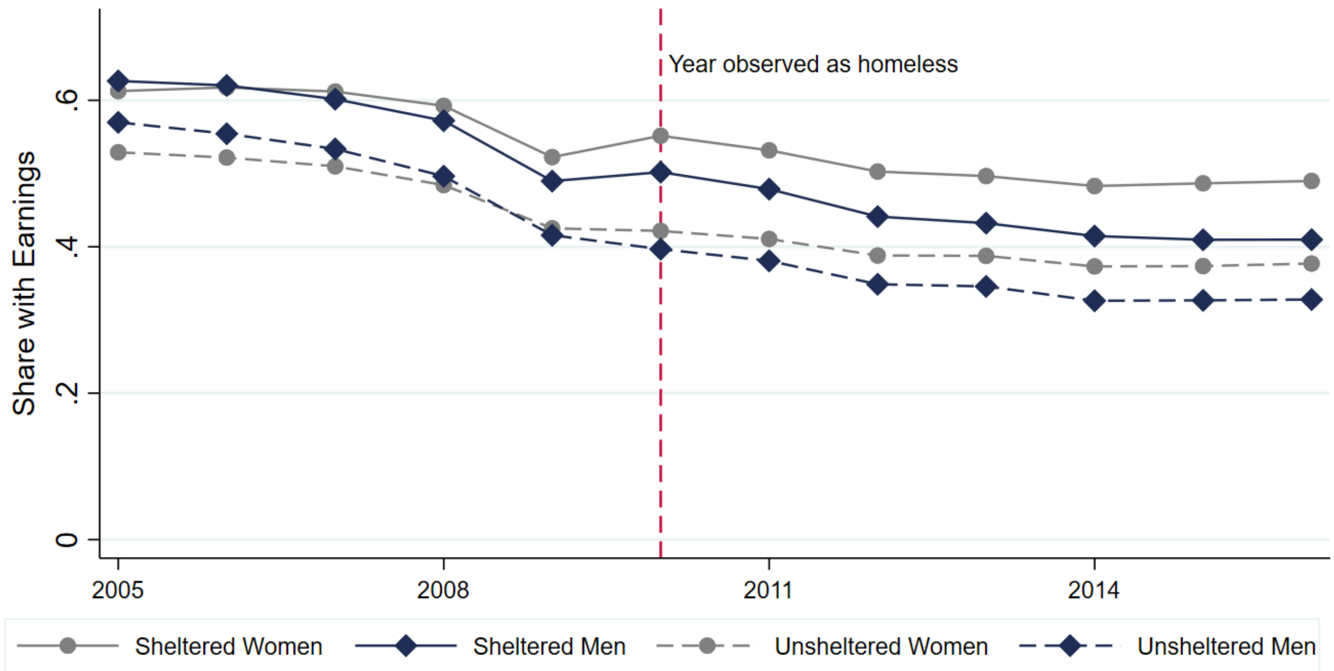
Chicago HMIS Shelter Users with First Enrollment in 2016, Ages 25-59



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

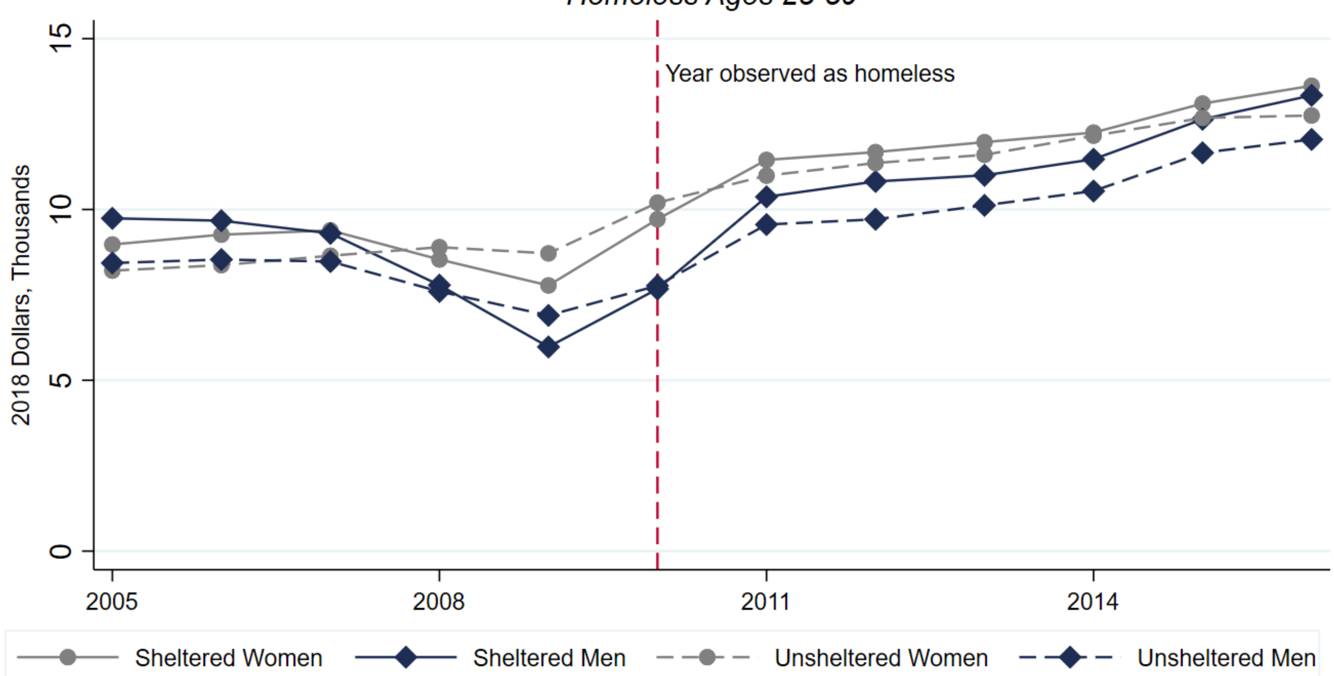
Homeless Ages 25-59



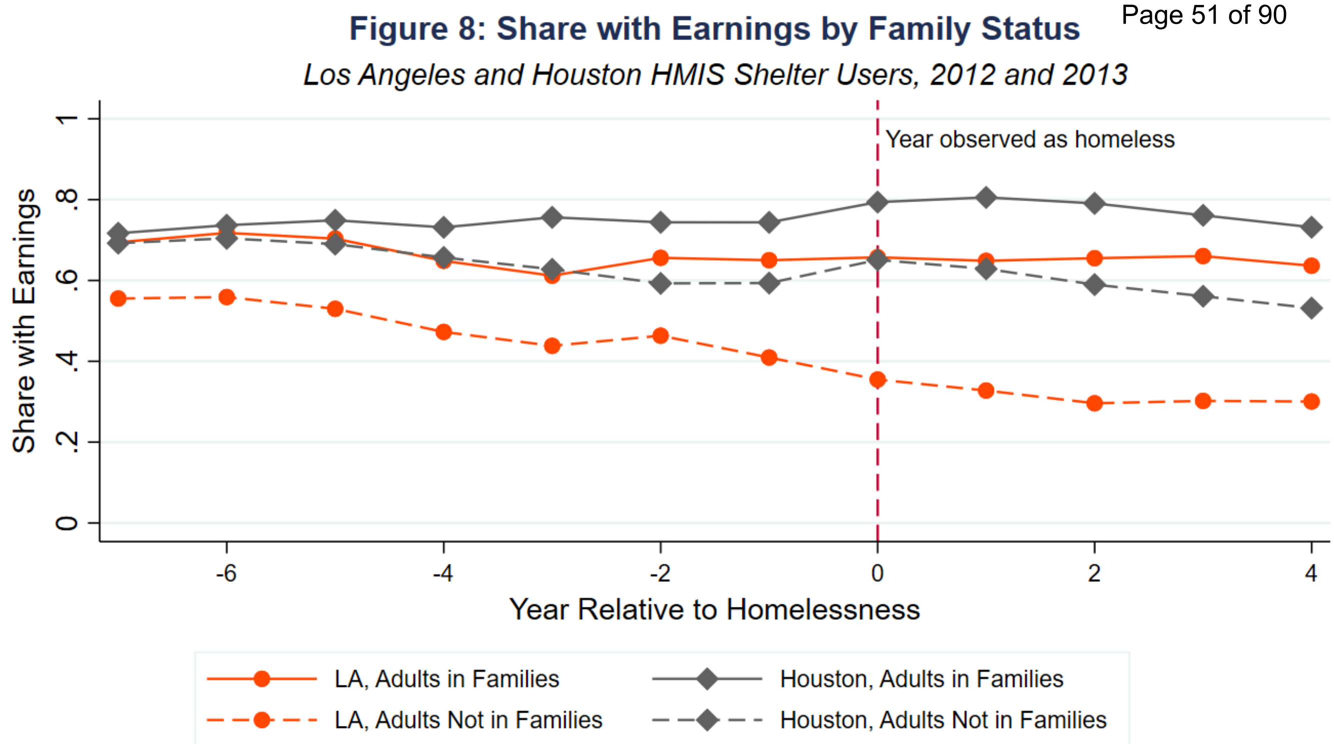
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

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

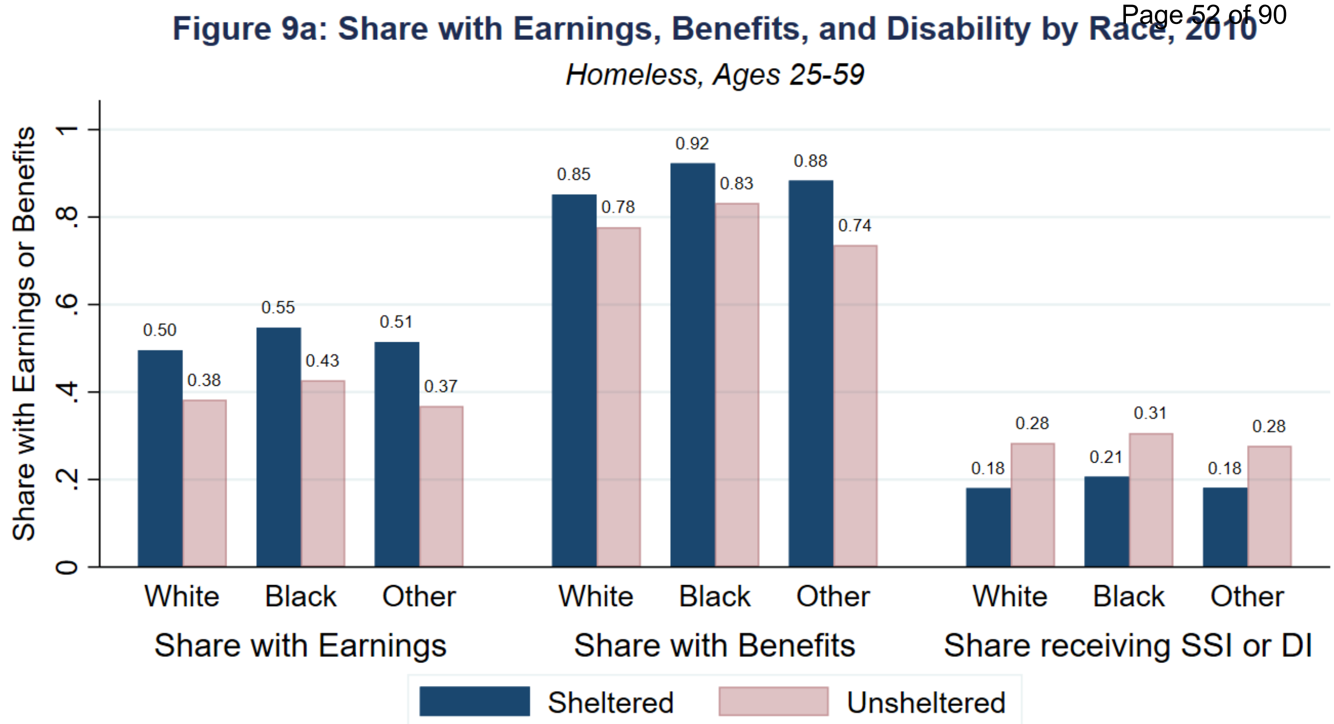
Homeless Ages 25-59



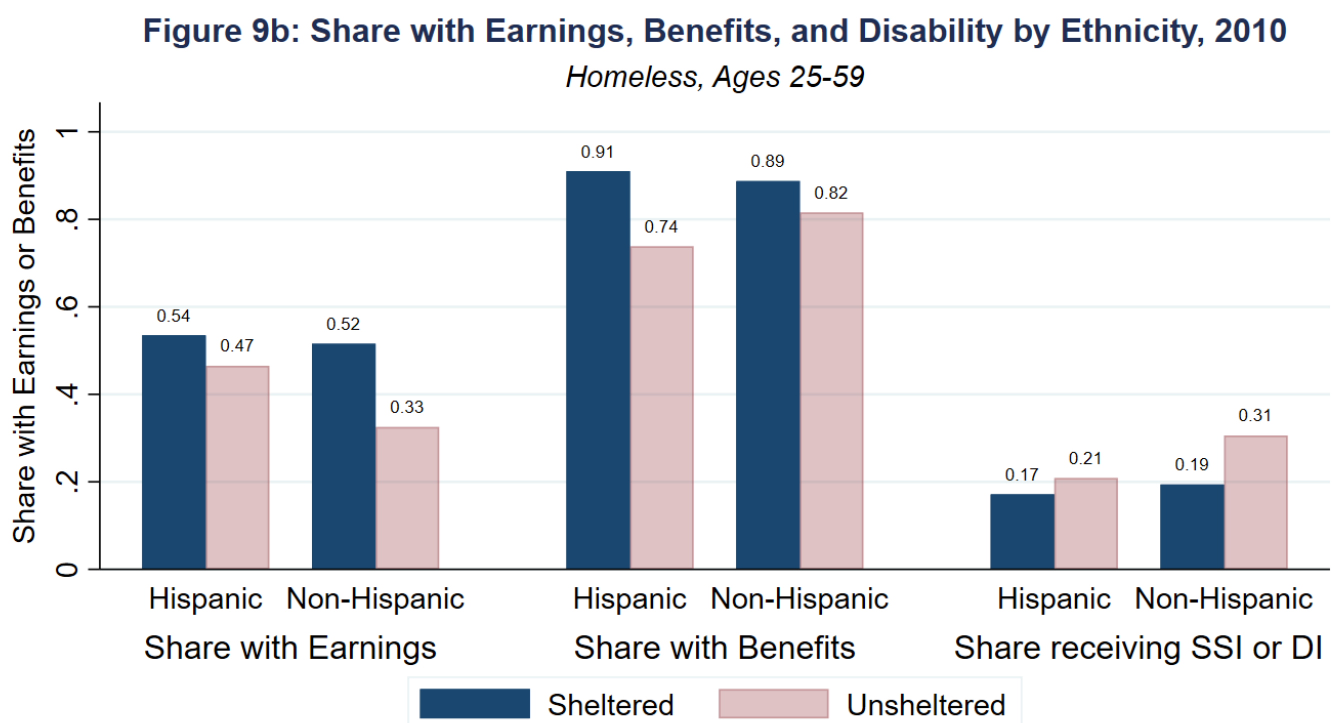
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



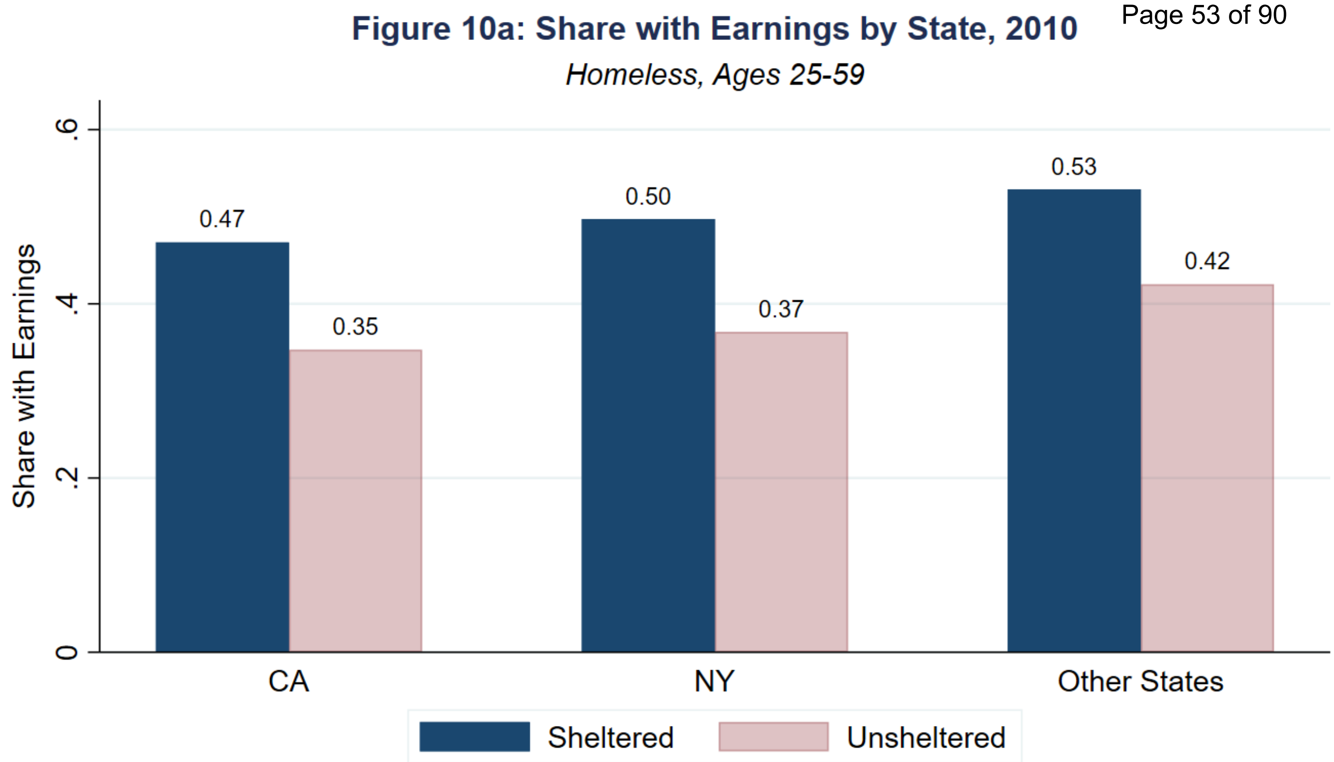
Sources: IRS 1040s (2003-2015), W2s (2005-2016), Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Sample contains those enrolled in HMIS shelters on March 30, 2012 or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



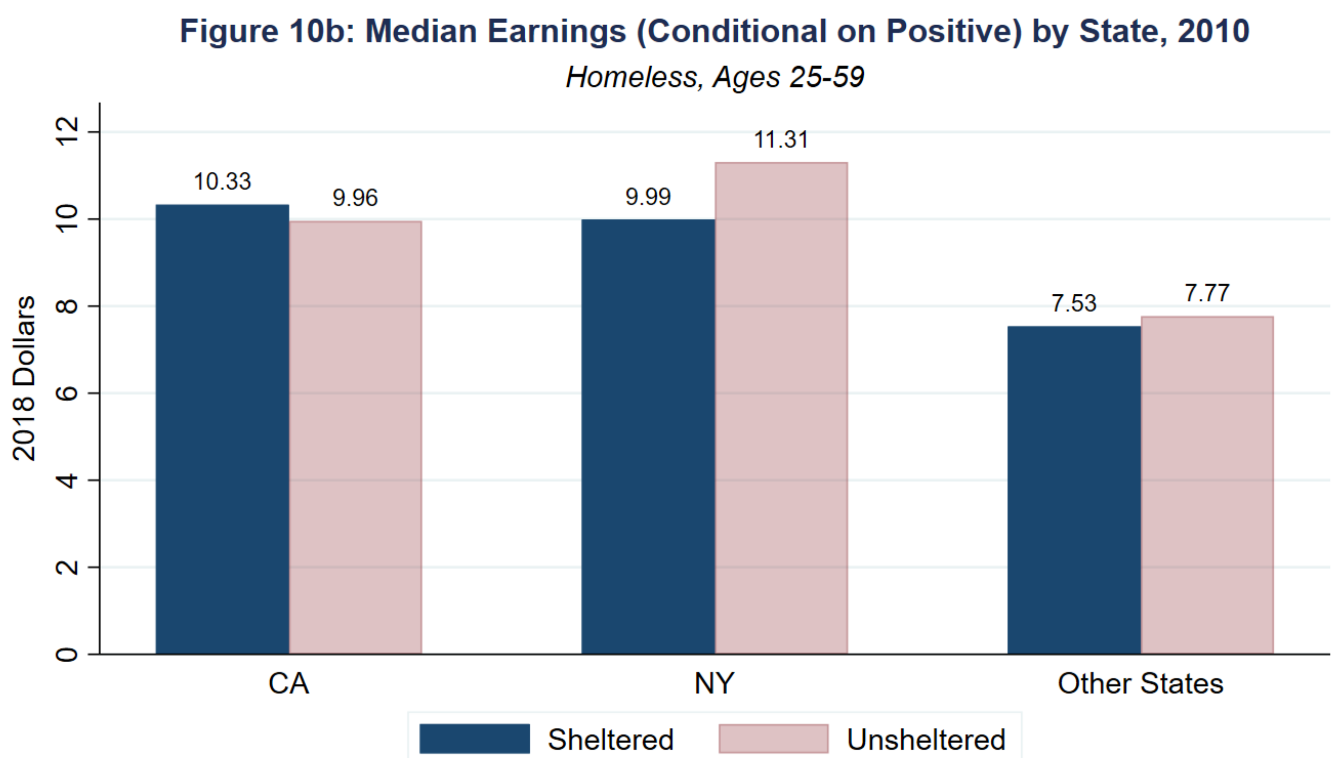
Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for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



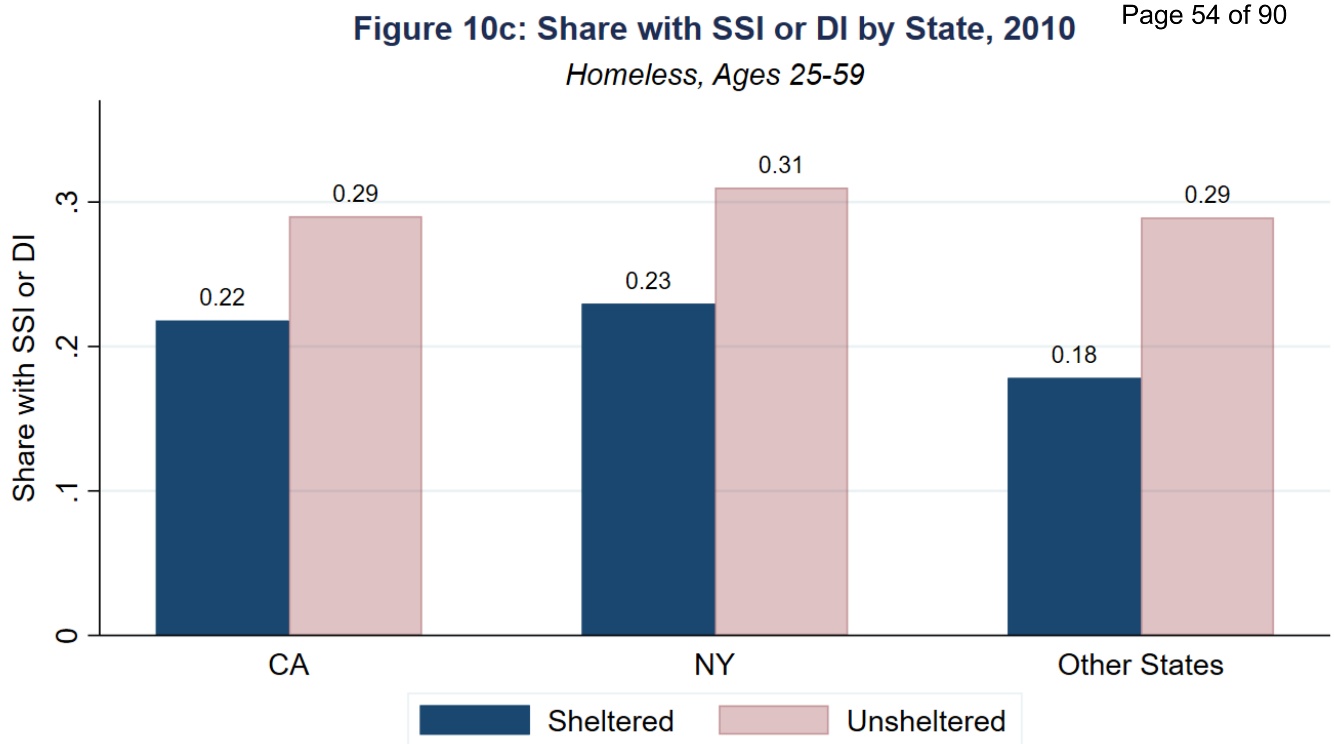
Sources: IRS 1040s (2003-2015), W2s (2005-2016), and 1099-Rs (2003-2015), HUD PIC/TRACS (2003-2016), USVETS (2007-2015), Medicare (2006-2014), Medicaid (2007-2015), SNAP for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for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



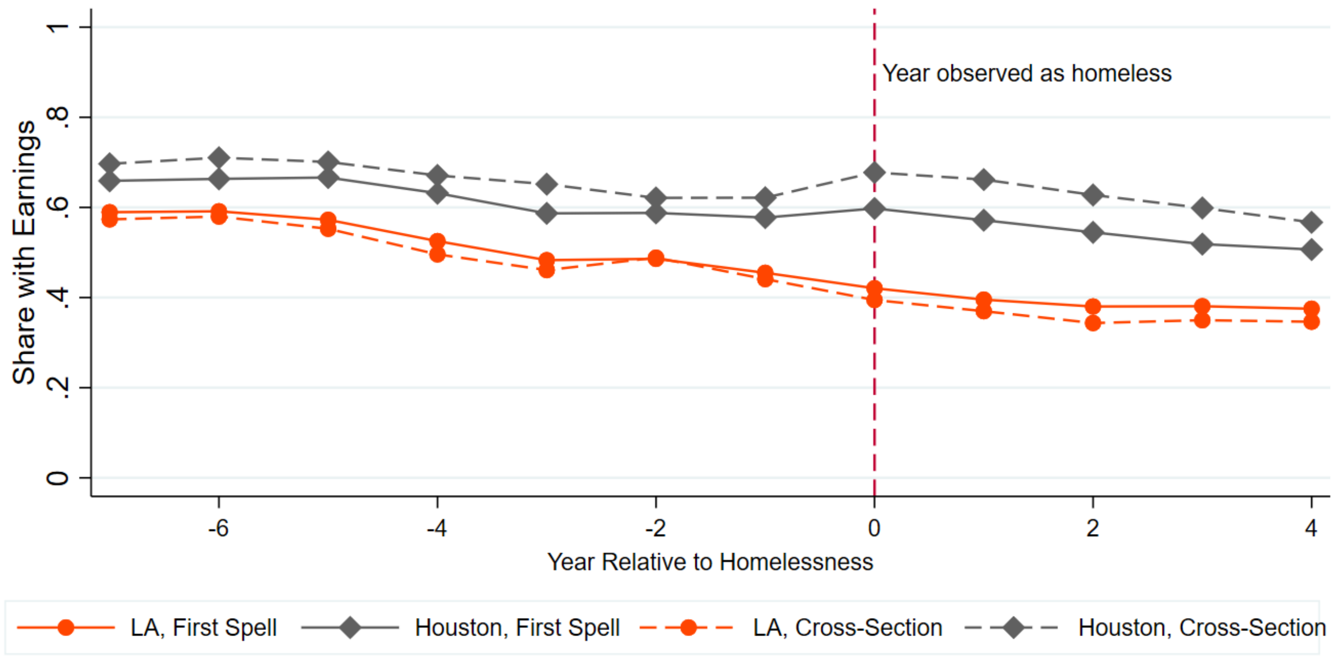
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



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

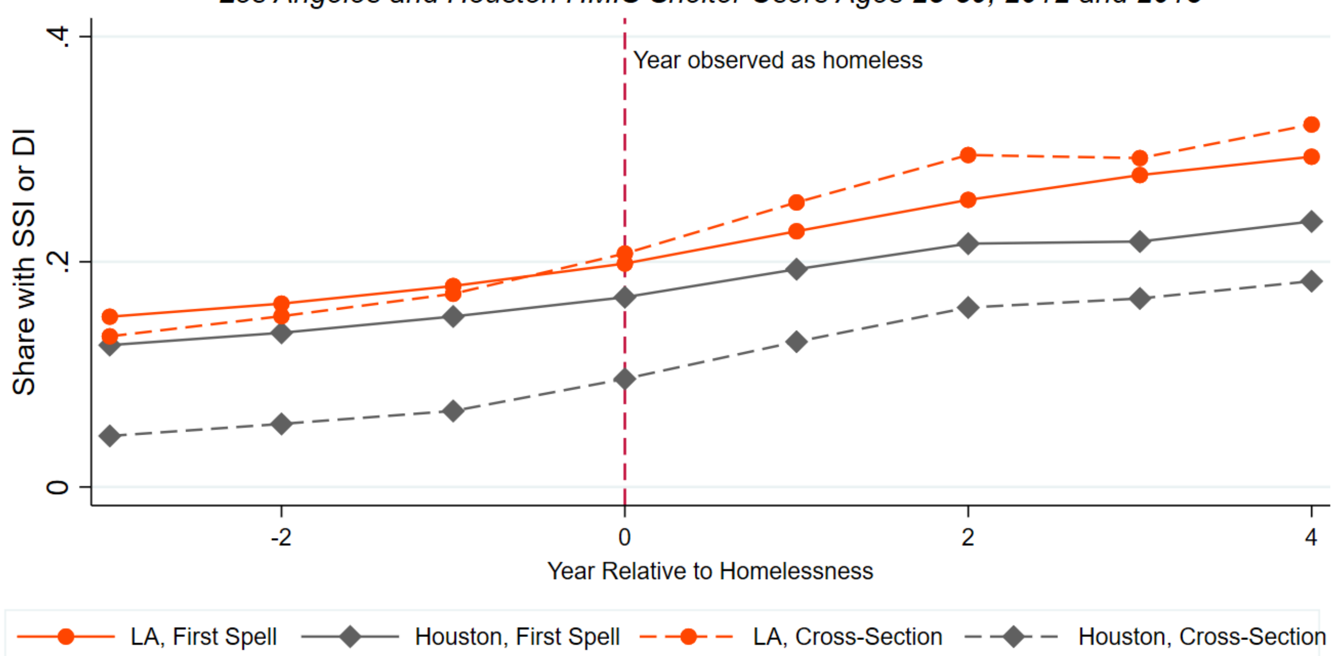
Los Angeles and Houston HMIS Shelter Users Ages 25-59, 2012 and 2013



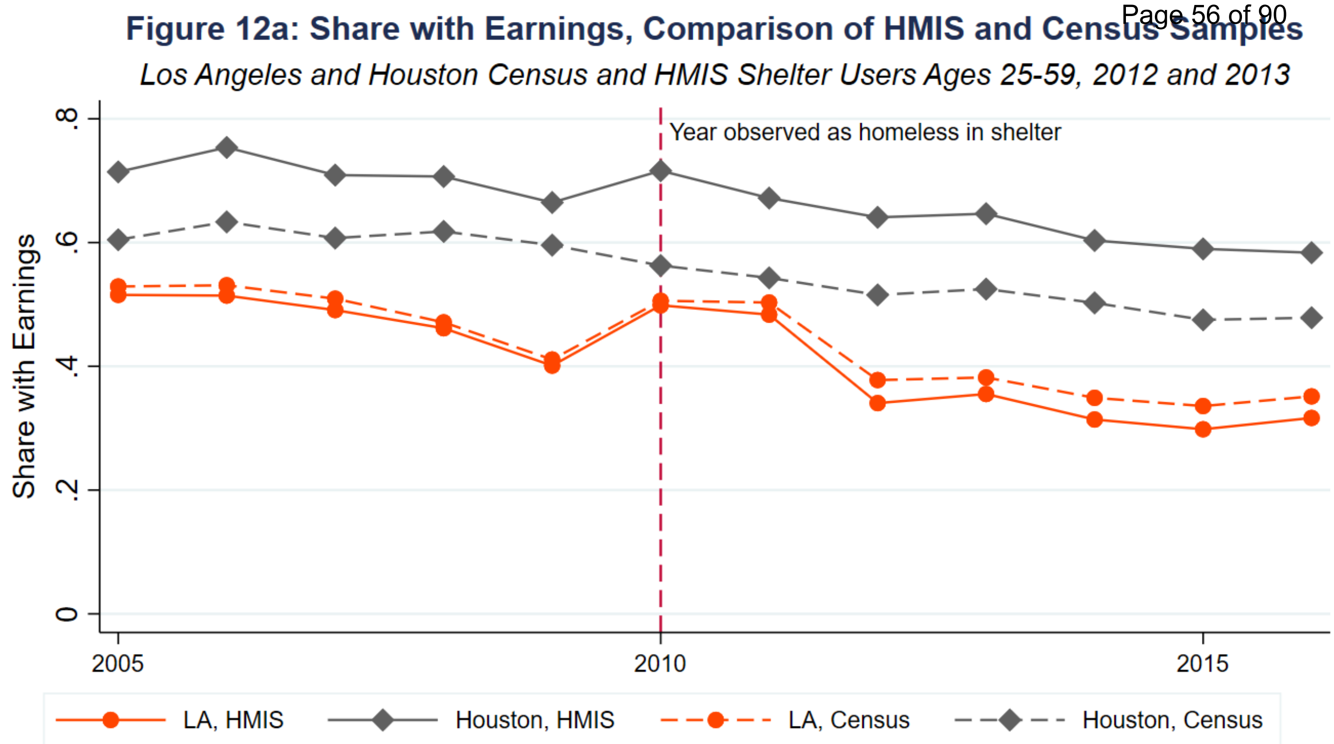
Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, 2003-2016 IRS 1040 Datasets, 2005-2016 W2 Datasets.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. "First spell" sample consists of those with first observed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

Figure 11b: Share with SSI or DI in HMIS Data, Comparison of Sample Time-Frames

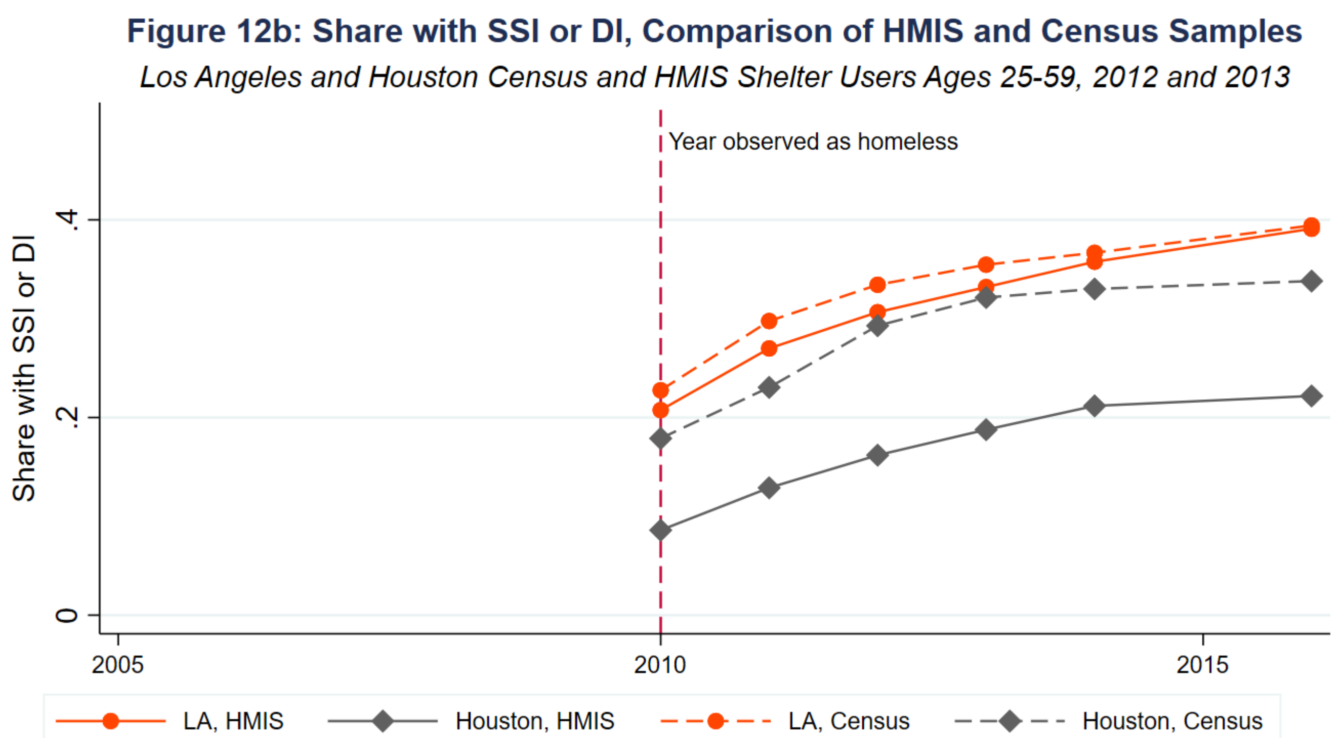
Los Angeles and Houston HMIS Shelter Users Ages 25-59, 2012 and 2013



Sources: Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, SSI Datasets (2010-2014, 2016), 2006-2016 Medicare 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.



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.



Sources: 2010 Census, Los Angeles (2004-2014) and Houston (2004-2015) HMIS datasets, SSI Datasets (2010-2014, 2016), 2006-2016 Medicare 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.

A. Appendix: Additional Robustness Checks

This section contains additional analyses to test the robustness of our findings to alternative samples, linkage methods, and years through a series of additional analyses using alternative Census and ACS homeless samples.

A.1 Income and Program Receipt using the ACS Sheltered Homeless Sample

We first calculate longitudinal employment and disability program receipt for sheltered homeless samples drawn from the 2010-2014 ACS and compare these results to the 2010 Census homeless. These analyses allow us to see whether homeless samples from years other than 2010 exhibit the same patterns. They also provide an additional check on whether our inverse probably weighting procedure in the Census leads to a representative sample, because the ACS permits us to estimate the probability of linkage using a wealth of additional predictors beyond the limited demographic characteristics available in the Census, including self-reported income and benefit measures that are highly correlated with our administrative outcomes of interest. Figures A1 and A2 (Table A15) show that our findings are robust to the use of ACS sheltered homeless samples. Both the levels and longitudinal patterns of employment and disability program receipt track closely in the two samples, bolstering the generality of our results beyond 2010 and supporting the validity of our approach to adjusting for non-linkage in the Census.

A.2 Robustness to Alternative Samples of the Census Homeless

We also calculate employment and benefit receipt for a version of the Census unsheltered homeless sample that includes those counted at outdoor locations (TNSOLs) and also for a version of the sheltered and unsheltered homeless Census samples that excludes people who were recorded in housing units as well as being counted as homeless in the 2010 Census. The first analysis serves 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. The second analysis accounts for the finding in Meyer et al. (2023) that about 40 percent of the unsheltered population and 20 percent of those in shelters were also counted as housed in the Census, raising concerns about misclassification of housed people as homeless. Figures A3-A6 (Tables A16 and A17) contain these results.

Our findings are robust to these alternative sample choices. Despite concerns about low linkage rates for people at TNSOLs, the decision to exclude these individuals appears to have little effect on our results. We also note that people who were double counted during the Census appear slightly more likely to be employed and slightly less likely receive benefits, differences which may reflect a small degree of misclassification but which could alternatively reflect heterogeneity in these outcomes between people with more or fewer connections to housed friends or family.

A.3 Potential Bias in Longitudinal SNAP Receipt from Migration

Our final robustness check examines possible downward bias in SNAP receipt that may arise due to migration between states for which we do and do not have SNAP records. People residing in SNAP states in 2010 who resided in other states for which we do not have these records would necessarily be indicated as non-recipients in those other years in our analyses. To explore this possibility, we link the 2010 Census homeless population to the 2000 Census to identify individuals who lived in the same states in both years, a subset that we consider less likely to have migrated than the typical homeless person. Figure A7 (Table A18) displays the results from this analysis. As expected, the peak in SNAP receipt surrounding 2010 is mitigated somewhat 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.

Appendix Tables

Table A1a: Summary of Connections to Formal Work, Safety Net, and Disability Programs, Ages 25-59 in 2010, 2005-2016

Sheltered and Unsheltered Homeless

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

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

[1] Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables 4-6.

[2] Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A1b: Summary of Connections to Formal Work, Safety Net, and Disability Programs, Ages 25-59 in 2010, 2005-2016

Single Housed Poor and Overall Housed

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

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

[1] Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables A3-A6.

[2] Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A2: Income and Benefit Receipt among All Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

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

[1] Earnings row reports the share of individuals with positive estimated earnings across IRS 1040 and W2 datasets, as defined in Tables A3-A6.

[2] Any benefits includes SNAP, HUD, VA, Medicare, and Medicaid benefits, as well as SSI benefits, when indicated.

Table A3a: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

*Sources and notes after Table A6.

Table A3b: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

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

*Sources and notes after Table A6.

Table A3c: Income and Benefit Receipt among Sheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016*

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

*Sources and notes after Table A6.

Table A4a: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

*Sources and notes after Table A6.

Table A4b: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016

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

*Sources and notes after Table A6.

Table A4c: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, 2003-2016

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

*Sources and notes after Table A6.

Table A5a: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

*Sources and notes after Table A6.

Table A5b: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

*Sources and notes after Table A6.

Table A5c: Income and Benefit Receipt among Single Housed Poor Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016*

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

*Sources and notes after Table A6.

Table A6a: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016

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

*Sources and notes after Table A6.

Table A6b: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016

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

*Sources and notes after Table A6.

Table A6c: Income and Benefit Receipt among All Housed Adults, Ages 25-59 in 2010 Decennial Census, 2005-2016

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

*Sources and notes after Table A6.

Table A7: TANF and General Assistance Receipt among Homeless and Comparison Groups, Ages 25-59 in 2010 Decennial Census, New York, 2007-2016

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

Sources: 2010 Decennial Census, 2019 Numident, 2007-2016 New York TANF dataset

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

Table A8: Monthly SNAP receipt among Chicago HMIS Shelter Users Ages 25-59

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

Source: Chicago (2014-2019) HMIS dataset, various states' SNAP datasets

Notes: Sample consists of people with first observed homeless spell in 2016.

Table A9a: Share of Sheltered Homeless with Income and Benefit Receipt by Gender, Ages 25-59 in 2010 Census

Panel A: Income and Benefit Receipt among Sheltered Homeless Women Ages 25-59 in 2010 Decennial Census, 2003-2016	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.613	0.618	0.612	0.593	0.523	0.552	0.532	0.503	0.497	0.483	0.487	0.490
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
50th percentile earnings (cond. on +)	$8,975	$9,262	$9,388	$8,536	$7,777	$9,715	$11,450	$11,680	$11,970	$12,250	$13,100	$13,620
	($108)	($115)	($108)	($110)	($119)	($106)	($92)	($103)	($117)	($130)	($135)	($135)
75th percentile earnings (cond. on +)	$18,140	$18,280	$17,620	$16,160	$15,380	$16,390	$18,770	$18,970	$19,450	$19,840	$21,650	$22,910
	($172)	($149)	($159)	($131)	($129)	($119)	($138)	($147)	($163)	($186)	($215)	($214)
50th percentile pre-tax income + in-kind transfers	$5,983	$5,454	$6,666	$5,376	$4,252	$6,906	$8,072	$7,569	$7,769	$7,250	$8,012	$8,284
	($366)	($360)	($209)	($196)	($152)	($237)	($271)	($275)	($267)	($273)	($271)	($260)
75th percentile pre-tax income + in-kind transfers	$13,680	$13,760	$15,360	$14,700	$13,900	$15,920	$17,170	$17,040	$17,250	$16,910	$18,070	$18,420
	($652)	($587)	($224)	($212)	($173)	($175)	($177)	($192)	($192)	($202)	($194)	($216)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.791	0.821	0.890	0.930	0.919	0.903	0.891	0.893	0.874	
			(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	
Share receiving SNAP	0.491	0.506	0.628	0.683	0.806	0.869	0.840	0.797	0.767	0.741	0.709	0.681
	(0.015)	(0.015)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Share with child in assistance unit (cond on +)	0.584	0.559	0.562	0.545	0.538	0.532	0.521	0.504	0.492	0.473	0.457	0.445
	(0.019)	(0.018)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Share enrolled in Medicaid			0.502	0.514	0.561	0.619	0.636	0.640	0.637	0.732	0.757	
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	
Share receiving SSI or DI (according to Medicare records)						0.200	0.253	0.293	0.315	0.331		0.344
						(0.003)	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)

Panel B: Income and Benefit Receipt among Sheltered Homeless Men Ages 25-59 in 2010 Decennial Census, 2003-2016	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.627	0.621	0.602	0.572	0.490	0.502	0.479	0.441	0.432	0.415	0.410	0.410
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50th percentile earnings (cond. on +)	$9,741	$9,672	$9,300	$7,786	$5,977	$7,674	$10,370	$10,820	$11,000	$11,470	$12,640	$13,340
	($90)	($92)	($86)	($84)	($77)	($70)	($99)	($106)	($111)	($130)	($150)	($148)
75th percentile earnings (cond. on +)	$21,260	$20,610	$19,280	$17,110	$14,660	$16,720	$20,900	$21,450	$22,040	$22,990	$25,180	$26,120
	($148)	($145)	($135)	($128)	($139)	($150)	($161)	($163)	($173)	($188)	($211)	($205)
50th percentile pre-tax income + in-kind transfers	$5,446	$4,816	$3,268	$2,264	$2,666	$2,896	$3,103	$2,794	$2,618	$2,389	$2,452	$2,635
	($318)	($264)	($139)	($46)	($11)	($56)	($89)	($65)	($63)	($53)	($72)	($89)
75th percentile pre-tax income + in-kind transfers	$15,700	$14,700	$13,530	$11,400	$10,140	$12,370	$14,220	$14,070	$14,150	$13,770	$14,460	$14,990
	($555)	($537)	($211)	($193)	($191)	($153)	($189)	($190)	($199)	($201)	($222)	($229)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.611	0.667	0.780	0.869	0.848	0.817	0.803	0.802	0.821	
			(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	
Share receiving SNAP	0.300	0.329	0.478	0.545	0.695	0.799	0.751	0.698	0.668	0.642	0.615	0.594
	(0.010)	(0.010)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share with child in assistance unit (cond on +)	0.158	0.140	0.141	0.125	0.120	0.119	0.117	0.109	0.106	0.099	0.095	0.091
	(0.014)	(0.010)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Share enrolled in Medicaid			0.223	0.242	0.284	0.359	0.392	0.411	0.419	0.551	0.616	
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	
Share receiving SSI or DI (according to Medicare records)						0.186	0.241	0.286	0.310	0.325		0.342
						(0.002)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)

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

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

Table A9b: Share of Unsheltered Homeless with Income and Benefit Receipt by Gender, Ages 25-59 in 2010 Census

Panel A: Income and Benefit Receipt among Unsheltered Homeless Women Ages 25-59 in 2010 Decennial Census, 2003-2016

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.529	0.522	0.510	0.484	0.425	0.422	0.411	0.388	0.388	0.373	0.374	0.377
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
50th percentile earnings (cond. on +)	$8,210	$8,371	$8,646	$8,897	$8,715	$10,200	$10,990	$11,360	$11,600	$12,160	$12,680	$12,750
	($206)	($204)	($208)	($217)	($226)	($216)	($223)	($211)	($216)	($235)	($257)	($276)
75th percentile earnings (cond. on +)	$18,770	$19,330	$19,420	$19,250	$18,850	$20,020	$21,020	$21,070	$21,490	$22,560	$24,140	$24,920
	($322)	($355)	($325)	($327)	($359)	($404)	($401)	($396)	($421)	($461)	($494)	($497)
50th percentile pre-tax income + in-kind transfers	$2,474	$2,380	$5,719	$3,789	$3,233	$3,933	$3,992	$3,738	$3,863	$3,275	$3,579	$4,560
	($294)	($310)	($408)	($313)	($206)	($305)	($327)	($305)	($342)	($307)	($334)	($408)
75th percentile pre-tax income + in-kind transfers	$10,000	$10,030	$16,090	$15,150	$13,940	$15,470	$16,170	$15,870	$16,130	$15,810	$17,030	$17,110
	($1132)	($1050)	($577)	($675)	($609)	($547)	($571)	($543)	($510)	($545)	($622)	($689)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)			0.728	0.745	0.783	0.820	0.831	0.823	0.823	0.832	0.850	
			(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	
Share receiving SNAP	0.547	0.555	0.578	0.605	0.662	0.715	0.718	0.702	0.691	0.687	0.670	0.652
	(0.021)	(0.021)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share with child in assistance unit (cond on +)	0.485	0.430	0.419	0.401	0.362	0.335	0.322	0.315	0.299	0.290	0.276	0.258
	(0.026)	(0.026)	(0.015)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Share enrolled in Medicaid			0.490	0.498	0.516	0.548	0.571	0.588	0.595	0.708	0.759	
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	
Share receiving SSI or DI (according to Medicare records)						0.335	0.362	0.395	0.414	0.422		0.432
						(0.006)	(0.006)	(0.006)	(0.006)	(0.006)		(0.007)

Panel B: Income and Benefit Receipt among Unsheltered Homeless Men Ages 25-59 in 2010 Decennial Census, 2003-2016

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Share with earnings	0.570	0.555	0.534	0.497	0.416	0.397	0.381	0.349	0.346	0.326	0.327	0.328
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
50th percentile earnings (cond. on +)	$8,434	$8,535	$8,477	$7,599	$6,899	$7,769	$9,560	$9,713	$10,120	$10,540	$11,660	$12,050
	($193)	($183)	($237)	($151)	($215)	($152)	($247)	($228)	($239)	($230)	($240)	($260)
75th percentile earnings (cond. on +)	$20,180	$20,010	$19,790	$18,210	$17,270	$19,620	$22,250	$22,110	$22,760	$24,010	$25,950	$27,020
	($360)	($324)	($437)	($288)	($401)	($408)	($510)	($409)	($459)	($426)	($449)	($424)
50th percentile pre-tax income + in-kind transfers	$2,349	$2,569	$2,952	$2,222	$2,538	$2,710	$2,630	$2,579	$2,525	$2,389	$2,439	$2,417
	($254)	($223)	($356)	($103)	($53)	($24)	($22)	($28)	($15)	($22)	($16)	($41)
75th percentile pre-tax income + in-kind transfers	$12,500	$11,960	$13,670	$11,880	$10,190	$11,050	$11,710	$11,290	$10,960	$10,260	$11,520	$11,760
	($833)	($659)	($621)	($704)	($631)	($631)	($635)	($637)	($651)	($693)	($689)	($687)
Share with benefits (SNAP, HUD, Medicaid, Medicare, or VA benefits)	0.380	0.457	0.617	0.682	0.742	0.793	0.789	0.781	0.787	0.796	0.822	
	(0.013)	(0.014)	(0.015)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	
Share receiving SNAP	0.363	0.381	0.475	0.544	0.626	0.688	0.670	0.653	0.645	0.631	0.616	0.594
	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)
Share with child in assistance unit (cond on +)	0.159	0.125	0.095	0.078	0.065	0.059	0.064	0.061	0.058	0.057	0.054	0.050
	(0.015)	(0.013)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Share enrolled in Medicaid			0.270	0.295	0.323	0.367	0.402	0.428	0.434	0.579	0.653	
			(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	
Share receiving SSI or DI (according to Medicare records)						0.276	0.314	0.346	0.363	0.372		0.383
						(0.007)	(0.007)	(0.007)	(0.006)	(0.006)		(0.007)

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)

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

Table A10: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 by Family Status (Point-in-Time Samples, 2012-2013)

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

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

Notes: Point-in-time samples consists of those who were in an HMIS shelter on March 30 of 2012 and 2013.

Table A11: 2010 Income and Benefit Receipt among Sheltered and Unsheltered Homeless Individuals Ages 25-59 in the 2010 Census, by Race and Ethnicity

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

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

Table A12: 2010 Income and Benefit Receipt among Sheltered and Unsheltered Homeless Individuals Ages 25-59 in the 2010 Census, by State

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

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

Table A13: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 - Point-in-Time and Interval-Based Results

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

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

Notes: Interval-based sample consists of people who had a first homeless spell in 2012 or 2013. Point-in-time sample consists of those who were in an HMIS shelter on March 30 of 2012 and 2(

Table A14: Income and Benefit Receipt among HMIS Shelter Users Ages 25-59 and Census Homeless in Los Angeles and Houston

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

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

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

Table A15: Income and Benefit Receipt Two Years Before and After Observed As Homeless, 2010-2014 ACS Sheltered Homeless Ages 25-59

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

Sources: 2010-2014 ACS, various administrative datasets

Note: Sample includes sheltered homeless individuals ages 25-59 at the time of survey.

Table A16: Income and Benefit Receipt among Unsheltered Homeless Individuals Ages 25-59 in 2010 Decennial Census, including TNSOLs, 2003-2016

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

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

Table A17: Income and Benefit Receipt among Sheltered Homeless Ages Individuals 25-59 in 2010 Decennial Census, excluding individuals counted in multiple housing statuses in the Census, 2003-2016

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

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

Table A18: Migration-Adjusted SNAP Receipt

Panel A: Migration Adjustment Approach #1

Baseline consists of all those who lived in SNAP state in 2010. Migration-adjusted sample consists of those who lived in the same SNAP state in 2000 and 2010.

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Sheltered	Baseline												
Homeless	Migration Adjusted	0.4366	0.4498	0.5852	0.6432	0.7668	0.8435	0.8090	0.7604	0.7363	0.7123	0.6846	0.6519
	SE	0.0138	0.0139	0.0060	0.0059	0.0047	0.0040	0.0044	0.0048	0.0050	0.0051	0.0053	0.0055
Sample size	Baseline												
	Migration Adjusted	1,300	1,300	6,800	6,800	8,100	8,100	8,100	8,000	7,900	7,800	7,700	7,600
Unsheltered	Baseline												
Homeless	Migration Adjusted	0.5004	0.4959	0.5364	0.5704	0.6445	0.7024	0.6941	0.6902	0.6739	0.6658	0.6492	0.6275
	SE	0.0183	0.0183	0.0103	0.0102	0.0089	0.0086	0.0086	0.0087	0.0089	0.0090	0.0092	0.0094
Sample size	Baseline												
	Migration Adjusted	750	750	2,400	2,400	3,000	3,000	3,000	2,900	2,900	2,800	2,800	2,700
Single Housed	Baseline												
Poor	Migration Adjusted	0.4082	0.4496	0.4428	0.4689	0.5417	0.5873	0.5951	0.5818	0.5647	0.5500	0.5342	0.5137
	SE	0.0202	0.0212	0.0131	0.0131	0.0112	0.0110	0.0110	0.0110	0.0111	0.0113	0.0114	0.0114
Sample size	Baseline												
	Migration Adjusted	1,800	1,800	4,300	4,300	5,800	5,800	5,800	5,800	5,700	5,700	5,600	5,600

Panel B: Migration Adjustment Approach #2

Baseline consist of 2010 Medicaid recipients in SNAP state in 2010. Migration-adjusted sample consists of Medicaid recipients in SNAP state in pre- and post-2010 window.

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Sheltered	Baseline			0.6097	0.6810	0.8409	0.9174	0.8689	0.8113	0.7734	0.7429	0.7082	0.6848
Homeless	SE			0.0043	0.0041	0.0031	0.0023	0.0028	0.0033	0.0036	0.0037	0.0039	0.0040
	Migration Adjusted			0.6872	0.7580	0.8786	0.9197	0.8992	0.8574	0.8222	0.7914	0.7537	0.7284
	SE			0.0039	0.0036	0.0025	0.0019	0.0018	0.0025	0.0029	0.0030	0.0030	0.0025
Sample size	Baseline			13,500	13,500	14,500	14,500	14,500	14,500	14,000	14,000	14,000	13,500
	Migration Adjusted			11,500	11,500	12,500	12,500	12,500	12,000	12,000	12,000	12,000	11,500
Unsheltered	Baseline			0.6410	0.7165	0.8046	0.8558	0.8288	0.8008	0.7844	0.7688	0.7509	0.7319
Homeless	SE			0.0207	0.0115	0.0084	0.0069	0.0079	0.0086	0.0090	0.0095	0.0101	0.0108
	Migration Adjusted			0.6869	0.7603	0.8236	0.8527	0.8464	0.8304	0.8197	0.8030	0.7841	0.7696
	SE			0.0266	0.0078	0.0046	0.0044	0.0040	0.0052	0.0049	0.0055	0.0056	0.0050
Sample size	Baseline			3,600	3,600	4,000	4,000	4,000	4,000	3,900	3,800	3,800	3,700
	Migration Adjusted			3,300	3,300	3,700	3,700	3,700	3,700	3,600	3,600	3,500	3,400
Single Housed	Baseline			0.6473	0.6930	0.7959	0.8432	0.8205	0.7911	0.7574	0.7459	0.7151	0.6951
Poor	SE			0.0130	0.0127	0.0097	0.0086	0.0093	0.0097	0.0102	0.0103	0.0107	0.0110
	Migration Adjusted			0.6932	0.7304	0.8081	0.8446	0.8474	0.8304	0.8041	0.7895	0.7573	0.7317
Sample size	SE			0.0111	0.0096	0.0051	0.0049	0.0044	0.0046	0.0063	0.0065	0.0074	0.0078
	Baseline			3,900	3,900	5,100	5,100	5,100	5,100	5,000	5,000	4,900	4,900
	Migration Adjusted			3,600	3,600	4,800	4,800	4,800	4,700	4,700	4,600	4,600	4,500

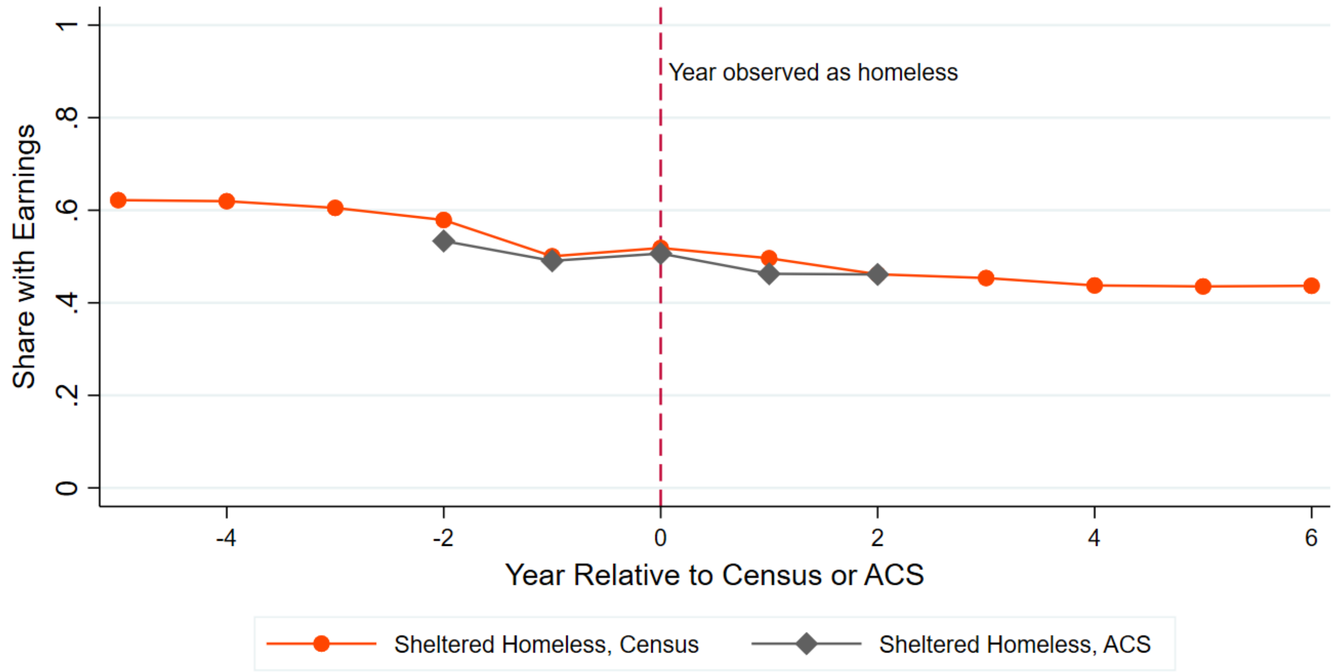
Sources: 2000 and 2010 Census, 2010 ACS, various states' SNAP datasets, various states' Medicaid datasets

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

Appendix Figures

Figure A1: Share with Earnings, Comparison of Census and ACS Homeless

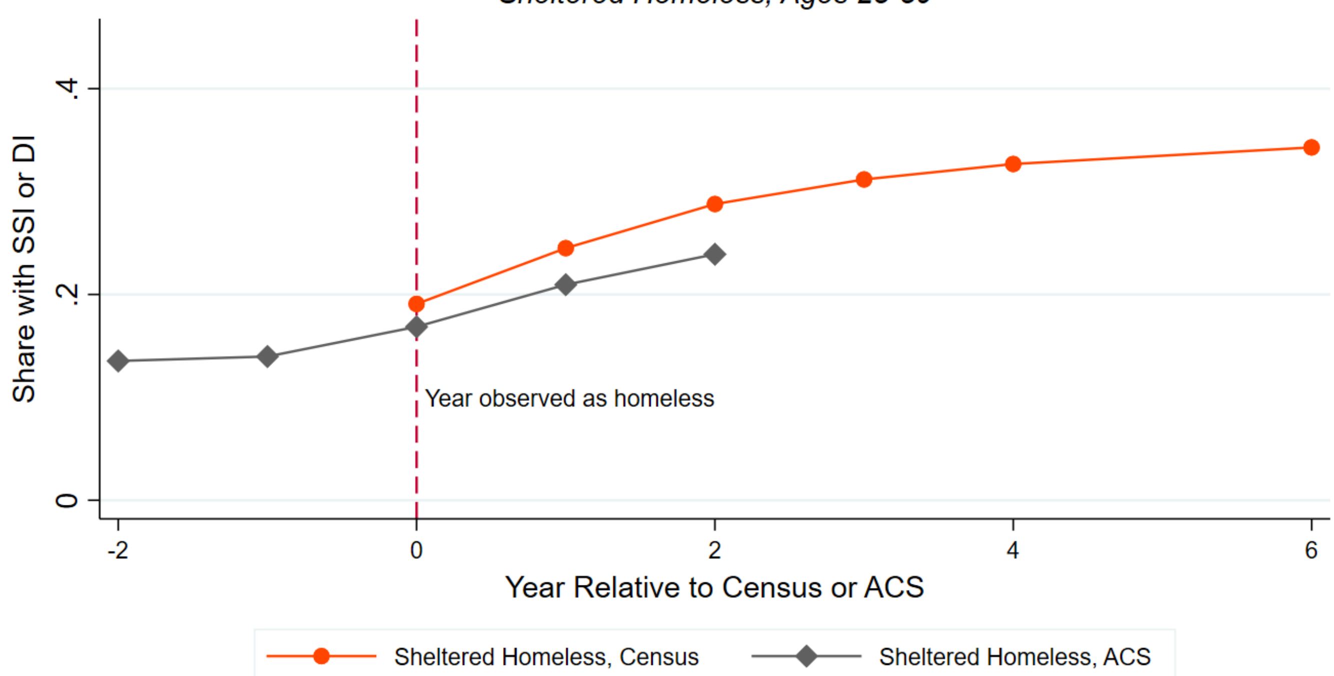
Sheltered Homeless, Ages 25-59



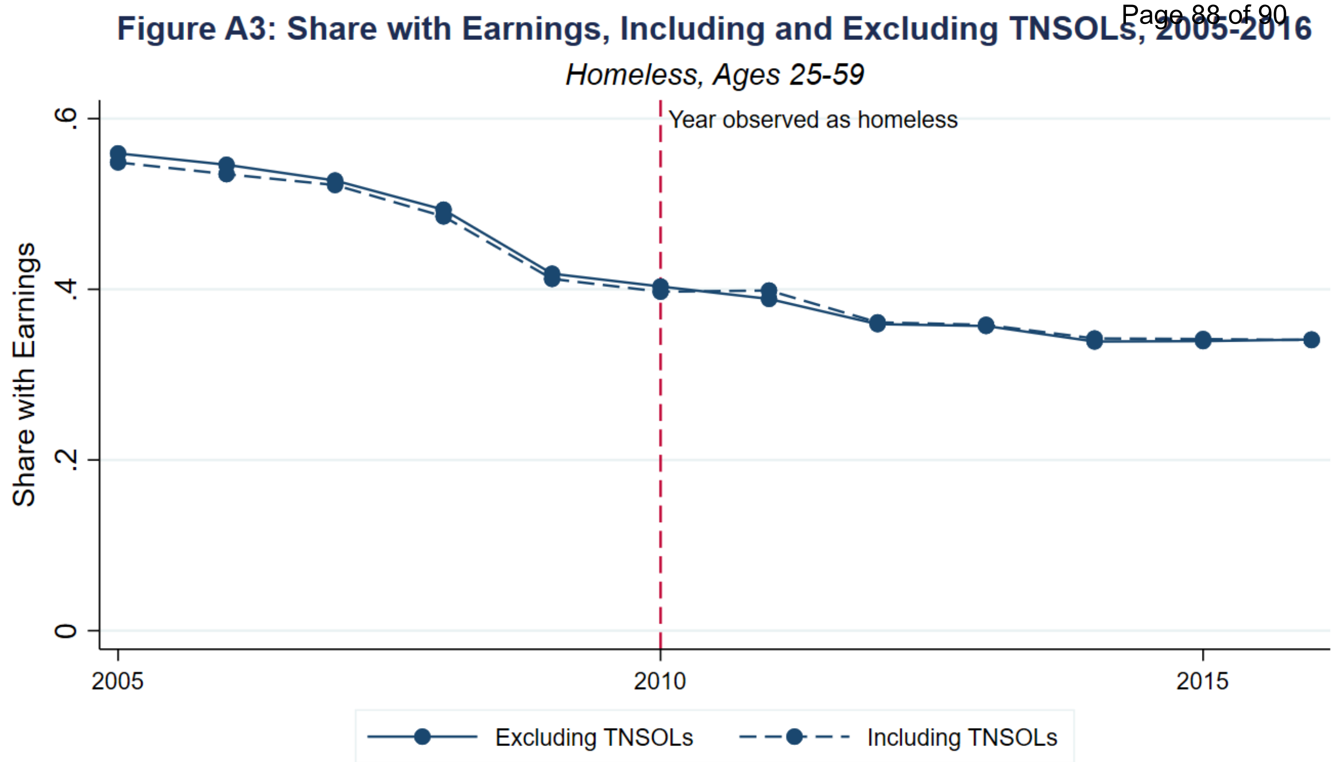
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census, 2010-2014 ACS.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure A2: Share with SSI or DI, Comparison of Census and ACS Homeless

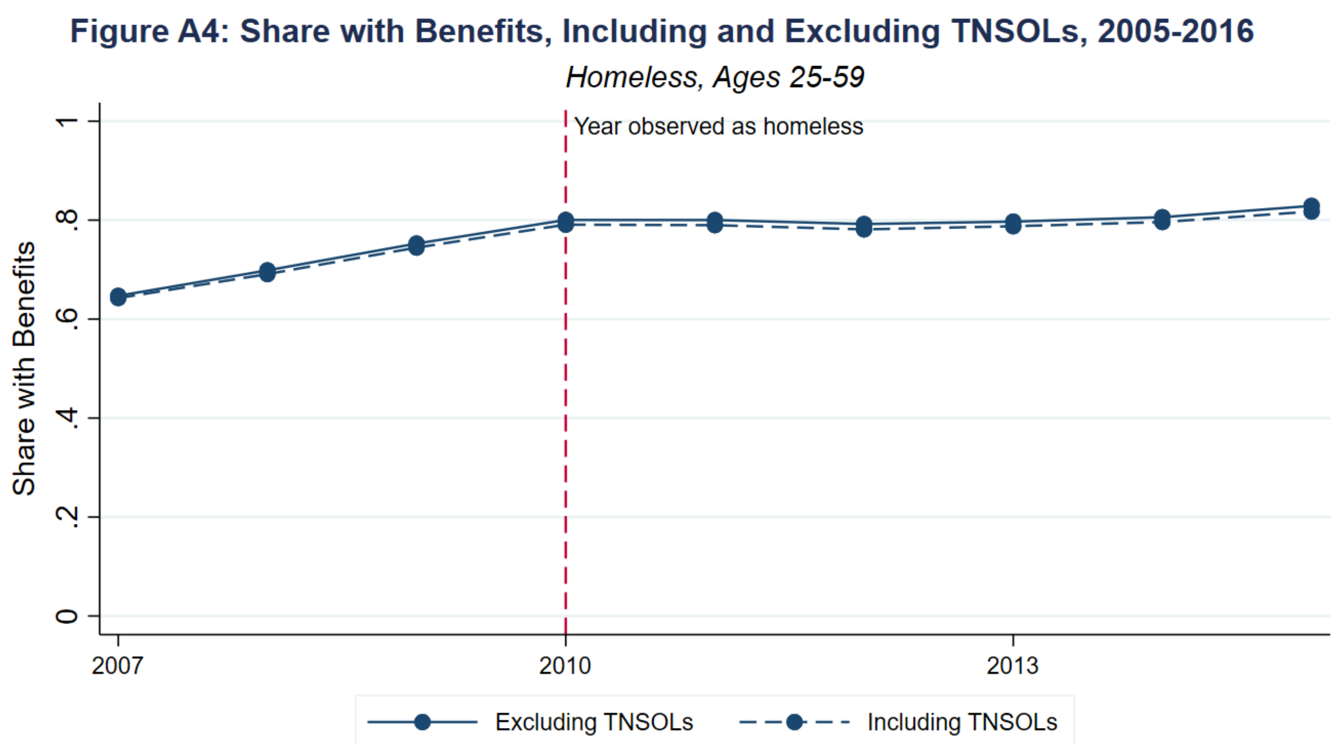
Sheltered Homeless, Ages 25-59



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.



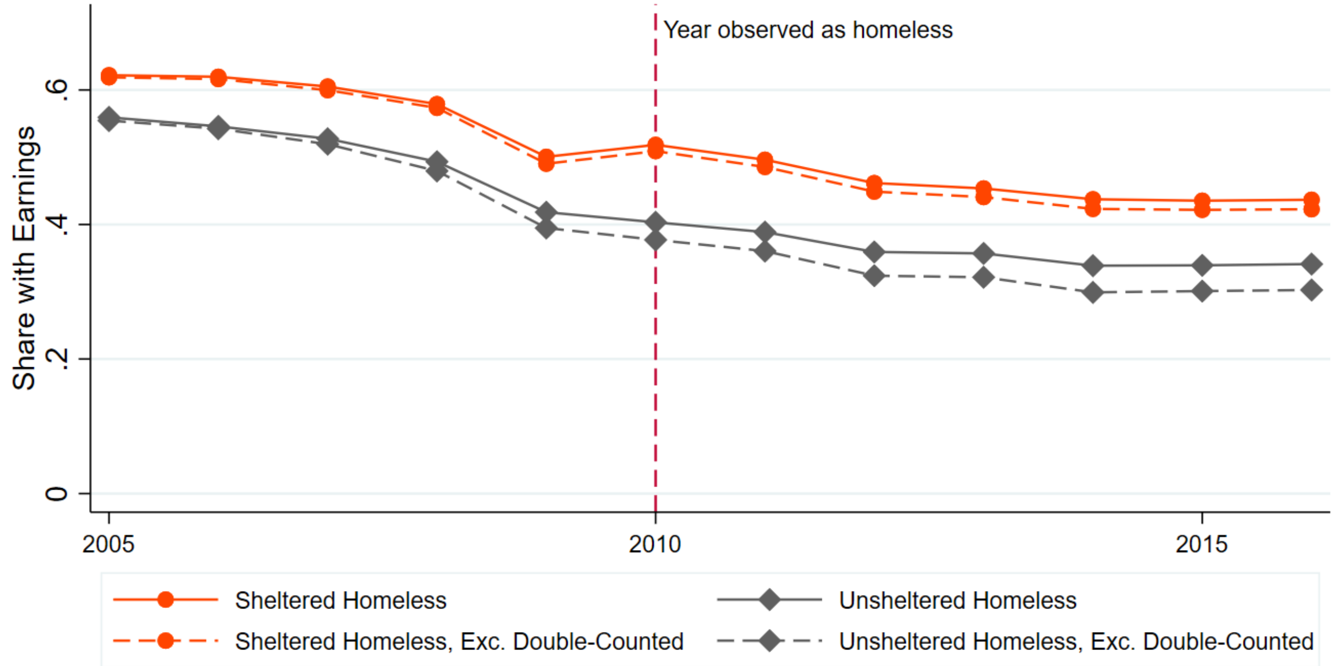
Sources: IRS 1040s (2003-2015), W2s (2005-2016), 2010 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.



Sources: 2010 Census, 2003-2016 HUD PIC & TRACS, 2007-2015 Administrative VA Dataset, 2006-2016 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016).
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure A5: Share with Earnings, Including and Excluding Double-Counted, 2005-2016

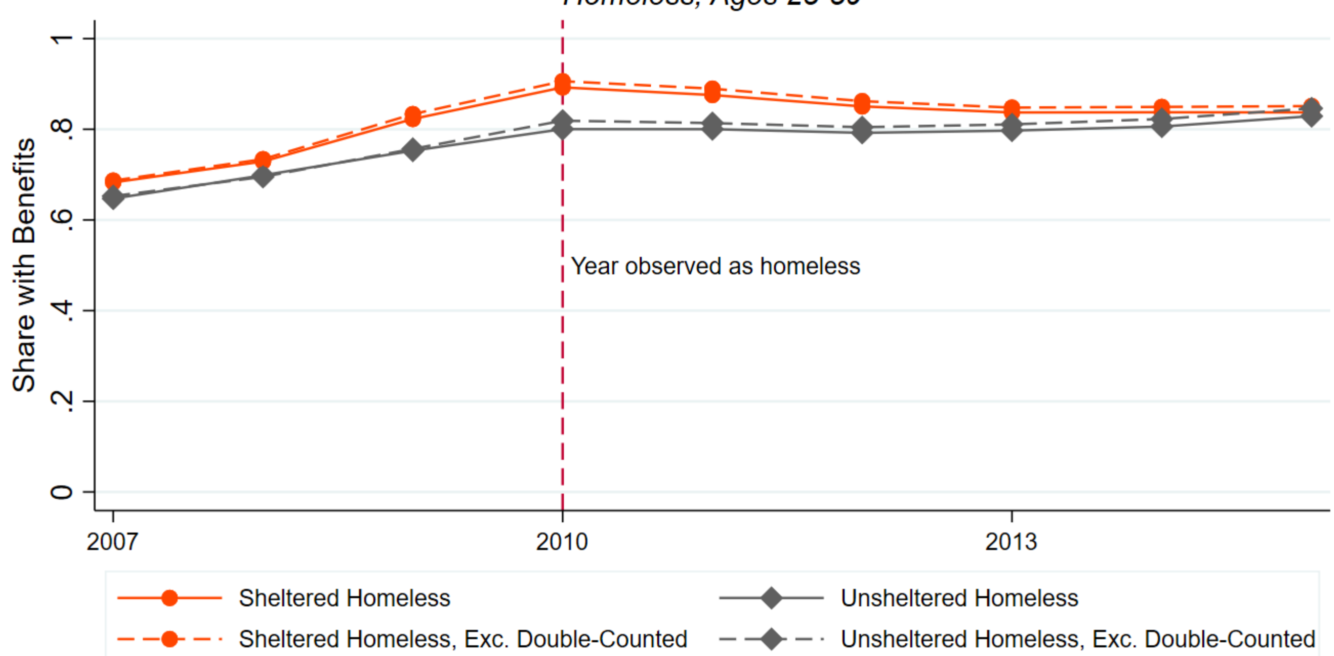
Homeless, Ages 25-59



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.

Figure A6: Share with Benefits, Including and Excluding Double-Counted, 2005-2016

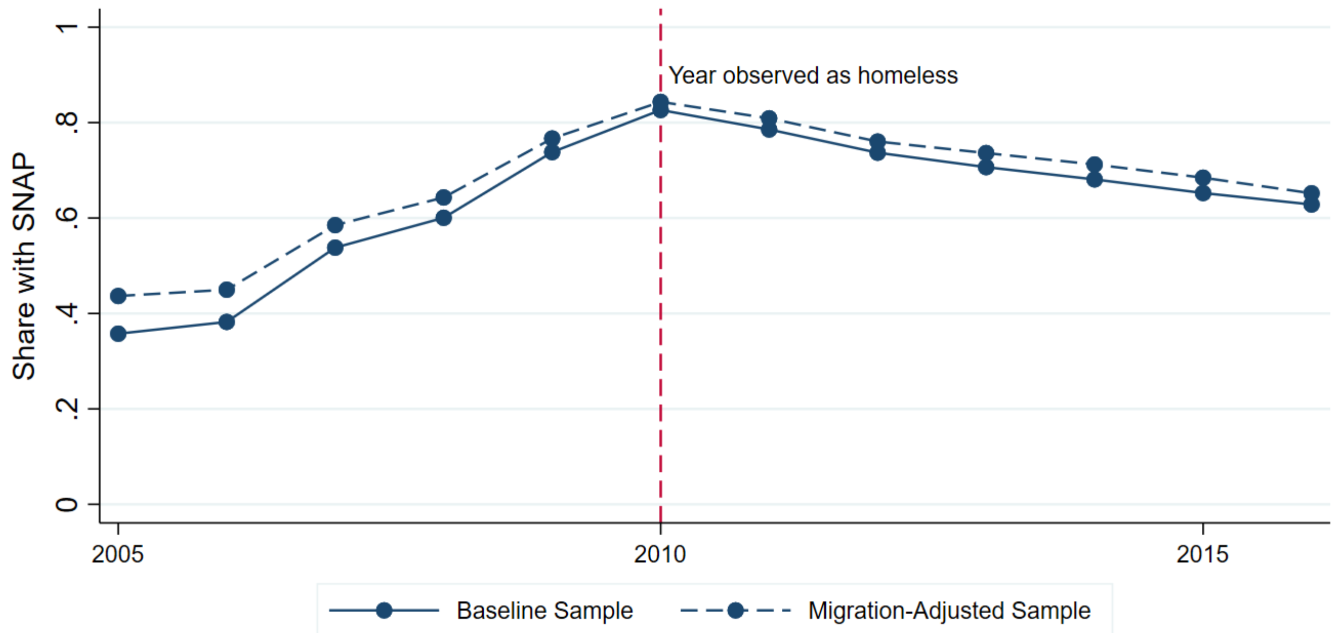
Homeless, Ages 25-59



Sources: 2010 Census, 2003-2016 HUD PIC & TRACS, 2007-2015 Administrative VA Dataset, 2006-2016 Medicare Datasets, 2007-2015 Medicaid dataset, SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016).
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015.

Figure A7: Baseline and Migration-Adjusted SNAP Receipt, 2005-2016

Homeless Ages 25-59



Sources: SNAP datasets for Illinois (2009-2016), Indiana (2004-2016), New York (2007-2016), New Jersey (2007-2016), and Tennessee (2004-2016), TANF/GA for New York (2007-2015), SSI (2010-2014, 2016), 2010 Census, 2000 Census.
Notes: Approved for release by the Census Bureau's Disclosure Review Board, authorization number CBDRB-FY2022-CES005-015. Baseline sample consists of homeless residing in SNAP states in 2010. Migration-adjusted sample consists of homeless residing in SNAP states in both 2010 and 2000.

U.S. Department of Housing and Urban Development

Archives

Glossary of Terms to Affordable Housing

Administrative Processes & Streamlining: Contains procedures by which developers receive permission to develop affordable housing. It includes the process for obtaining zoning changes, building permits, and occupancy permits. The topic also refers to receiving approvals from each government agency involved in the development process, as well as any required public hearings or citizen meetings. It includes both the pre-construction planning activities and the review activities that occur during construction.

Reference: www.huduser.org/rbc/categories.html

Affordable Housing: Affordable housing is generally defined as housing on which the occupant is paying no more than 30 percent of gross income for housing costs, including utilities.

Reference: www.hud.gov

Building and Housing Codes: State and local ordinances that prescribe certain minimum standards for construction, rehabilitation, or occupancy of affordable housing. It also relates to the acceptance or rejection of new building designs, materials, or technology intended to reduce the cost of affordable housing.

Reference: www.huduser.org/rbc/categories.html

Fair Housing and Neighborhood Deconcentration: This category refers to state and local laws that prohibit discrimination based on race, color, religion, sex, handicap, familial status, and national origin. It also refers to actions taken by state and local governments to enforce or evade these laws.

Reference: www.huduser.org/rbc/categories.html

Fees and Dedications: This category contains state and local requirements for the payment of fees, dedication of property, or installation of infrastructure to meet the increased demand on public services that result from a particular development.

Reference: www.huduser.org/rbc/categories.html

Housing Authority: Housing authorities are public corporations with boards appointed by the local government. Their mission is to provide affordable housing to low- and moderate-income people. In addition to public housing, housing authorities also provide other types of subsidized housing.

Reference: http://www.phada.org/ha_list.php

Impact Fees: Impact fees are imposed to charge the owners of newly developed properties for the "impact" the new development will have on the community. Fees can be used for such things as transportation improvements, new parks, and expansion of schools. Impact fees are not used to maintain existing facilities, but instead are used to create new facilities in proportion to the number of new developments in the area.

Reference: www.answers.com

Inclusionary Zoning: Usually practiced in urban areas, is planning communities and developments that will provide housing to all income brackets. Inclusionary zoning ordinances often require any new housing construction to include a set percentage of affordable housing units.

The positive aspects of Inclusionary zoning include the production of affordable housing at little cost to local government, the creation of income-integrated communities, and the lessening of sprawl. Negative aspects of inclusionary zoning may include shifting the cost of providing affordable housing, segmenting the upwardly mobile poor, and inducing growth.

Reference: www.answers.com

Land Trusts: A trust created to effectuate a real estate ownership arrangement in which the trustee holds legal and equitable title to the property subject to the provisions of a trust agreement setting out the rights of the beneficiaries whose interests in the trust are declared to be personal property.

Reference: www.answers.com

Low income Housing Tax Credit: Many for-profit and nonprofit-developed rental properties use these federal income tax credits. The Washington State Housing Finance Commission allocates these credits to developers to build or fix up low-income housing. Large corporations, institutions, pension funds, and insurance companies invest in the housing as a method to gain the tax credits and reduce their income tax obligations. These apartments serve residents below 60% of median income and must accept Section 8 vouchers.

Reference: www.phada.org/ha_list.php

Market Rate Rent: The prevailing monthly cost for rental housing. It is set by the landlord without restrictions.

Reference: www.phada.org/ha_list.php

Median Income: This is a statistical number set at the level where half of all households have income above it and half below it. The U.S. Department of Housing and Urban Development Regional Economist calculates and publishes this median income data annually in the Federal Register.

Reference: www.phada.org/ha_list.php

Nonprofit Housing: Nonprofit housing is developed by nonprofit corporations with a community board of directors and mission. Most housing developed by nonprofit housing developers is affordable with rents or prices below market-rate. Income generated from the housing is put back into the mission of the organization, rather than being distributed to stockholders or individual investors as would be the case in for-profit housing.

Reference: www.phada.org/ha_list.php

Nonprofit Housing Developer: A nonprofit organization with a mission that involves the creation, preservation, renovation, operation or maintenance of affordable housing.

Reference: www.phada.org/ha_list.php

Operating Subsidy: This is a type of subsidy going to property owners to reduce the management, maintenance and utility costs of housing. It is needed for projects housing extremely low-income residents who can't afford rents covering the actual costs of housing.

Reference: www.phada.org/ha_list.php

Planning & Growth Restrictions: This refers to barriers and solutions included relate to the process of developing a comprehensive land use plan and the restrictions placed on future development based on a map of the community. The topic also covers activities such as smart growth programs, sewer and building permit moratoriums, or requirements for fiscal impact studies.

Reference: www.huduser.org/rbc/categories.html

Rent Controls: Defined as state and local government actions that restrict rent increases or service fee charges to tenants.

Reference: www.huduser.org/rbc/categories.html

Redevelopment/ Infill: This refers to the rules under which abandoned or underused property is redeveloped. This topic includes inner city redevelopment, single lot infill, and brownfields redevelopment, as well as the process for obtaining the state and local government authorization to proceed with such work.

Reference: www.huduser.org/rbc/categories.html

Section 8 Housing: Many Section 8 contracts have expired or will expire soon, and the property owners must now decide whether to renew their contract or leave the program ("opt out"). Most of these contracts are now renewed on a one-year basis. Projects with high risk of opting out typically have rents set by the Section 8 contract below the prevailing market rents for comparable units. Owners thus have an incentive to leave the program and convert their property to private market rentals.

Reference: www.huduser.org/rbc/categories.html **Section 8 Vouchers**: This federal program is administered by the local housing authority. Eligible tenants receive vouchers they can use to help them pay for apartments in the private market.

Reference: www.huduser.org/rbc/categories.html

State and Local Tax Policies: Barriers and solutions which impact housing affordability, and include laws related to property taxes, tax assessments, transfer taxes, and sales taxes on building materials. It also refers to tax abatements or concessions and homestead exemptions.

Reference: www.huduser.org/rbc/categories.html

Subsidized Housing: A generic term covering all federal, state or local government programs that reduce the cost of housing for low- and moderate-income residents. Housing can be subsidized in numerous ways—giving tenants a rent voucher, helping homebuyers with downpayment assistance, reducing the interest on a mortgage, providing deferred loans to help developers acquire and develop property, giving tax credits to encourage investment in low- and moderate-income housing, authorizing tax-exempt bond authority to finance the housing, providing ongoing assistance to reduce the operating costs of housing and others. Public housing, project-based Section 8, Section 8 vouchers, tax credits, the State Housing Trust Fund, and Seattle Housing Levy programs are all examples of subsidized housing. Subsidized housing can range from apartments for families to senior housing high-rises. Subsidized simply means that rents are reduced because of a particular government program. It has nothing to do with the quality, location or type of housing. In fact, a number of Seattle's subsidized housing developments have received local and national design awards.

Reference: http://www.phada.org/ha_list.php

Zoning, Land Development, Construction and Subdivision Regulations: Rules and regulations that affect the use of land. It also contains rules and regulations that permit an owner to divide his land into smaller tracts. These activities include barriers, such as exclusionary zoning, as well as solutions, such as bonus density zoning. It also includes private restrictions on the use of property, such as deed restrictions.

Reference: www.huduser.org/rbc/categories.html

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insisted it was the Regal. "I ain't trying to pull nobody over in *the Daytona*," he'd say, feigning offense. Quentin was well manicured, built but not muscular, with curly hair and lots of jewelry—a thick chain, a thicker bracelet, rings. Sherrena thought he looked like a dope dealer but gave him her real number anyway. Quentin called Sherrena for three months before she agreed to let him take her out for ice cream. It took him another six years to marry her.

When Quentin pulled Sherrena over, she was a fourth-grade teacher. She talked like a teacher, calling strangers "honey" and offering motherly advice or chiding. "You know I'm fixing to fuss at you," she would say. If she sensed your attention starting to drift, she would touch your elbow or thigh to pull you back in.

Four years after meeting Quentin, Sherrena was happy with their relationship but bored at work. After eight years in the classroom, she quit and opened a day care. But "they shut it down on a tiny technicality," she remembered. So she went back to teaching. After her son from an earlier relationship started acting out, she began homeschooling him and tried her hand at real estate. When people asked, "Why real estate?" Sherrena would reply with some talk about "long-term residuals" or "property being the best investment out there." But there was more to it. Sherrena shared something with other landlords: an unbending confidence that she could make it on her own without a school or a company to fall back on, without a contract or a pension or a union. She had an understanding with the universe that she could strike out into nothing and through her own gumption and intelligence come back with a good living.

Sherrena had bought a home in 1999, when prices were low. Riding the housing boom a few years later, she refinanced and pulled out $21,000 in equity. Six months later, she refinanced again, this time pulling $12,000. She used the cash to buy her first rental property: a two-unit duplex in the inner city, where housing was cheapest. Rental profits, refinancing, and private real-estate investors offering high-interest loans helped her buy more.

She learned that the rental population comprised some upper- and middle-class households who rent out of preference or circumstance, some young and transient people, and most of the city's poor, who were excluded both from homeownership and public housing.[1] Landlords operated in different neighborhoods, typically clustering their properties in a concentrated area. In the segregated city, this meant that landlords focused on housing certain kinds of people: white ones or black ones, poor families or college students.[2] Sherrena decided to specialize in renting to the black poor.

Four years later, she owned thirty-six units, all in the inner city, and took to carrying a pair of cell phones with backup batteries, reading *Forbes*, renting office space, and accepting appointments from nine a.m. to nine p.m. Quentin quit his job and started working as Sherrena's property manager and buying buildings of his own. Sherrena started a credit-repair business and an investment business. She purchased two fifteen-passenger vans and started Prisoner Connections LLC, which for $25 to $50 a seat transported girlfriends and mothers and children to visit their incarcerated loved ones upstate. Sherrena had found her calling: inner-city entrepreneur.

Sherrena parked in front of Lamar's place and reached for a pair of eviction notices. The property sat just off Wright Street, with empty lots and a couple of street memorials for murder victims: teddy bears, Black & Mild cigars, and scribbled notes lashed to tree trunks. It was a four-family property consisting of two detached two-story buildings, one directly behind the other. The houses were longer than they were wide, with rough-wood balconies painted blue-gray like the trim and vinyl siding that was the brownish-white of leftover milk in a cereal bowl. The house facing the street had two doors, for the upper and lower units, and a pair of wooden steps leading to each, one old with peeling paint, the other new and unvarnished.

Lamar lived in the lower unit of the back house, which abutted the alley. When Sherrena pulled up, he was outside, being pushed in a wheelchair by Patrice, whose name was on the other eviction notice. He had snapped on his plastic prosthetic legs. An older black man, Lamar was wiry and youthful from the waist up, with skin the color of wet sand. He had a shaved head and a thin mustache, flecked with gray. He wore a yellow sports jersey with his keys around his neck.

"Oh, I got two at the same time," Sherrena tried to say lightly. She handed Lamar and Patrice their eviction notices.

"You almost been late," Patrice said. She wore a headwrap, pajama pants, and a white tank top that showed off her tattoo on her right arm: a cross and a ribbon with the names of her three children. At twenty-four, Patrice was half Lamar's age, but her eyes looked older. She and her children lived in the upper unit of the front house. Her mother, Doreen Hinkston, and her three younger siblings lived below her, in the bottom-floor unit. Patrice creased her eviction notice and jammed it into a pocket.

"I'm fixin' to go to practice," Lamar said from his seat.

"What practice?" Sherrena asked.

"My kids' football practice." He looked at the paper in his hand. "You know, we fixin' to do the basement. I'm already started."

"He didn't tell me about that," Sherrena replied, "he" being Quentin. Sometimes tenants worked off the rent by doing odd jobs for landlords, like cleaning out basements. "You better call *me.* Don't forget who the boss is," Sherrena joked. Lamar smiled back at her.

As Patrice began pushing Lamar down the street, Sherrena went over a checklist in her head. There were so many things to deal with—repairs, collections, moves, advertisements, inspectors, social workers, cops. The swirl of work, a million little things regularly interrupted by some big thing, had been encroaching on her Sunday soul food dinners with her mom. Just a month earlier, someone had been shot in one of her properties. A tenant's new boyfriend had taken three pumps to the chest, and blood had run down him like a full-on faucet. After police officers had asked their questions and balled up the yellow tape,

Sherrena and Quentin were stuck with the cleanup. Quentin set on it with a couple guys, rubber gloves, and a Shop-Vac. "Here you come with a boyfriend that I don't know anything about?" Sherrena asked the tenant. Quentin dealt with messes; Sherrena dealt with people. That was the arrangement.

Then, a few days after the shooting, another tenant phoned Sherrena to say that her house was being shut down. Sherrena didn't believe it until she pulled up and spotted white men in hard hats screwing green boards over her windows. The tenants had been caught stealing electricity, so the We Energies men had disconnected service at the pole and placed a call to the Department of Neighborhood Services (DNS). The tenants had to be out that day.[3]

In Milwaukee and across the nation, most renters were responsible for keeping the lights and heat on, but that had become increasingly difficult to do. Since 2000, the cost of fuels and utilities had risen by more than 50 percent, thanks to increasing global demand and the expiration of price caps. In a typical year, almost 1 in 5 poor renting families nationwide missed payments and received a disconnection notice from their utility company.[4] Families who couldn't both make rent and keep current with the utility company sometimes paid a cousin or neighbor to reroute the meter. As much as $6 billion worth of power was pirated across America every year. Only cars and credit cards got stolen more.[5] Stealing gas was much more difficult and rare. It was also unnecessary in the wintertime, when the city put a moratorium on disconnections. On that April day when the moratorium lifted, gas operators returned to poor neighborhoods with their stacks of disconnection notices and toolboxes. We Energies disconnected roughly 50,000 households each year for nonpayment. Many tenants who in the winter stayed current on their rent at the expense of their heating bill tried in the summer to climb back in the black with the utility company by shorting their landlord. Come the following winter, they had to be connected to benefit from the moratorium on disconnection. So every year in Milwaukee evictions spiked in the summer and early fall and dipped again in November, when the moratorium began.[6]

Sherrena watched the DNS hard hats march around her property. There were few things that frustrated landlords more than clipboard-in-hand building inspectors. When they were not shutting down a property, they were scrutinizing apartments for code violations. Upon request, DNS would send a building inspector to any property. The service was designed to protect the city's most vulnerable renters from negligent landlords, but to Sherrena and other property owners, tenants called for small, cosmetic things—and often because they were trying to stop an eviction or retaliate against landlords. Sherrena thought about the money she had just lost: a few thousand dollars for electrical work and unpaid rent. She remembered taking a chance on this family, feeling sorry for the mother who had told Sherrena she was trying to leave her abusive boyfriend. Sherrena had decided to rent to her and her children even though the woman had been evicted three times in the past two years. "There's me having a heart again," she thought.

Sherrena drove off Wright Street and headed north. Since she was in this part of town, she decided to make one more stop: her duplex on Thirteenth and Keefe. Sherrena had let a new tenant move in the previous month with a partial rent and security deposit payment.

The tenant was sitting on her stoop in a long-sleeved flannel shirt, hushing a colicky baby and talking with her mother, who was leaning against a car. Seeing Sherrena, the young woman wasted no time. "My son is sick because my house is cold," she said. Her voice was tired. "The window have a hole in it, and I've been waiting patiently. I mean, I'm ready to move."

Sherrena tilted her head, confused. The window had a hole, not a crater, and it was warm enough outside that children were still swimming in Lake Michigan. How could the house be cold?

"I done called the city," the mother added, peeling herself off the car. She was slender and tall, her hair frizzed by the late-summer humidity.

Sherrena took a breath. There were worse houses on the block, but Sherrena knew her place on Thirteenth Street wasn't up to code. She would say almost no house in the city was, a commentary on the mismatch between Milwaukee's worn-out housing stock and its exacting building code. Thanks to the tenant's mother, an inspector would arrive in a few days. He would jiggle the stair banister, photograph the hole in the window, shimmy the unhinged front door. Every code violation would cost Sherrena money.

"That wasn't right for you to do that," Sherrena said, "because I was working with her."

"Then fix the window," the mother replied.

"We will! But if she don't call us to let us know—"

"She don't have no phone, that's why I called!" the mother interrupted.

As the conversation grew louder, a crowd gathered. "Who's she?" a young boy asked. "Landlord," came a reply.

"I didn't know you were going to call the building inspector, Momma," the tenant said, nervously.

"It's too late now. The damage is done," Sherrena said. She shook her head and, hands on her hips, looked at the young woman with the baby. "It's always the ones that I try to help that I have the problems out of. And I'm not saying that you a problem, but it's just that, somebody else is involved, and you the one living here. So it puts you in a spot."

"Well, let me ask you something." The tenant's mother stepped closer and the crowd with her. "If this was your daughter and these were your grandkids, what would you do?"

Sherrena didn't step back. She looked up at the mother, noticing her gold front tooth, and answered, "I would have definitely made a connection with the landlord and not called the city."

Sherrena pushed past the crowd and stepped briskly to her car. When she got home, she opened the door and yelled, "Quentin, we done walked straight into some bullshit!"

Sherrena sat down in her paper-cluttered home office. The office was one of five bedrooms in Sherrena and Quentin's home, which sat in a quiet middle-class black neighborhood off Capitol Drive. The house had a finished basement with an inset Jacuzzi tub. Sherrena and Quentin had furnished it with beige leather furniture, large brass and crystal light fixtures, and gold-colored curtains. The kitchen was spacious and unused, since they ate out most days. Typically the only things in the refrigerator were restaurant doggie bags.

"Huh?" Quentin called back, coming down the stairs.

"The girl downstairs at Thirteenth Street? Her momma done called the building inspector. . . . Her mother was outside talking *shit*!"

Quentin listened to the story and said, "Put her out."

Sherrena thought about it for a moment, then agreed. She reached in a drawer and began filling out a five-day eviction notice. The law forbade landlords from retaliating against tenants who contacted DNS. But landlords could at any time evict tenants for being behind on rent or for other violations.

By the time Quentin and Sherrena pulled the Suburban onto Thirteenth Street, night had fallen. The apartment door was open. Sherrena walked right through it without knocking and handed the young tenant an eviction notice, saying, "Here. I hope you get some assistance."

A man followed Sherrena out the door and stood on the unit porch. "Excuse me," he called out as Sherrena met Quentin in the street. "You're *evicting* her?"

"She told me she wanted to move, so that let me know she wasn't going to pay anything else," Sherrena answered.

"She told you she wanted the windows fixed."

Quentin interjected, looking at Sherrena, "He ain't got nothin' to do with it."

"I got *everything* to do with it, blood. This my stepdaughter here!"

"You don't even stay here though, man!" Quentin yelled back.

"Ain't nobody want to live like that. . . . Fuck you mean, I don't have nothing to do with it?"

Quentin opened the Suburban's door and pulled out his security belt, equipped with handcuffs, a small baton, and a canister of Mace the size of a small fire extinguisher. Quentin had been here before. There was the tenant who told him he was going to take his security deposit out of Quentin's pocket. There was the one who said he was going to shoot him in the face.

The tenant's mother joined the stepfather on the dark porch. "Are you evicting her?" she asked.

"She didn't pay her rent," Sherrena said. "Do *y'all* have her rent to pay?"

"I don't give a shit, man," the stepfather was saying almost to himself. What he didn't give a shit about wasn't the eviction but whatever was going to transpire there, at that very moment, on that dark street.

"I don't either!" Quentin shot back.

"I'll whip that motherfuckin' ass, nigga. . . . Don't say I ain't got nothin' to do with it."

"*You don't!*" Sherrena yelled as Quentin tugged her back to the Suburban. "You don't!"

Days after the tenant left, Sherrena took a call from a caseworker at Wraparound, a local social services agency. The caseworker had a client who needed a place to live with her two boys. Wraparound would pay her security deposit and first month's rent, which sounded good to Sherrena. The new tenant's name was Arleen Belle.

PUBLIC HEALTH

Nitrogen dioxide exposure, health outcomes, and associated demographic disparities due to gas and propane combustion by U.S. stoves

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Gas and propane stoves emit nitrogen dioxide (NO_2) pollution indoors, but the exposures of different U.S. demographic groups are unknown. We estimate NO_2 exposure and health consequences using emissions and concentration measurements from >100 homes, a room-specific indoor air quality model, epidemiological risk parameters, and statistical sampling of housing characteristics and occupant behavior. Gas and propane stoves increase long-term NO_2 exposure 4.0 parts per billion volume on average across the United States, 75% of the World Health Organization's exposure guideline. This increased exposure likely causes ~50,000 cases of current pediatric asthma from long-term NO_2 exposure alone. Short-term NO_2 exposure from typical gas stove use frequently exceeds both World Health Organization and U.S. Environmental Protection Agency benchmarks. People living in residences <800 ft^2 in size incur four times more long-term NO_2 exposure than people in residences >3000 ft^2 in size; American Indian/Alaska Native and Black and Hispanic/Latino households incur 60 and 20% more NO_2 exposure, respectively, than the national average.

INTRODUCTION

Gas stoves are used in approximately 50 million U.S. homes (*1*) and millions more worldwide (*2*, *3*). Gas and propane combustion in stoves emits hazardous air pollutants, including nitrogen dioxide (NO_2), benzene (C_6H_6), carbon monoxide (CO), formaldehyde (H_2CO), and ultrafine particles (*4*–*12*). Nitrogen dioxide and benzene emissions are of particular concern, as typical gas stove use can elevate indoor concentrations of these pollutants above health benchmarks (*5*, *6*, *8*, *10*, *11*). Long-term exposure (averaged over a year) to NO_2 has been linked to increased incidence and exacerbation of pediatric asthma (*13*–*16*), incidence and mortality from chronic obstructive pulmonary disease (COPD) (*17*–*19*), and incidences of lung cancer, preterm birth, and diabetes mellitus (*20*). Given the abundance of gas and propane stoves and the dangers of additional NO_2 exposure generally, quantifying the burden of NO_2 exposures and health outcomes from gas and propane combustion by stoves is needed for assessing public safety.

Previous studies estimating disease burdens attributable to combustion by gas stoves have limitations that reduce their abilities to assess exposure as a function of different behaviors or across different socioeconomic, racial, or ethnic groups. First, constraining estimates of indoor NO_2 exposure from direct measurements of indoor concentrations is challenging because the data are sparse and because observed concentrations can fluctuate with ventilation and stove use (*21*, *22*). Second, studies that correlate health outcomes with the presence or absence of a gas stove (rather than with direct pollutant exposure) typically do not capture large differences in housing size and layout, ventilation, or behavior that may substantively affect exposure across groups (*23*–*25*), hindering investigations of health disparities mediated through such factors. Existing meta-analyses calculating odds ratios (ORs) of specific health outcomes associated with gas stoves have relied either on correlations between measured indoor NO_2 concentrations and health outcomes, as opposed to directly quantifying NO_2 exposure, or have used the presence of gas stoves as a proxy for NO_2 exposure (*16*, *26*).

Gaps in current epidemiological knowledge can be addressed using detailed assessments of the population-wide distribution of long-term (year-averaged) and short-term (hour-averaged) NO_2 exposure attributable to combustion by natural gas (which is composed of >90% methane) and propane stoves. Previous studies have quantified NO_2 emission rates from gas stoves (*6*, *10*, *27*) but not, to our knowledge, from propane stoves. Previous studies (*5*, *8*, *10*, *28*–*31*) have also measured the resulting indoor NO_2 concentrations in a handful of residences representing a single building type or a local geography. Models have focused either on individual buildings (*32*–*34*) or on a specific, local geography (*35*) or, if encompassing a broader geography, have omitted variation in cooking and occupancy patterns (*36*). The two previous studies that assessed exposure in multiple building types relied on models that treat residences as open boxes that lacked interior walls rather than as homes with discrete rooms and hallways (*35*, *36*); hence, these single-zone models do not capture higher short-term exposures while people are cooking or spending additional time in the kitchen.

We constructed a population-level model of NO_2 exposure from combustion by gas and propane stoves using the National Institute of Standards and Technology's (NIST's) CONTAM multizone indoor air quality model (*37*) and our field measurements of NO_2 emission rates from gas and propane stoves. We ran the model on more than 31,100 combinations of input variables whose distributions and weights we obtained from our field measurements combined with published datasets for the U.S. housing stock and relevant behaviors of the U.S. population (see Materials and Methods). This model allowed us to estimate NO_2 exposure attributable to gas and

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propane stoves stratified by various environmental, behavioral, and demographic parameters, including residence size and layout, time spent with windows open, frequency of range hood use, range hood capture efficiency, and time spent in the kitchen and other rooms. We also updated previously published (*10*) NO_2 emission rates from gas stoves with field measurements of 50 additional homes (over 70 total homes when including measurements of propane and electric stoves), bedroom NO_2 concentrations in six houses for 8 hours during and following stove use, and NO_2 emission rates from propane stoves. We validated the CONTAM model by comparing our modeled and measured NO_2 concentrations in a set of 18 test houses of various sizes and floorplans, in each case directly measuring NO_2 concentrations in multiple rooms before, during, and––for several hours, at least––after gas and propane stove use ended.

Using the validated CONTAM model, we estimated long- and short-term NO_2 exposure attributable to combustion by gas and propane stoves for the U.S. population overall and in subpopulations, including various income levels and racial/ethnic groups (see Materials and Methods). We then used well-established epidemiological relationships (*26*, *38*) for NO_2 exposure to estimate the excess cases of pediatric asthma and adult mortality attributable to long-term NO_2 exposure from gas and propane stoves. We compare our results against estimates of pediatric asthma burden attributable to gas stoves overall (*16*).

RESULTS

Agreement between the CONTAM model and measured NO_2 concentrations

We assessed the performance of our indoor air model by comparing its outputs against NO_2 measurements in 18 test residences before, during, and after gas stove use. These residences ranged in size from 280 to 1650 ft^2 (25 to 150 m^2). They included both apartments and single- and multistory detached homes in the following locations: San Francisco Bay Area, CA; Los Angeles, CA; Bakersfield, CA; Denver, CO; Houston, TX; New York City, NY; and Washington, DC. We included scenarios with windows open and closed and with an outside-venting range hood both on and off. We observed close agreement between modeled and actual NO_2 concentrations ($r^2 = 0.64$, slope = 0.89, SE of slope = 0.11, $P \ll 0.01$; see Fig. 1 for plots of the largest and smallest test residences; see fig. S1A for a regression of modeled versus actual concentrations and fig. S1B for boxplots summarizing all measured residences). The model results showed no evidence of systematic bias relative to measurements as assessed statistically (fig. S1 and table S1). Without an outside-venting range hood on and with either one burner or one burner and one oven on, concentrations in over half of the kitchens, living rooms, and bedrooms tested exceeded the Environmental Protection Agency's (EPA's) 1-hour ambient exposure benchmark of 100 parts per billion volume (ppbv) (*39*) and the World Health Organization's (WHO's) 1-hour (i.e., short-term) exposure guideline of 200 μg/m^3 (~100 ppbv) (*40*). Surveys show that range hoods are used only 15 to 39% of the time (*41*, *42*).

Nitrogen dioxide emission factors from propane stoves and updated emission factors for gas stoves

Nitrogen dioxide emissions occurred only with fossil fuel use and scaled linearly with the amount of fuel burned, as assessed by CO_2 emissions, across 10 propane and 50 natural gas stoves (Fig. 2 and fig. S3A; $r^2 = 0.61$ for gas and 0.70 for propane; $P \ll 0.01$ for each). In contrast to the results for fossil fuel combustion, all 7 induction and 12 electric coil and radiant stoves that we measured had zero NO_2 emissions (i.e., emissions were statistically indistinguishable from zero; see Fig. 2 and table S3).

NO_2 emissions from propane and gas combustion were statistically identical when normalized per joule of fuel burned (table S2). Because NO_2 forms in flames as a function of temperature (*43*) and the adiabatic flame temperatures of methane and propane differ by less than 1% (*44*), it is unsurprising that gas and propane burners emitted the same amount of NO_2 per joule of fuel burned.

Estimates of NO_2 emission factors calculated from the 50 gas stoves measured newly in this work were statistically identical to the emission factors measured previously for 32 gas stoves by Lebel *et al.* (*10*). Combining data from this work with the data from Lebel *et al.*, we calculated median NO_2 emission factors for gas stoves to be 8.7 [95% confidence interval (CI): 8.2, 9.3] ng J^{-1} for gas burners on high and 8.2 [95% CI: 7.5, 9.2] ng J^{-1} for burners on low. See fig. S3B and table S3 for emission rates and emission factors per joule for all burner and oven types measured. We used results from the pooled set of 82 burners in our modeling.

NO_2 concentrations in bedrooms and with range hoods on

Bedroom NO_2 concentrations tested during oven use, with interior doors open and the range hood off exceeded the U.S. EPA's 1-hour ambient benchmark (*39*) and the WHO's 1-hour exposure guideline (*40*) within 25 min in half the homes we tested (three of six homes). In two test cases, bedroom NO_2 levels remained above health-based guidelines for 2 to 3 hours after the oven was turned off (houses 1 and 2; Fig. 3A). We found that an outside-venting range hood reduced peak NO_2 concentrations in some cases (Fig. 3B) but that some outside-venting range hoods are ineffective at reducing NO_2 concentrations (Fig. 3C). Across a subset of five randomly selected homes, we found that outside-venting hoods reduced hour-averaged kitchen NO_2 concentrations by between 10 and 70% (mean reduction in concentration = 35%, $n = 5$; fig. S15). This result is consistent with prior work assessing the efficacy of installed range hoods, which found that most hoods operating in homes have capture efficiencies well below 70% (*45*, *46*). Our measurements both with and without hoods on further support our model's finding that gas and propane stove use increases long- and short-term NO_2 exposures (see below).

Modeled long- and short-term NO_2 exposure

We estimated long- and short-term NO_2 exposure attributable to gas and propane stoves by combining our measured NO_2 emissions data with published housing characteristics and with published statistical distributions of resident use patterns. These variables included how much time a person spent cooking, how much gas was burned (i.e., how many burners/ovens were used plus cooking duration), time spent with windows open, percentage of cooking time with the range hood on, and capture efficiency of the range hood used—all applied in a multizone indoor air quality model (see Materials and Methods). We calculated CIs using a Monte Carlo method (see Materials and Methods). See the "Definitions" section for more details on how we calculated long-term (year-averaged) and short-term (hour-averaged) exposures.

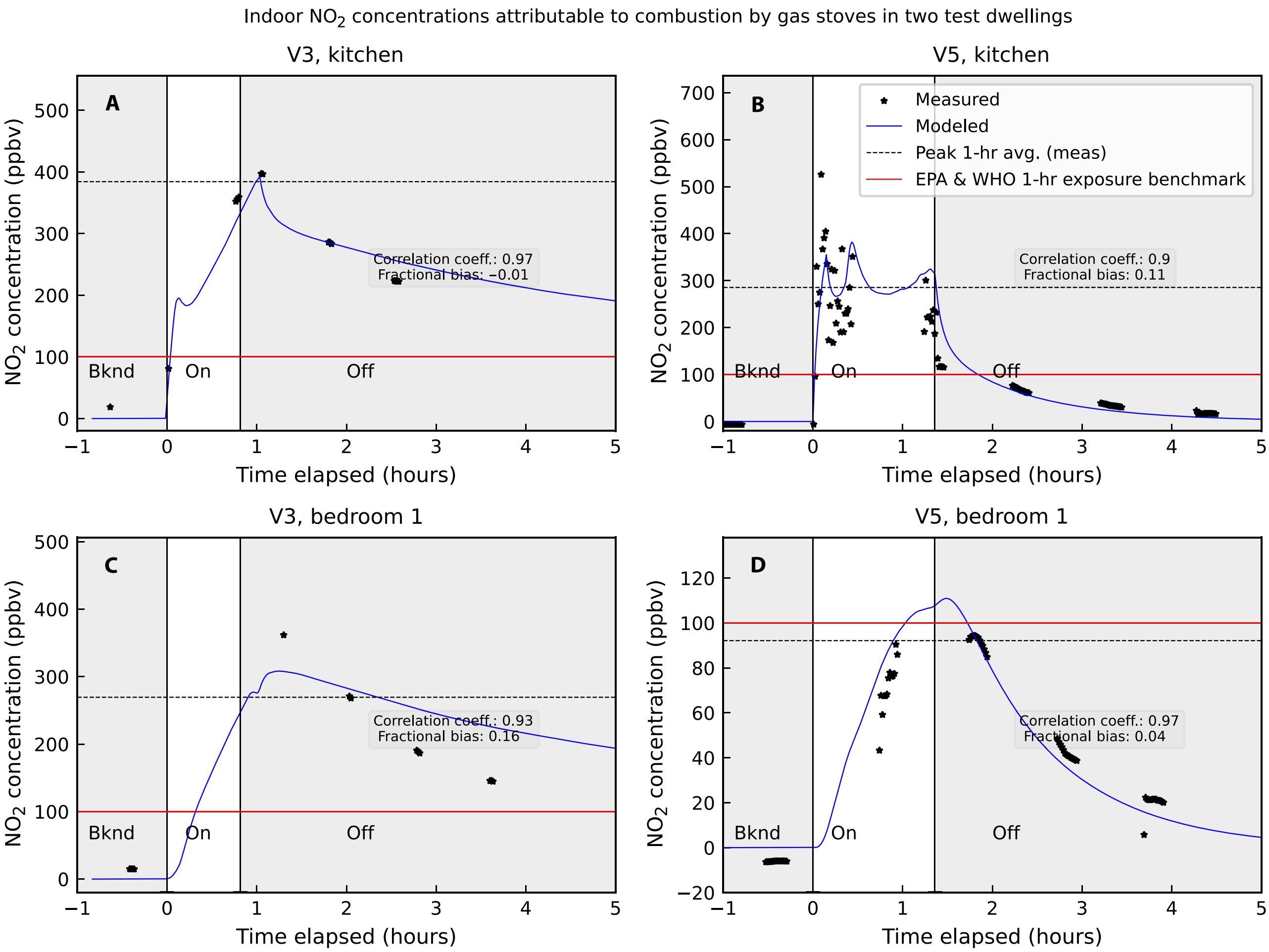

Fig. 1. Measured and modeled NO_2 concentrations in two test residences. ("V3" on the left and "V5" on the right). NO_2 concentrations measured (black points) and modeled (blue lines) in the (**A**) kitchen and (**C**) bedroom (farthest from the kitchen) of a 900-ft^2 (85-m^2) house, "V3," and in the (**B**) kitchen and (**D**) bedroom of a 1500-ft^2 (140-m^2) house, "V5" (see table S2 for metrics for each house). "Background" ("Bknd") represents NO_2 concentrations in a given room before lighting the stove, "On" represents concentrations with one stove burner on high and the oven set to 350°F (175°C), and "Off" represents concentrations after turning off the stove burner and oven. "Time elapsed" represents hours since lighting the burner and oven. The white background demarcates the interval in which the burner and oven were in use. The horizontal black line represents the highest concentrations measured in each room, time-averaged over 1 hour. The solid horizontal red line represents the U.S. Environmental Protection Agency's (EPA's) 1-hour ambient exposure benchmark of 100 ppbv (*39*) and the World Health Organization's (WHO's) 1-hour exposure guideline of 200 μg/m^3 (~100 ppbv) (*40*). A range hood was not used in the tests shown here, though we tested the CONTAM model with a range hood on and window open. See fig. S2 for analogous plots and fig. S1 for summary plots of all tests including tests with range hoods on and windows open. The correlation coefficients (*r*) and fractional biases of the modeled concentrations are reported for each room and for all rooms together (see table S1).

Based on our results, gas and propane stoves in the United States elevate long- and short-term NO_2 exposure substantially. We estimate that U.S. median gas and propane stove use increases long-term NO_2 exposure by 4.0 [95% CI: 2.4, 6.1] ppbv. Maximum daily hour-averaged exposure to NO_2 from median gas and propane stove use in the United States exceeds 200 μg/m^3 (~100 ppbv), the WHO's 1-hour indoor exposure guideline (*40*), on 12 [95% CI: 4, 24] days of the year (3.3% of days), averaged across the population. Home cooks who are in the 95th percentile of stove use encounter ~110 days per year exceeding 200 μg/m^2 (see below).

These long- and short-term stove-attributable exposures are large relative to common health benchmarks. For instance, the 4.0 ppbv of stove-attributable long-term exposure comprises 75% of the WHO's annual NO_2 exposure guideline (*47*) (Fig. 4) and 50% of the U.S.-averaged outdoor NO_2 concentration (*48*) in 2021. In addition to exceeding the WHO 1-hour exposure guideline, stove-attributable exposures would also exceed the U.S. EPA's outdoor standard of no more than 2% of days with maximum NO_2 concentrations exceeding 100 ppbv (*39*) if this standard were applied indoors (fig. S5). Although the U.S. EPA does not currently regulate indoor air pollution (*39*), Canada does—its hour-averaged indoor NO_2 standard is 170 μg/m^3 [~90-ppbv NO_2], slightly lower than the WHO standard (*40*, *49*).

Long- and short-term exposure burdens from combustion by gas and propane stoves are unequally distributed across the U.S. population. Gas and propane stoves increase the long-term

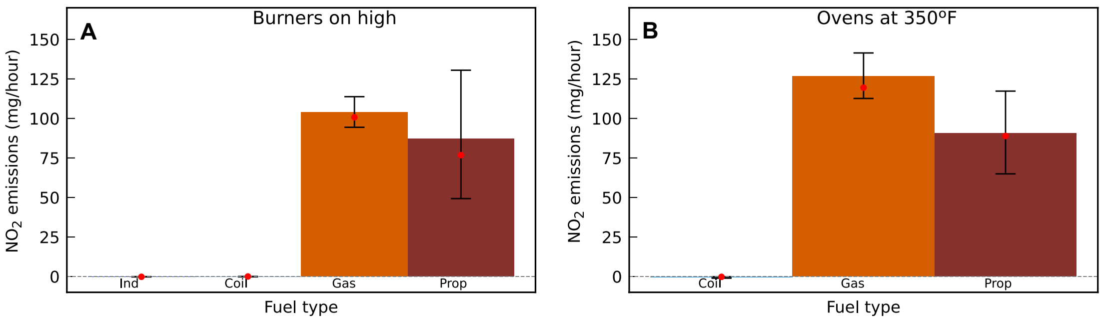

Fig. 2. Mean and median NO_2 emissions by fuel type. Emissions reported in milligrams of NO_2 per hour by fuel type (electric induction, electric coil/radiant, gas, and propane) for burners on high (**A**) and for ovens set to 350°F (175°C) (**B**). The red points are median values, the bar heights are mean values, and the black error bars are the 95% CIs of the mean (calculated using a bootstrap method as described in the methods).

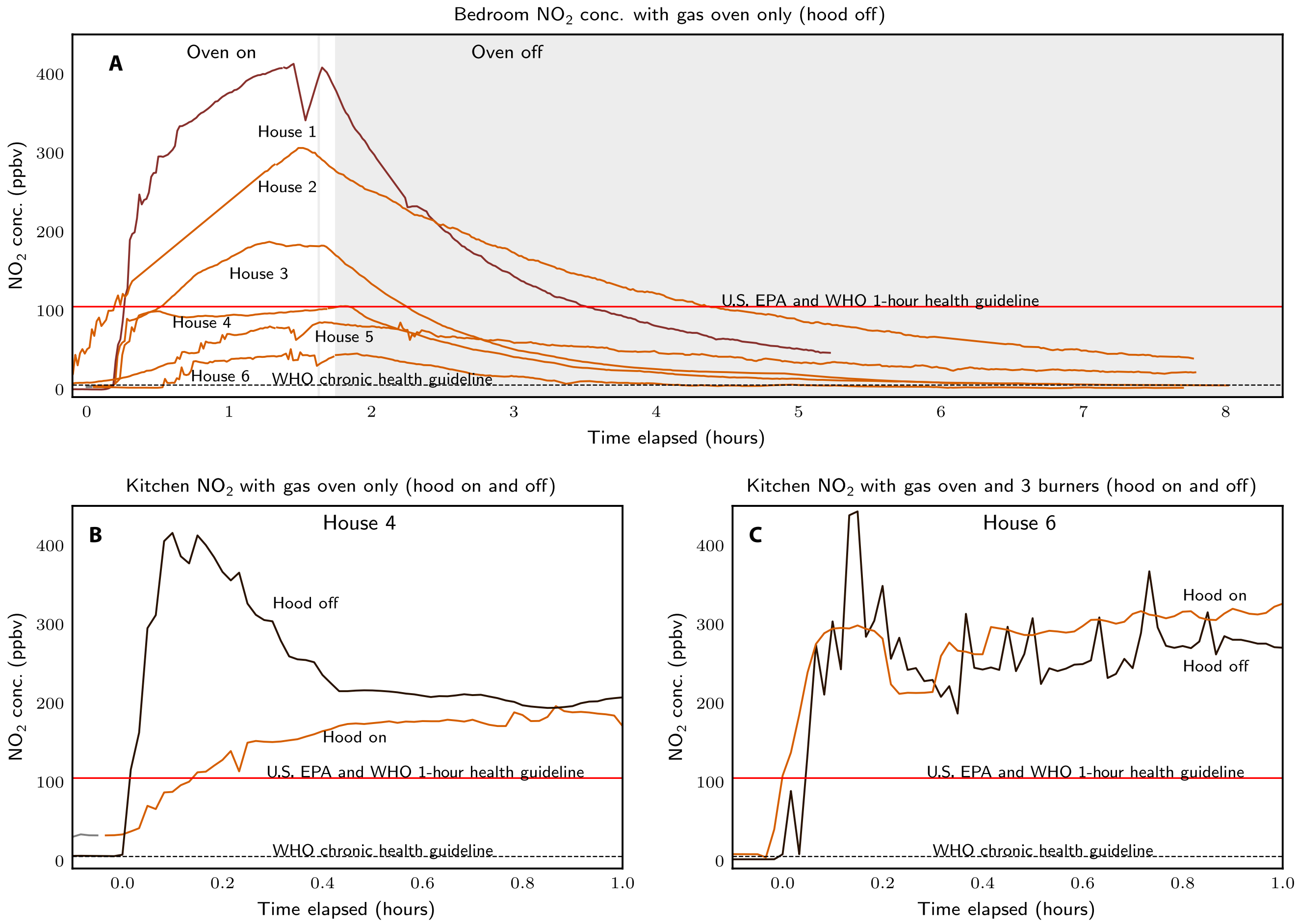

Fig. 3. Timecourses of NO_2 concentrations in bedrooms during and after oven use. (**A**) NO_2 concentrations (parts per billion volume) measured in bedrooms furthest from kitchens with the oven set to 475°F (245°C) for 1.5 hours and then turned off for 3.5 to 6.5 hours to mimic a common "bread-baking" scenario. Air-sampling hoses in houses 2, 3, 4, 5, and 6 were placed in the farthest bedrooms ~8 m down the hall from the kitchen; the sampling hose in house 1 was also in the farthest bedroom, but it was only ~4 m from the kitchen. (**B**) NO_2 concentrations measured in the kitchen of house 4 with the oven set to 475°F for 1 hour with the house's outside-venting hood off (dark brown) and on (orange), and (**C**) NO_2 concentrations measured in the kitchen of house 6 with three burners on high and the oven set to 350°F (175°C), corresponding with a higher-use scenario in the RECS database, for 1 hour with the house's outside-venting hood on (orange) and, for comparison, off (dark brown). The red horizontal line represents the U.S. EPA's 1-hour ambient concentration benchmark of 100 ppbv (*39*) and the WHO's 1-hour exposure guideline of 200 μg/m^3 (~100 ppbv) (*40*); the horizontal dashed line near the bottom of the plot represents the WHO's long-term exposure guideline of 10 μg/m^3 (*60*).

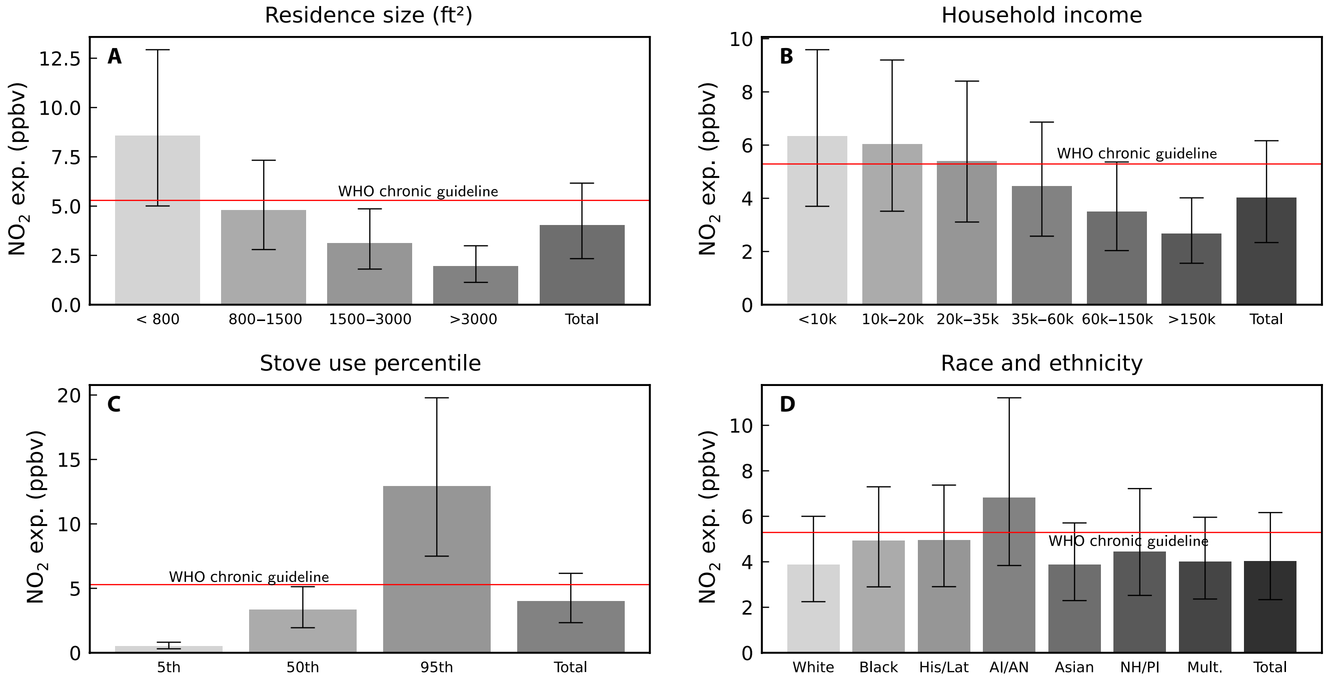

Fig. 4. Additional long-term NO_2 exposure attributable to combustion by gas and propane stoves in the United States. NO_2 exposure stratified by: (**A**) Home size (ft^2). 800 ft^2, 75 m^2; 800–1500 ft^2, 75–140 m^2; 1500–3000 ft^2, 140–280 m^2; >3000 ft^2, >280 m^2. (**B**) RECS respondent household income (US$ per year; k, $1000). (**C**) Amount of gas or propane stove use as a percentile in the population as measured by burner minutes and oven minutes (proportional to total enthalpy of gas or propane burned; see Materials and Methods). (**D**) Race/ethnicity self-reported to RECS. The racial and ethnic categories identified by RECS include (*1*): His/Lat, Hispanic or Latino; AI/AN, American Indian or Alaska Native; NH/PI, Native Hawaiian or Pacific Islander; Mult., multiracial. In each panel, "Total" refers to the average across the U.S. population. The red horizontal line in each plot is the WHO's annual NO_2 guideline (*47*). Error bars represent 95% CIs calculated using a Monte Carlo method (see Materials and Methods).

NO_2 burden of people living in residences <800 ft^2 (75 m^2) in size by 8.6 [95% CI: 5.1, 13] ppbv, more than four times the exposure of people living in residences >3000 ft^2 (280 m^2) in size (2.0 [95% CI: 1.2, 3.0] ppbv; Fig. 4A). Short-term exposures are also substantially higher for people living in smaller residences; people living in residences <800 ft^2 experience more than nine times as many days with 100-ppbv exceedances as people living in residences >3000 ft^2 in size (fig. S5A).

The relationship between increased exposure and smaller residence size also drives disparities in exposure burden borne by different U.S. subpopulations. For instance, people in households making <$10,000 per year, as recorded by the Residential Energy Consumption Survey (RECS) (*1*), are exposed to 6.3 [95% CI: 3.7, 9.5]–ppbv long-term NO_2 from gas and propane stoves. This additional exposure is more than twice that of people in households making >$150,000 per year (Fig. 4B). Short-term exposures follow the same pattern of increased risk for poorer residents; people in households making <$10,000 per year are exposed to three times as many days with 100-ppbv exceedances as people in households making >$150,000 per year (fig. S5B).

Racial and ethnic disparities arise in exposures attributable to gas and propane combustion from stoves, as well. Using RECS' racial/ethnic categories, we found that people in households with American Indian/Alaska Native respondents experience the highest stove-attributable long-term NO_2 exposure (6.8 [95% CI: 4.0, 10.0] ppbv), followed by Hispanic/Latino and Black households (5.0 [95% CI: 2.9, 7.3] and 4.9 [95% CI: 2.9, 7.2] ppbv, respectively). These exposure levels represent 60, 20, and 20% more than the average U.S. stove-attributable exposure, respectively, and, for all three groups, exceed WHO's total annual exposure benchmark just from using a gas stove—before including any contribution from outdoor air pollution (*47*). Households with white (3.9 [95% CI: 2.3, 5.9] ppbv) and Asian (3.9 [95% CI: 2.3, 5.7] ppbv) respondents experienced the lowest stove-attributable long-term NO_2 exposures of all racial/ethnic groups identified in the RECS database (Fig. 4C; $P < 0.01$ for pairwise group comparison of white and Asian exposures versus Black, Hispanic/Latino, and American Indian/Alaska Native exposures). Short-term exposures follow the same outcomes as long-term exposures; people in households with Hispanic/Latino, Black, and American Indian/Alaska Native respondents experience between 40 and 100% more days with 100-ppbv exceedances than the national average (fig. S5C). The racial and ethnic disparities we observed are primarily influenced by differences in average residence sizes: 29, 23, and 23% of American Indian/Alaska Native, Hispanic/Latino, and Black respondents, respectively, live in residences <800 ft^2 in size, whereas only 12 and 20% of white and Asian respondents do, respectively (*1*).

Both long- and short-term NO_2 stove-attributable exposures are strongly affected by behavioral factors, including the duration and intensity of stove use (i.e., how much gas is burned), range hood use and window opening, and time spent in the kitchen. The dominant factor predicting NO_2 exposure in our analysis was the total amount of gas or propane burned. People in residences in the 95th percentile of duration of burner and oven use (corresponding with two burners on medium for 30 min daily in the morning, and four on medium for 30 min and the oven set to 350°F (175°C) for roughly 2.25 hours in the evening) (*41*) were exposed to 3 times more than the average long-term stove-attributable NO_2 and 25 times more than people in households in the 5th percentile of burner and oven use (i.e., one burner on medium for 5 min daily in the morning and two on for 5 min in the evening with no oven used; Fig. 4D). Short-term exposures follow the same trend: People in houses in the 95th percentile of duration of burner and oven use experience 110 [95% CI: 50, 170] days per year with a 100-ppbv exceedance while people in the 5th percentile typically experience zero (fig. S5D). See data S1 for numerical values and Materials and Methods for a more detailed description of the distribution of burner and oven use.

Model sensitivity

We assessed the sensitivity of the CONTAM model combined with our exposure calculations by altering parameters systematically and estimating the effects of parameter changes on long- and short-term NO_2 exposure risk. We varied the levels of each input parameter from the 5th to 95th percentiles (or minimum to maximum values, if distribution statistics were unavailable), holding all other parameters constant at their default values (see table S7). Our analysis showed that long-term NO_2 exposure was most sensitive to duration and intensity of gas stove use (as measured by total burner minutes and oven minutes, which are proportional to enthalpy of gas or propane burned; see Materials and Methods).

The next-most important behavioral factors in determining exposure (after the amount of fuel burned) were mechanical and natural ventilation and time spent in the kitchen. People who lack an outside-venting hood or who do not use their hoods are exposed to 25% more long-term stove-attributable NO_2 than average. Meanwhile, people with a 75% capture efficiency outside-venting hood who use it every time they cook are exposed to 70% less long-term stove-attributable NO_2 than average. The effect on long-term stove-attributable NO_2 of opening and closing windows (one window modeled in the kitchen and at least three additional windows, opened or closed all at once; see Materials and Methods) was comparable to the average benefit of using a range hood (Fig. 5).

However, opening a window was far less helpful in reducing short-term exposures, measured by days per year with a 1-hour averaged NO_2 exposure >100 ppbv. Whereas people who leave their windows closed are exposed to nine times more long-term NO_2 than people who leave their windows open, people who leave their windows closed are exposed to only 1.5 times more days per year with a 100-ppbv exceedance (compare the relative sizes of the burnt orange bars in Fig. 5, A and B).

Prevalence and economic burden of stove-attributable adverse health outcomes

Combining data from the 2020 RECS (*1*) with the 2024 meta-analysis of Puzzolo *et al.* (*26*) of the association between pediatric asthma and gas stoves, we estimate that gas and propane stoves in the United States are responsible for 200 [95% CI: −20, 410] thousand current cases of pediatric asthma. Our central estimate represents roughly 10% the number of pediatric asthma cases attributable to pollution from all road traffic (*50*). Following the calculation of Nurmagambetov *et al.* (*51*), applying the EPA's value of a statistical life (VSL) to asthma-induced deaths and combining this cost with asthma-related medical costs yields an annual societal cost of gas and propane stoves of \$1 (0, 2) billion. Our estimate of pediatric asthma population-attributable fraction (PAF) (see Table 1) is smaller than but statistically indistinguishable from that reported by Gruenwald *et al.* (*24*), who relied on an older meta-analysis (*16*).

Our estimate of long-term NO_2 exposure attributable to gas stoves allows us to address what portion of pediatric asthma attributed to gas stoves overall may be due specifically to long-term NO_2 exposure. Our central estimate for pediatric asthma attributable to long-term NO_2 exposure from stoves (Table 1) is ~25% of the estimate for stoves overall. This discrepancy may be due to several potential factors. These may include (i) that the majority of stove-attributable pediatric

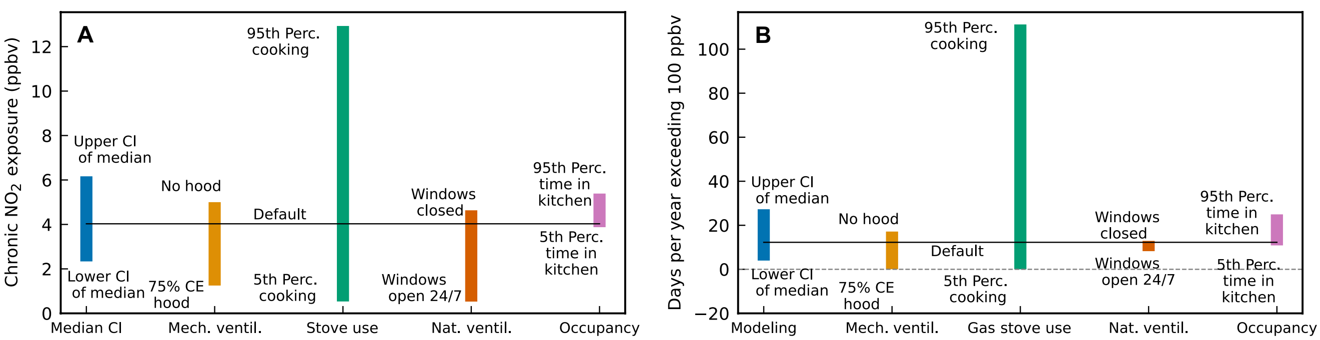

Fig. 5. Sensitivity analysis of exposure estimates. Modeled increase in (**A**) long-term NO_2 exposure (parts per billion volume) and (**B**) days with 1-hour 100-ppbv exceedances attributable to gas and propane stoves at median values of model input parameters and at high and low ends of the observed distributions. The black horizontal line in each panel indicates the modeled exposure (A) and exceedances (B) assuming default input values of all parameters (see table S7). The blue vertical range at the left of each panel spans the 90% CI of the median (from 5th to 95th percentiles; see Materials and Methods). Light orange ranges span central estimates of exposure corresponding with maximum and minimum reasonable use cases for mechanical ventilation (based on surveys and direct measurements; see Materials and Methods). Green ranges span central estimates of exposure corresponding with values modeled between the 5th and 95th percentiles of joules of gas or propane burned. Burnt orange ranges span central estimates of exposures corresponding with the maximum and minimum reasonable use cases for window opening (based on surveys, see Materials and Methods). Lilac ranges to the right span values modeled for 5th to 95th percentiles of kitchen occupancy. "CI" and "CE" stand for confidence interval and capture efficiency, respectively.

Table 1. Pediatric asthma outcomes attributable to long-term exposure to NO_2 pollution from gas and propane stoves. Modeled population attributable fraction (PAF) and annual burden attributable to the presence of gas and propane stoves (i.e., as a function of having a gas stove independent of any exposure estimate) and to long-term NO_2 exposure from gas and propane stoves in the United States. The right-most column reports the odds ratio (OR) used to calculate the asthma burden attributable to gas stoves overall (*26*) and the relative risk (RR) per 15-ppb increase in annual indoor NO_2 exposure used to calculate the asthma burden attributable to NO_2 exposure (*16*). Parenthetical numbers indicate 95% CIs calculated using a Monte Carlo method (see Materials and Methods) or, for OR and RRs, come from values reported in the literature (*16*, *26*). See data S2 and S3 and fig. S6 for a breakdown by individual U.S. states and for gas and propane stove prevalence by state (*1*).

Attribution	Pediatric asthma PAF	Modeled current pediatric asthma burden (thousand cases)	Pediatric asthma OR or RR
Presence or absence of gas stove	3.8 [0.0, 8.0] %	180 [−20, 380]	1.09 [0.99, 1.19] (OR)
Presence or absence of propane stove	0.36 [0.00, 0.75] %	17 [−2, 36]	1.09 [0.99, 1.19] (OR)
Long-term NO_2 from gas stoves	0.91 [−1.33, 3.0] %	43 [−63, 142]	1.09 [0.91, 1.31] (RR per 15 ppb)
Long-term NO_2 from propane stoves	0.09 [−0.13, 0.0.29] %	4 [−6, 14]	1.09 [0.91, 1.31] (RR per 15 ppb)

asthma cases are due to additional factors such as short-term NO_2 exposure and other gas stove pollutants; (ii) that estimates of pediatric asthma attributable to stoves do not fully account for confounding variables and could be too high; and (iii) that our model underestimated the true long-term NO_2 exposure attributable to gas and propane stoves (see limitations discussed in our conclusion and in our methods).

Exposure to NO_2 outdoors has been associated with statistically significant increases in all-cause adult mortality, though quantifying its direct effect is challenging because of potential confounding with exposure to co-occurring outdoor pollutants such as particulate matter in automobile exhaust and other combustion sources (*38*, *52*, *53*). Assuming that meta-analyses of outdoor NO_2 and all-cause adult mortality may be applied to long-term exposure to indoor NO_2, our analysis suggests that long-term NO_2 exposure from gas and propane stoves in the United States may be responsible for up to 19,000 [95% CI: 8500, 34,000] deaths annually—0.67 (0.29, 1.2)% of total U.S. adult deaths—or roughly 40% the number of deaths attributable to secondhand smoke (*54*). Applying the U.S. EPA's VSL (*55*) to each death yields an annual societal cost of gas and propane stoves of \$250 (75, 480) billion (data S2), or approximately \$4500 per year per U.S. household with a gas or propane stove, based on 2020 RECS data (*1*). These estimates likely overestimate the health and cost burdens attributable to NO_2 because of additional pollutants found in traffic-related air pollution. However, they also underestimate health and cost burdens because our estimates account for only long-term NO_2 exposures and not short-term exposures to high concentrations, which routinely exceeded 100 ppbv in our measurements (see Figs. 1 and 3). Better disambiguation between the effects of NO_2 and $PM_{2.5}$ as well as more studies on short-term NO_2 effects are needed to constrain NO_2 mortality estimates.

DISCUSSION

Gas stoves are common globally and in U.S. homes. Emissions from gas and propane stove combustion degrade indoor air quality (*3*, *10*, *40*, *56*, *57*) and are associated with adverse health outcomes that include pediatric asthma and hospitalizations (*23*–*25*, *52*, *58*, *59*). We report updated field estimates of NO_2 emission rates for gas stoves and previously unreported emission rates of NO_2 from propane stoves. We combined our emissions measurements with the NIST's CONTAM indoor air model and other published datasets; in doing so, we produced a population-level estimate of the distribution of NO_2 exposure and health outcomes attributable to gas and propane stoves as a function of specific behaviors and for different income and race and ethnicity groups (see Materials and Methods).

Consistent with previous research (*10*, *24*, *25*), we find that combustion from gas and propane stoves represents a major source of long- and short-term NO_2 exposure that can exceed U.S. and WHO guidelines just by using a stove, independent of any outdoor NO_2 exposures. Demographic detail provided by the RECS (*1*) and the precision afforded by the multizone CONTAM model (*37*) allowed us to extend previous research to the entire United States and to exposures in specific rooms, estimating both short- and long-term exposure as a function of behavioral and demographic variables such as gas and propane stove use, time spent in the kitchen and other rooms, and the income and race of occupants. Our findings also quantified the importance of gas and propane stove use (i.e., joules burned) compared with ventilation and occupancy in determining indoor NO_2 exposure. We also found that housing size greatly influences exposure. Differences in housing size partly drive income-based and racial disparities in stove-attributable NO_2 exposure, though there are other potentially relevant factors not captured by our model, such as social differences in cooking and ventilation behavior and differences in the time spent indoors and outdoors.

Our estimated health consequences of gas and propane stove use are large. We found that gas and propane stoves may contribute up to 19,000 adult deaths annually in the United States. We also estimated that long-term NO_2 exposure from gas and propane stoves is responsible for approximately 50,000 current cases of pediatric asthma. In addition, the total number of current pediatric asthma cases attributable to pollution from gas and propane stoves is likely closer to 200,000. That number of cases is approximately 10% of pediatric asthma attributable to pollution from road traffic and corresponds with a societal cost of roughly \$1 billion annually.

Additional research could enhance future estimates of adverse health outcomes associated with gas and propane stoves. First, we assessed only one pollutant, NO_2, in this exposure assessment. Because gas stoves also emit carbon monoxide (CO), benzene, formaldehyde, and ultrafine particles (*7*, *9*–*11*), which are linked to adverse health outcomes beyond asthma (*40*), our estimates of disease burden and societal cost almost certainly underestimate the full health consequences of combustion from gas and propane stoves. Second, the granularity of our modeling was limited by the availability of data on burner and range hood use for different geographies and demographic groups. Gathering and incorporating these data into an exposure model may produce a more precise estimate of socioeconomic and racial disparities in gas stove-attributable NO_2 exposure. Third, our study's quantification of all-cause mortality was limited by potential confounding of NO_2 with other coproduced pollutants outdoors. Future work focusing on the effect of indoor NO_2 on mortality, COPD, or other adverse health outcomes would enable modeling of the stove-attributable component of these diseases. Fourth, our study did not estimate the health effects of our measured short-term exposure to high NO_2 concentrations. High-quality epidemiological studies assessing the health effects of short-term NO_2 exposure would allow the results of this study and future work to be used to model adverse health outcomes associated with short-term stove-attributable NO_2. Fifth, our study relied on data for the United States only; incorporating behavioral and housing stock data from outside the United States would expand the scope of exposure estimates to other countries and continents. To address this shortcoming, we are undertaking indoor pollution measurements associated with gas stoves in countries that include Australia, the United Kingdom, the Netherlands, Italy, and China.

Although successful policies have reduced sources of air pollutants such as NO_2 in the United States (*48*), indoor air quality remains largely unmeasured and unregulated (*39*). Our research shows that pollution from gas and propane stoves disproportionately affects lower-income people and racial and ethnic minorities and that gas and propane stoves are responsible for substantial pediatric asthma and adult mortality. Our results also highlight the importance of including indoor sources of air pollution in future policies designed to protect people from pollutants such as NO_2, benzene, and carbon monoxide.

MATERIALS AND METHODS

Definitions

We defined a "cooktop" as a flat surface with two to six individual cooking elements and "burners" as cooking elements using a gas or propane flame. We defined gas, propane, and electric ovens as enclosed spaces heated by gas, propane, or electricity, respectively. We defined a "stove" (also called a "range") as a freestanding unit that contains both a cooktop and an oven. We defined an "outside-venting range hood" as an exhaust fan located directly above a stove, cooktop, or oven that sends kitchen air outdoors. We defined a "recirculating range hood" as a range hood that returns exhaust air to the kitchen rather than venting it outside.

Throughout the paper we used the term "concentration" for its accessibility in place of the more strictly correct term "molar mixing ratios." We assumed a temperature of 25°C and a pressure of 1 atm when converting between true concentrations and molar mixing ratios, which yields the conversion 1-ppbv $NO_2 = 1.89\ \mu g\ m^{-3}\ NO_2$. We also used a conversion of 1-ppbv $NO_2 = 1.89\ \mu g\ m^{-3}$ to convert relative risks (RR) reported in units of micrograms per cubic meter to units of parts per billion volume.

We used CONTAM, a multizone indoor air model developed by the NIST, to model indoor NO_2 concentrations (*37*). We validated the model by comparing its predictions against measured NO_2 concentrations in a set of 18 test residences referred to as "validation residences" or "validation homes." We then used the validated model to estimate NO_2 concentrations in a set of other residence footprints (detached houses, duplexes and multiplexes, mobile homes, and apartments) for which we lacked measured NO_2 data. We refer to these as the "model residences" or "model homes."

We define "long-term" exposures in terms of parts per billion volume of NO_2 exposure averaged over a year and "short-term" exposures in terms of the number of days per year on which daily maximum hour-averaged NO_2 exposure exceeds 200 μg/m^3 (~100 ppbv), the WHO hour-averaged NO_2 standard (*60*).

We used commonly accepted definitions of epidemiological terms: (*38*, *61*) "population attributable fraction" (PAF) is the fraction of cases of a health outcome in a population attributable to an exposure; "odds ratio" (OR) is the ratio of the odds that a health outcome will occur given an exposure to the odds that the same health outcome will occur without the exposure; "relative risk" (RR) is the ratio of the probability of a health outcome in the exposed population divided by the probability in the unexposed population; "incidence" is the number of new cases of a disease per time interval (1 year, unless stated otherwise); "prevalence" is the total number of active cases of the disease in the population at a given time; and "burden" is the number of health outcomes (either at a given time or per unit time) attributable to an exposure.

Instrumentation

We measured NO_2 concentrations using a Teledyne T200P analyzer. We measured CO_2 and N_2O concentrations using an Aeris carbon dioxide/nitrous oxide MIRA Ultra Mobile LDS analyzer and measured CH_4 and C_2H_6 using an Aeris methane/ethane MIRA Ultra Mobile LDS analyzer. The calibrations of the analyzers were checked weekly and whenever transported.

Site selection

We measured NO_2 emission rates from 50 gas, 11 propane, and 14 electric stoves in 20 counties in California, Colorado, Texas, New York, and Washington, D.C. between January 2022 and July 2023 (fig. S7). Our measurements included 24 gas, 9 propane, and 14 electric stoves for which we previously reported benzene emission factors (*11*) (see table S4 for a summary of the characteristics of stoves we sampled and table S3 for a comparison against other published emission rates). Our set of sample residences also included a range of kitchen sizes (15 to 150 m^3) in private houses, apartments, and several Airbnb rentals, where we could measure longer uninterrupted time courses. We selected residences through online participant sign-up pages and neighborhood and community associations. We performed CONTAM validations tests (see below) on an 18-home subset of our sample, whose open floor area (excluding closed-off rooms and garages) varied in size from 250 to 1650 ft^2 and included 10 detached houses and eight apartments in three U.S. states (table S3).

Emission rate calculations and statistics

We calculated NO_2 and CO_2 emission rates from gas and propane combustion by measuring the increase in NO_2 concentration through time in sealed kitchens of known volumes, an approach analogous to that used in our previous work to measure NO_x, methane, and benzene emission factors from stoves (*10*, *11*). We converted measured concentrations into emission rates using Eq. 1

$$f = \frac{V_k}{t - t_0}(C_t - C_o + \Sigma_{i=1}^{n}(C_{t_i} - C_{bkg})(e^{-\lambda(t_i - t_{(i-1)})} - 1) \quad (1)$$

where t_i is the timestamp of the ith datapoint, t_0 is the initial time, f is the mean gas emission rate over the course of a measurement (in volume per time), V_k is the kitchen volume, λ is the kitchen chamber's air exchange constant (in reciprocal time), n is the number of gas concentration datapoints (typically 12) collected in a given measurement period, C_{ti} is the gas concentration at time t_i (in parts per billion volume), and C_0 is the concentration inside the chamber at the start of the measurement, and C_{bkg} is the background gas concentration outside the kitchen chamber (see the "Correction for air exchange" section, below). We assume that C_b is equal to the gas concentration we measure inside the kitchen immediately after airing it out with fresh outdoor air. We converted volumetric emission rates into gravimetric emission rates using the temperature measured in the kitchen.

We measured the energy output from gas burners and ovens using the flow rate of CO_2 and the enthalpy of combustion of methane to calculate the joules (J) of energy emitted per unit time.

We calculated the kitchen volume (V_k) and air exchange constant (λ) using 300- to 500-ml injections of a known volume of either ethane (C_2H_6) or nitrous oxide (N_2O) as a dilution tracer, using fans to mix the kitchen air, a method validated by Lebel *et al.* (the slope of laser-measured versus tracer gas–measured room volume is 1.1 [95% CI: 0.9, 1.3]; adjusted $r^2 = 0.91$) (*10*). The estimated kitchen volume is the injected tracer gas volume divided by the peak tracer gas concentration immediately following injection, and the air exchange constant is the tracer gas's decay constant through time after the peak concentration (see the "Correction for air exchange" section, below).

We calculated mean and median 95% CIs of emission rates from a 25,000 replicate bootstrap sample set (*62*, *63*) using a method described by Lebel *et al.* and by Kashtan *et al.* (*10*, *11*): We generated each replicate sample in the bootstrap by randomly sampling with replacement the set of emission factors in question to form a random sample of equal size to the set of emission factors in question. For instance, the bootstrap gas burners on high consisted of 25,000 replicates of size 50, generated by randomly sampling (with replacement) the set of 50 emission rates for gas burners on high. We then calculated 95% CIs for the means and medians of these bootstraps (*62*, *63*). We calculated statistical significance between gas and propane stove emissions using the two-sided Mann-Whitney *U* test (also known as the Wilcoxon rank sum test).

Our method for measuring NO_2 emission factors was the same as that used in Kashtan *et al.* to measure benzene, and similar to that used by Lebel *et al.*, to measure methane and NO_2. We sampled kitchen air approximately 1.5 m off the ground using a 7 liter min^{-1} pump drawing air through a polytetrafluoroethylene (PTFE) hose attached to our analyzers outside the sampling area. Where necessary to estimate emissions factors (but never when measuring concentrations), we created enclosed kitchen partitions by closing the kitchen's doors and windows, closing off open spaces with plastic, and placing fans in each kitchen to mix the air (being careful not to disturb the flame). We measured NO_2 concentration in the closed chamber for at least 15 min before igniting the stove to verify that no other sources or sinks were present (see fig. S8A).

The 5- to 8-hour time course NO_2 concentrations reported in the "NO_2 concentrations in bedrooms and with range hoods on" section were measured using no plastic partitions anywhere and with all interior doors open in six different houses. To avoid mixing the air, we did not use fans or other means of active air circulation during these concentration-based time courses. In all six houses for which we did the 8-hour time courses, we set the oven to 475°F (245°C), a temperature commonly used to bake bread, for 1.5 hours with the hood off. We continued monitoring NO_2 concentrations for 3.5 to 6.5 additional hours in the farthest bedroom from the kitchen after turning the oven off.

Correction for air exchange

Because it is impossible to seal kitchens perfectly, we corrected for air exchange between the chamber and the air outside the chamber. We calculated the air exchange constant for each kitchen by injecting 300- to 500-ml volumes of ethane or nitrous oxide and measuring changes in concentration through time as described in Materials and Methods and in Lebel *et al.* (*10*).

Kitchen volume is calculated using Eq. 2

$$V_k = \frac{V_i}{C_{tracer\_peak}} \tag{2}$$

where V_k is the kitchen volume, V_i is the volume of injected tracer (ethane or nitrous oxide), and C_{tracer_peak} is the peak ethane concentration following injection.

The concentration of the tracer, ethane or nitrous oxide, after injection follows an exponential decay attributable to air exchange and is described by Eq. 3

$$C_{tracer,t} - C_{tracer,b} = C_{tracer,0}e^{-\lambda t} \tag{3}$$

where $C_{tracer,t}$ is the concentration of the tracer at time t, $C_{tracer,b}$ is the background concentration of the tracer, $C_{tracer,0}$ is the concentration of the tracer in the kitchen before injection (typically very close to background), t is time, and λ is the air exchange constant.

Rearranging, we can calculate the air exchange constant λ using Eq. 4

$$\lambda = \frac{\ln\left(\frac{C_{tracer,0}}{C_{tracer,t} - C_{tracer,b}}\right)}{t} \tag{4}$$

Then, the corrected gas concentration $\widehat{C}_{g,t}$ for the ith datapoint collected is given by Eq. 5

$$\widehat{C}_{t_i} = C_{t_i} + \Sigma_{i=1}^{n}(C_{t_i} - C_{bkg})(e^{-\lambda(t_i - t_{(i-1)})} - 1) \tag{5}$$

where t_i is the time of the ith datapoint, $\widehat{C}_{t_i}$ is the corrected gas concentration at time t_i, C_{bkg} is the background gas concentration outside the kitchen chamber, C_{t_i} is the true gas concentration at time t_i, and C_0 is the initial gas concentration in the chamber (usually almost the same as C_{bkg}).

The flow rate of the gas can then by calculated using the linear model given by Eq. 6

$$f = \frac{V_k(\widehat{C}_t - C_0)}{t - t_0} = \frac{V_k}{t - t_0}(C_t - C_0 + \Sigma_{i=1}^{n}(C_{t_i} - C_{bkg})(e^{-\lambda(t_i - t_{(i-1)})} - 1) \tag{6}$$

where f is the gas flow rate (expressed as volume per time) and t_0 is the initial time.

We used Eq. 6 to calculate flow rates for CH_4, and CO_2. This method is the same as that used by Lebel *et al.* (*10*).

Modeling population-level exposures and health risks

We used CONTAM to model indoor NO_2 concentrations resulting from gas and propane stove use under different conditions. All quantities not measured, such as wall and door leakage areas and wind pressure profiles, used the default values in the ASHRAE Handbook-Fundamentals based on a house's age and height (*64*). We assumed a previously reported (*32*) NO_2 decay rate of -2.4×10^{-4} s^{-1}.

Validation of the CONTAM multizone model

We validated our CONTAM model by comparing measured and modeled NO_2 concentrations in 18 test houses. In each test house, we measured the NO_2 emission rate of a specific combination of burners and oven on known settings using the methods described above (see table S2). After fully airing out the house, we then measured the NO_2 concentrations in one to four different rooms (including at least the kitchen and another room or, in studio-style apartments, a single zone representing a combined kitchen/living space) for 40 min to an hour with the given burner/oven combination on and for another 1 to 3 hours with all burners and oven off. Note that the 18 1-hour–and–40-min– to 4-hour CONTAM validation measurements are distinct from the 6 8-hour bedroom measurements.

For validation measurements, all internal doors in residences were left open. In several instances, we measured both with windows open and closed and with an outside-venting range hood on or off. Because we had only one Teledyne NO_2 analyzer, we sampled sequentially from each room in question using a valve system to cycle between rooms so as not to disturb the sampling hoses or to have to enter the rooms (see fig. S8B).

After obtaining time-resolved concentration measurements, we modeled NO_2 concentrations in each residence using CONTAM. We constructed each residence in CONTAM based on laser distance measurements (see table S2 for a summary of home sizes and characteristics). We modeled each room as a single zone, except for hallways which we represented using two to four zones, depending on length. In each validation house, we inputted into CONTAM the NO_2 emission rate we measured from the burner/oven combination being tested. We also inputted into CONTAM weather profiles [obtained from OpenWeather Marketplace; (*65*)], corresponding with the address and time-period of each validation measurement.

Because interior airflow is strongly influenced by temperature gradients, time-resolved temperature gradients in multiple zones of each residence were required to accurately model NO_2 concentrations attributable to stoves. We measured temperature profiles of each room in 11 of the 18 validation homes (see fig. S9 for CONTAM floorplans of each of the 11 homes) and observed strong overall agreement between modeled and measured NO_2 concentrations in the 11 houses for which we have temperature data (see Results).

We could not scale such a time-resolved model to the entire U.S. housing stock because internal temperature profiles are variable and we thus could not use house-specific time-resolved temperature gradients as inputs in our nationwide model. To extend our model, we also verified that we could replace airflow due to temperature variation with a fixed-bidirectional airflow at each open door and still accurately predict kitchen, living room, and bedroom NO_2 concentrations averaged across several residences.

We considered a range of different bidirectional flow values between 300 and 1300 m^3/hour and found empirically that setting bidirectional flow to 1000 m^3/hour [590 cfm; within the range of turbulent flow rates observed in real interior doorways; (*66*)] minimized the error between averaged measured and modeled hour-averaged and day-averaged concentrations (see table S5; figs. S4 and S10 show results for different bidirectional flow rates; day-averaged concentrations extrapolated from measured and modeled values at the end of the measurement period using a decay rate of -2.4×10^{-4} s^{-1}). We calculated error as $100\% \times \frac{\text{Measured} - \text{Modeled}}{\text{Measured}}$.

NO_2 exposure calculations using CONTAM

We used CONTAM to model time-resolved NO_2 concentrations under different scenarios in each of the 7632 residences with gas, propane, and mixed-fuel stoves included in the United States Energy Information Administration's 2020 RECS. The 2020 RECS is a survey of 18,500 households in all 50 states and the District of Columbia that reports information on participants' energy use, housing characteristics, and demographics, and which assigns each participating household a representation weight such that results may be extrapolated to the entire U.S. population (*1*).

We combined our CONTAM modeling with the RECS data by assigning each RECS household to 1 of 24 distinct CONTAM floorplans that most resembled the RECS household in question based on housing type, floor area, number of stories, presence or absence of a forced air system, and home age. We selected the 24 floorplans from a pool of 209 residences constructed in CONTAM by Persily *et al.* (*67*) to represent the U.S. housing stock. The 24 floor plans represent diverse yet common types of homes that encompass the characteristics of the 7632 RECS residences (see fig. S11 for an assignment flowchart and table S6 for a summary of the 24 floorplans). We represented with a single floorplan homes that only differed from one another in factors out of the scope of this study (e.g., foundation type and room types). We assigned RECS residences to our set of floorplans according to, in order of decreasing prioritization, type of home, floor area, number of stories, presence or absence of a forced air system, and home age.

We left each model floorplan unchanged except for the following: because windows were not included in the default floorplans in CONTAM, we added one National Fenestration Research Council standard window (1.2 m × 1.5 m or 4 ft × 5 ft) to an exterior wall in every bedroom, living room, and kitchen (*68*); as discussed above, to simulate indoor air transport we replaced each modeled open door with bidirectional flow at a rate of 1000 m^3/hour (590 cfm); because we adjust the modeled NO_2 emission rate to account for outside-venting range hoods (for instance, we model a 50% capture efficiency outside-venting hood by reducing the emission rate by 50%), we removed modeled range hoods in floorplans that had them so as not to double-count range hoods. We left central forced-air systems unchanged and assigned their schedule on the basis of modeled ambient temperature (see table S7).

We captured a range of behaviors and environments by assigning a weighted distribution of scenarios to each RECS household. We used prior surveys and direct measurement studies to select three or four distinct values for each of six parameters: range hood use, stove use, window use, ambient temperature, windspeed, and occupancy, for a total of $4 \times 3 \times 3 \times 4 \times 3 \times 3 = 1296$ combined scenarios for each floorplan. We modeled each scenario for each of the 24 CONTAM floorplans and then calculated peak 1-hour–averaged and day-averaged NO_2 concentrations associated with each scenario. On the basis of existing data on each parameter and on the number of heating degree days and cooling degree days expected for the specific location of each RECS residence, we assigned relative weights for each of the 1296 modeled scenarios for each RECS residence. The weights of each value are presented in table S7. We also performed a sensitivity analysis on all six parameters (see Results).

We calculated the distribution of national long-term NO_2 exposure burden by iterating through all 7632 RECS representative residences with gas or propane stoves and for each residence calculating the weighted mean of the 1296 modeled day-averaged NO_2 exposures. We then multiplied this mean by the residence's weight in the RECS database and normalized for total number of residences represented in the RECS database. We calculated the distribution of the percentage of days with 1-hour–averaged NO_2 exposure exceeding 100 ppbv in an analogous fashion: for each RECS residence, we calculated the percentage of modeled exposure days with a 100-ppbv exceedance, then multiplied the value by the given residence's weight and normalized for total number of residences represented by RECS.

Estimation of pediatric asthma attributable to gas and propane stoves overall and to NO_2 exposure from gas and propane stoves

We estimated the PAF of asthma incidence attributable to the use of gas and propane stoves compared with the use of electric stoves using ORs reported by Puzzolo *et al.* (*26*), who conducted a meta-analysis featuring multiyear, multicohort, geographically diverse studies. Because Puzzolo *et al.* did not report ORs or RRs per unit of indoor NO_2, we estimated the PAF of asthma incidence due to long-term NO_2 exposure from gas and propane stoves using Lin *et al.*'s 2013 estimate (*16*), which also featured multiyear, multicohort, geographically diverse studies focusing exclusively on indoor NO_2. Following Gruenwald *et al.* (*24*), we used ORs in place of RRs, as pediatric asthma affects less than 10% of the U.S. child population (*69*).

To our knowledge, there are no meta-analyses assessing the effect of indoor NO_2 on mortality. To estimate the PAF of deaths attributable to long-term NO_2 exposure from gas and propane stoves, we thus used the RRs reported by a meta-analysis featuring multiyear, multicohort, geographically diverse studies of ambient NO_2 (*38*). Potential confounding with other coproduced ambient pollutants, such as particulate matter, increases the uncertainty of our mortality calculations. While Buonocore *et al.* used the RR for all-cause mortality associated with NO_2 reported by Faustini *et al.*'s 2014 meta-analysis (*70*), we instead opted for an RR reported in a newer meta-analysis by Atkinson *et al.* (*38*), which exclusively incorporated cohort studies (1.02 [95% CI: 1.01, 1.03] per 10 $\mu g/m^3$ increment in long-term NO_2 concentration, smaller than Faustini *et al.*'s value of 1.04 [95% CI: 1.02, 1.06] per 10 $\mu g/m^3$).

Consistent with prior epidemiological work assessing the influence of long-term NO_2 exposure on respiratory diseases (*15*, *71*, *72*), we assumed a log-linear concentration-response function and calculated health outcome burdens as

$$\text{Burden} = Inc_g \Sigma_n P_n \times W_n \times (1 - e^{-\beta \Delta c_n}) \quad (7)$$

where values are summed over all $n = 7632$ RECS residence types with gas or propane ranges or cooktops in the RECS database, Burden is the number of adverse health outcomes (death or pediatric asthma) attributable to NO_2 from stoves, Inc_g is the current incidence rate of the adverse health outcome in question in the geography in question, P_n is the number of people living in the nth household, W_n is the number of households the nth RECS household represents in the U.S. housing stock, β is the concentration response factor (calculated as $\frac{\ln(RR)}{\Delta c}$), which is assumed to be constant, and Δc_n is the median year-averaged gas-stove-attributable NO_2 exposure in the nth residence. We calculated burden separately for pediatric asthma and adult mortality using the appropriate P_n, based on child and adult occupancy of RECS houses.

We calculated pediatric asthma burden using a U.S. pediatric asthma incidence rate averaged between 2006 and 2008 (12.5 cases per 1000 children) (*69*) multiplied by the current U.S. population under 18. We used state-by-state incidence of pediatric asthma from the U.S. Centers for Disease Control and Prevention from 2021 (*73*), the most recent date for which data stratified by state were available. We calculated state-stratified asthma rates only in states for which the incidence rate was reported.

Because the total population covered by the RECs database (62 million children, 239 million adults) is slightly lower than today's U.S. population (258 million adults and 73 million children) (*74*), likely because of occupancy data that is older than the most recent U.S. census, we proportionally adjusted our calculated burdens to match the current U.S. adult and child population

$$\text{Burden}_{\text{adj}} = \text{Burden}_{\text{orig}} \times \frac{Pop_{\text{current}}}{Pop_{\text{RECS}}} \quad (8)$$

Following Mansournia (*75*), we calculated PAFs from calculated burdens and baseline incidence of deaths and pediatric asthma as

$$\text{PAF} = \frac{\text{Burden}}{\text{Incidence}} \quad (9)$$

where Incidence is the number of new deaths or pediatric asthma cases per year in the geography in question. When calculating PAFs for individual states, we used state-specific incidence estimates, and when calculating national PAFs, we used national incidence estimates.

Because the uncertainty in RRs may be correlated with uncertainty in exposure, we conservatively assumed a wide uncertainty in PAFs. Rather than add fractional errors of RR and Δc_n in quadrature, we calculated our lower uncertainty bound using the lower bound of each reported RR and of each Δc_n estimate we calculated. We performed the analogous calculation for upper bounds.

Following Buonocore *et al.* (*61*), we calculated the valuation of excess deaths using the VSL from the EPA's BenMAP (*55*), $13.1 ($7.9, $18.5) million per death when adjusted to U.S. $ 2023, and the valuation of asthma incidence from an analysis by Nurmagambetov *et al.* (*51*), $5300 ($4120, $6490) per year per pediatric asthma case. We assumed that uncertainties in health outcome burdens and valuations were independent.

Uncertainty

We calculated uncertainty in exposure and health outcomes using a Monte Carlo method. To calculate uncertainty in exposure, we computed a Monte Carlo distribution resulting from the combination of three input distributions representing three key elements of the model: (i) measured NO_2 emission factors, (ii) estimated burner intensities used, and (iii) the distribution of NO_2 exposures modeled in different CONTAM scenarios, normalized to amount of gas burned and weighted according to the prevalence of each scenario, according to Eq. 10A and 10B

$$MC_{\text{mean}} = \text{mean}(EF * BI * CE * WE) \quad (10A)$$

$$MC_{\text{median}} = \text{median}(EF * BI * CE * WE) \tag{10B}$$

where *EF*, *BI*, and *CE* are randomly sampled (with replacement) values from the distributions of emission factors, burner intensities, and ratios of CONTAM-modeled exposures (normalized to gas burned), respectively, and *WE* is the weight corresponding to the particular CONTAM-modeled exposure *CE* selected. Because we have sparse data on the frequency with which people cook with burners on low, medium, and high (*41*), we assumed a normal distribution for burner intensity expressed as a fraction of emissions on high (mean = 0.5; SD = 0.1). See the "Limitations" section for further discussion.

Each sample *EF* and *CE* contained a number of elements equal to the minimum number of elements in each of the included distributions. For gas, this was 390 (number of gas emission factors) and for propane it was 20. Because *BI* was drawn from a known normal distribution, each sample *BI* contained only one element. MC_{mean} and MC_{median} are the mean and median, respectively, of the product of a single set of *X*-element input samples, where $X = 390$ for gas and 20 for propane. We calculated MC_{mean} and MC_{median} over 10,000 iterations to form a Monte Carlo distribution of the mean and median and calculated 95% CIs for mean and median exposure based on the Monte Carlo distributions.

We calculated central-estimate, lower-bound, and upper-bound long-term exposure for each floorplan as the average of the central estimate, lower bound, and upper bound of modeled day exposures, respectively. We calculated short-term exposure exceedances as the fraction of modeled days with a maximum 1-hour average exposure exceeding 100 ppb and converted the fraction to days per year by multiplying by 365. We used the central estimate, lower bound, and upper bound of modeled day exposures to calculate our CI in an analogous fashion to long-term exposures.

We used the same method to calculate uncertainties in our estimates of health outcomes and costs associated with exposure to NO_2. This time, we combined the distribution of concentrations calculated by Eq. 10A with a normal distribution of RRs reported for asthma (*16*) or mortality (*38*), according to Eq. 11

$$MC_{\text{health}_{\text{mean}}} = \text{mean}\left(1 - e^{\frac{\ln(RR)}{\Delta c} \times MC_{\text{conc}}}\right) \tag{11}$$

where $MC_{\text{healthmean}}$ is the mean of a single result in the Monte Carlo distribution of health outcome risks (pediatric asthma or adult mortality), *RR* is a relative risk value randomly sampled (with replacement) from a normal distribution, according to 95% CIs provided by Lin *et al.* and Atkinson *et al.* (*16*, *38*) for asthma and mortality, respectively, and MC_{conc} is a long-term exposure value randomly sampled (with replacement) from the 10,000-element normal distribution produced by running Eq. 10A 10,000 times. We then calculated the 95% CI of this Monte Carlo distribution. We calculated uncertainties in costs using the same method, this time drawing values from our calculated distribution of predicted health outcome burdens and from a distribution of per-case costs derived from uncertainties provided in the literature (see above).

We performed an analysis of the sensitivity of our calculated adverse health outcome burdens to the choice of concentration-response model. We did so by calculating the estimated burden of pediatric asthma and adult all-cause mortality attributable to long-term NO_2 from stoves using a log-linear model, a linear model, and a log-linear model with a 2-ppbv no-effect threshold, three models mentioned in recent long-term NO_2 literature (*13*, *15*, *71*, *72*). In each case, we calculated 95% CIs using a Monte Carlo method analogous to that described above for the calculation of log-linear adverse health outcome burden. The observed differences between models were modest and statistically indistinguishable (fig. S13).

Limitations

Our study assessed only one pollutant from gas stoves, NO_2. Because gas stoves also emit CO, benzene, formaldehyde, and ultrafine particulate matter (*7*, *9–12*, *76*), our estimates of disease burden and societal cost almost certainly underestimate the full health consequences of gas and propane stoves.

Results are based on measurements and assumptions throughout the modeling chain. We can partition the modeling chain, and associated uncertainties and limitations, as follows:

1) NO_2 emission rates of gas and propane burners and ovens.

To our knowledge, before Lebel *et al.*, NO_2 emission rates from gas stoves were last systematically quantified in 1985, but summary statistics were not reported. Other researchers have since reported emission factors per joule but not emission rates per time (see table S3 for a comparison of our results and previously reported emission rates and emission factors). Our modeling thus used emission rates measured in this work and by Lebel *et al.* (*10*). Our work and results from Lebel *et al.* (*10*) have constrained median NO_2 emission rates from gas burners on high and ovens to ±15% (see table S3). Larger uncertainties (up to ±50% for burners on high) remain for propane burner and propane oven emissions (see table S3). Moreover, our independent estimates in this paper for NO_2 emissions were statistically indistinguishable from those in Lebel *et al.* (see fig. S4 and table S3 for emission rates and table S8 for a summary of uncertainties).

2) Modeled indoor NO_2 concentrations from CONTAM, given a set of known input parameters.

We constrained uncertainties in modeled concentrations at ±18% (with positive values indicating an underestimate; see table S5). Our set of validation measurements included 18 homes and spanned a range of characteristics and measurement conditions. However, given time constraints it was impossible to validate the model on every combination of input parameters.

3) The population-wide distribution of burner minutes and oven minutes used per day, range hood use and capture efficiency, window opening schedules, outdoor temperatures, and outdoor windspeeds (the input parameters in step 2).

As demonstrated in our sensitivity analyses, there is a broad range in how frequently people use their stoves and their range hoods (and range hoods' efficacy) and open their windows, and these input parameters can alter estimated exposure (see Fig. 4). Of these inputs, stove use (i.e., length of time and number and intensity of burner and oven usage) had the largest spread and effect on exposure estimates. To our knowledge, no U.S.-wide study of burner and oven use exists, so we relied on a direct-measurement study by Zhao *et al.* (*41*) of stove use in 54 single family houses and 17 low-income apartments in California.

4) Other behavioral assumptions.

Apart from the behaviors listed above, there were other behaviors for which we lacked information. Two such behaviors that affect exposure are burner intensity and interior door opening. We inferred burner intensity based on reported cooking behaviors (see table S7), but because we lack measured data, our assumption that "on" burners are set to 50% of "high" may be an over- or underestimate of NO_2 emissions. We attempted to account for this uncertainty by adding a ± 10% normally distributed uncertainty to our exposure and health outcome estimates. We assumed that all interior doors of houses remain open. Compared with an assumption of more closed doors, our open-door assumption results in lower exposure to people in and near the kitchen and higher exposure to others in the house. While this should not substantively affect our population-averaged estimates of long-term exposure, it may lead us to underestimate exposure for primary cooks in a given household and to overestimate exposure for people who spend little time in the kitchen. This issue applies to both long-term and short-term exposure estimates but is more relevant to short-term exposures.

5) Assignment of each residence in the RECS database to a specific floorplan in CONTAM.

We assigned each residence in the RECS database to 1 of 24 floorplans and thus were unable to perfectly match each RECS residence to a given floorplan. For example, we split apartments into >1000 ft^2 (>90 m^2) and <1000 ft^2, representing the 65th percentile of floorspace for apartments with gas or propane stoves [the median is 900 ft^2 (80 m^2)] (*1*). This assignment (and analogous assignments for other variables) thus result in the floorspace of roughly equal numbers of RECS residences being over- and underestimated and thus should not substantively affect our population-averaged exposure estimates. However, it may underestimate differences in exposure due to housing size and other characteristics.

6) Conversion of exposure estimates to estimates of disease burden.

We relied on RR values from recent meta-analyses to calculate stove-attributable pediatric asthma and mortality (*16*, *26*, *38*). For pediatric asthma, we relied on meta-analysis assessing indoor NO_2 only (*16*). Because no meta-analysis has assessed indoor NO_2 and mortality, to our knowledge, we calculated mortality using a meta-analysis on outdoor NO_2. Our estimate of mortality is thus limited in its precision by potential confounding pollutants that co-occur with outdoor NO_2, such as particulate matter, and by the variability in RRs reported by different studies. We applied a mortality RR of 1.02 (1.01, 1.03)) per 10 $\mu g/m^3$ of long-term NO_2 exposure derived from meta-analysis by Atkinson *et al.* (*38*) that included only long-term, cohort studies. Other meta-analyses (*70*, *77*) have estimated higher RRs than what we used. For instance, a 2014 meta-analysis (*70*) on NO_2 exposure and mortality used by Buonocore *et al.* to calculate premature deaths from upstream oil and gas production (*61*) calculated $RR = 1.04$ (1.02, 1.06) per 10 $\mu g/m^3$ increase in long-term NO_2. We propagated uncertainty bounds provided by Atkinson *et al.* but recognize that there is additional uncertainty and that choosing meta-analyses with broader inclusion criteria than used by Atkinson *et al.* may have resulted in higher mortality estimates than those we calculated.

Supplementary Materials

This PDF file includes:
Figs. S1 to S15
Tables S1 to S8
Legends for data S1 to S3
References

Other Supplementary Material for this manuscript includes the following:
Data S1 to S3

REFERENCES AND NOTES

1. U.S. Energy Information Administration, "Residential Energy Consumption Survey (RECS)" (2020); www.eia.gov/consumption/residential/data/2020/.
2. E. I. Australian Bureau of Statistics, "Energy Use and Conservation" (2014); www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/4602.0.55.001Main+Features1Mar%20 2014?OpenDocument.
3. Statista, Share of Gas Oven and Range Ownership in Ireland, UK (2017); www.statista.com/.
4. E. D. Palmes, C. Tomczyk, J. DiMattio, Average N0_2 concentrations in dwellings with gas or electric stoves. *Atmos. Environ.* **11**, 869–872 (1977).
5. C. D. Hollowell, G. W. Traynor, "Combustion-Generated Indoor Air Pollution" in *13th International Colloquium on Polluted Atmospheres* (Paris, 1978).
6. Mueller Associates, "Indoor air quality environmental information handbook: Combustion sources" (1985); https://doi.org/10.2172/6011403.
7. R. Fortmann, P. Kariher, R. Clayton, "Indoor Air Quality: Residual Cooking Exposures" (2001); https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/97-330a.pdf.
8. B. C. Singer, R. Z. Pass, W. W. Delp, D. M. Lorenzetti, R. L. Maddalena, Pollutant concentrations and emission rates from natural gas cooking burners without and with range hood exhaust in nine California homes. *Build. Environ.* **122**, 215–229 (2017).
9. Z. Zheng, H. Zhang, H. Qian, J. Li, T. Yu, C. Liu, Emission characteristics of formaldehyde from natural gas combustion and effects of hood exhaust in Chinese kitchens. *Sci. Total Environ.* **838**, 156614 (2022).
10. E. D. Lebel, C. J. Finnegan, Z. Ouyang, R. B. Jackson, Methane and NO_x emissions from natural gas stoves, cooktops, and ovens in residential homes. *Environ. Sci. Technol.* **56**, 2529–2539 (2022).
11. Y. S. Kashtan, M. Nicholson, C. Finnegan, Z. Ouyang, E. D. Lebel, D. R. Michanowicz, S. B. C. Shonkoff, R. B. Jackson, Gas and propane combustion from stoves emits benzene and increases indoor air pollution. *Environ. Sci. Technol.* **57**, 9653–9663 (2023).
12. S. S. Patra, J. Jiang, X. Ding, C. Huang, E. K. Reidy, V. Kumar, P. Price, C. Keech, G. Steiner, P. Stevens, N. Jung, B. E. Boor, Dynamics of nanocluster aerosol in the indoor atmosphere during gas cooking. *PNAS Nexus* **3**, (2024).
13. H. Khreis, C. Kelly, J. Tate, R. Parslow, K. Lucas, M. Nieuwenhuijsen, Exposure to traffic-related air pollution and risk of development of childhood asthma: A systematic review and meta-analysis. *Environ. Int.* **100**, 1–31 (2017).
14. S. C. Anenberg, D. K. Henze, V. Tinney, P. L. Kinney, W. Raich, N. Fann, C. S. Malley, H. Roman, L. Lamsal, B. Duncan, R. V. Martin, A. van Donkelaar, M. Brauer, R. Doherty, J. E. Jonson, Y. Davila, K. Sudo, J. C. I. Kuylenstierna, Estimates of the Global Burden of Ambient PM2.5, Ozone, and NO2 on asthma incidence and emergency room visits. *Environ. Health Perspect.* **126**, 107004 (2018).
15. P. Achakulwisut, M. Brauer, P. Hystad, S. C. Anenberg, Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: Estimates from global datasets. *Lancet Planet. Health* **3**, e166–e178 (2019).
16. W. Lin, B. Brunekreef, U. Gehring, Meta-analysis of the effects of indoor nitrogen dioxide and gas cooking on asthma and wheeze in children. *Int. J. Epidemiol.* **42**, 1724–1737 (2013).
17. Z. Zhang, J. Wang, W. Lu, Exposure to nitrogen dioxide and chronic obstructive pulmonary disease (COPD) in adults: A systematic review and meta-analysis. *Environ. Sci. Pollut. Res. Int.* **25**, 15133–15145 (2018).
18. P. Huangfu, R. Atkinson, Long-term exposure to NO_2 and O_3 and all-cause and respiratory mortality: A systematic review and meta-analysis. *Environ. Int.* **144**, 105998 (2020).
19. C. Hoffmann, M. Maglakelidze, E. von Schneidemesser, C. Witt, P. Hoffmann, T. Butler, Asthma and COPD exacerbation in relation to outdoor air pollution in the metropolitan area of Berlin Germany. *Respir. Res.* **23**, 64 (2022).
20. Z. Chen, N. Liu, H. Tang, X. Gao, Y. Zhang, H. Kan, F. Deng, B. Zhao, X. Zeng, Y. Sun, H. Qian, W. Liu, J. Mo, X. Zheng, C. Huang, C. Sun, Z. Zhao, Health effects of exposure to sulfur dioxide, nitrogen dioxide, ozone, and carbon monoxide between 1980 and 2019: A systematic review and meta-analysis. *Indoor Air* **32**, e13170 (2022).
21. R. Topp, J. Cyrys, I. Gebefügi, J. Schnelle-Kreis, K. Richter, H. E. Wichmann, J. Heinrich; INGA Study Group, Indoor and outdoor air concentrations of BTEX and NO_2: Correlation of repeated measurements. *J. Environ. Monit.* **6**, 807–812 (2004).
22. M. Hulin, M. Simoni, G. Viegi, I. Annesi-Maesano, Respiratory health and indoor air pollutants based on quantitative exposure assessments. *Eur. Respir. J.* **40**, 1033–1045 (2012).
23. M. A. Bédard, M. E. Reyna, T. J. Moraes, E. Simons, S. E. Turvey, P. Mandhane, J. R. Brook, P. Subbarao, Association between gas stove use and childhood asthma in the Canadian CHILD Cohort Study. *Can. J. Public Health* **114**, 705–708 (2023).
24. T. Gruenwald, B. A. Seals, L. D. Knibbs, H. D. Hosgood, Population attributable fraction of gas stoves and childhood asthma in the United States. *Int. J. Environ. Res. Public Health* **20**, 75 (2022).
25. L. D. Knibbs, S. Woldeyohannes, G. B. Marks, C. T. Cowie, Damp housing, gas stoves, and the burden of childhood asthma in Australia. *Med. J. Aust.* **208**, 299–302 (2018).
26. E. Puzzolo, N. Fleeman, F. Lorenzetti, F. Rubinstein, Y. Li, R. Xing, G. Shen, E. Nix, M. Maden, R. Bresnahan, R. Duarte, L. Abebe, J. Lewis, K. N. Williams, H. Adahir-Rohani, D. Pope, Estimated health effects from domestic use of gaseous fuels for cooking and heating in

high-income, middle-income, and low-income countries: A systematic review and meta-analyses. *Lancet Respir. Med.* **12**, 281–293 (2024).
27. B. C. Singer, M. G. Apte, D. R. Black, T. Hotchi, D. Lucas, M. M. Lunden, A. G. Mirer, M. Spears, D. P. Sullivan, Natural Gas Variability in California: Environmental Impacts and Device Performance Experimental Evaluation of Pollutant Emissions from Residential Appliances. doi: 10.2172/980736 (2009).
28. J. Gillespie-Bennett, N. Pierse, K. Wickens, J. Crane, S. Nicholls, D. Shields, M. Boulic, H. Viggers, M. Baker, A. Woodward, P. Howden-Chapman; Housing, Heating, and Health Team, Sources of nitrogen dioxide (NO_2) in New Zealand homes: Findings from a community randomized controlled trial of heater substitutions. *Indoor Air* **18**, 521–528 (2008).
29. A. Esplugues, F. Ballester, M. Estarlich, S. Llop, V. Fuentes, E. Mantilla, C. Iñiguez, Indoor and outdoor concentrations and determinants of NO_2 in a cohort of 1-year-old children in Valencia, Spain. *Indoor Air* **20**, 213–223 (2010).
30. J. M. Logue, T. E. McKone, M. H. Sherman, B. C. Singer, Hazard assessment of chemical air contaminants measured in residences. *Indoor Air* **21**, 92–109 (2011).
31. A. L. Hodshire, E. Carter, J. M. Mattila, V. Ilacqua, J. Zambrana, J. P. D. Abbatt, A. Abeleira, C. Arata, P. F. Decarlo, A. H. Goldstein, L. H. Ruiz, M. E. Vance, C. Wang, D. K. Farmer, Detailed investigation of the contribution of gas-phase air contaminants to exposure risk during indoor activities. *Environ. Sci. Technol.* **56**, 12148–12157 (2022).
32. S. J. Emmerich, A. K. Persily, Multizone Modeling of Three Residential Indoor Air Quality Control Options. [Preprint] (1996); www.nist.gov/publications/multizone-modeling-three-residential-indoor-air-quality-control-options.
33. A. K. Persily, "A Modeling Study of Ventilation, IAQ and Energy Impacts of Residential Mechanical Ventilation" (1998); www.nist.gov/publications/modeling-study-ventilation-iaq-and-energy-impacts-residential-mechanical-ventilation.
34. P. Fabian, G. Adamkiewicz, J. I. Levy, Simulating indoor concentrations of NO_2 and PM2.5 in multifamily housing for use in health-based intervention modeling. *Indoor Air* **22**, 12–23 (2012).
35. J. M. Logue, N. E. Klepeis, A. B. Lobscheid, B. C. Singer, Pollutant exposures from natural gas cooking burners: A simulation-based assessment for Southern California. *Environ. Health Perspect.* **122**, 43–50 (2014).
36. T. Fazli, B. Stephens, Development of a nationally representative set of combined building energy and indoor air quality models for U.S. residences. *Build. Environ.* **136**, 198–212 (2018).
37. W. S. Dols, B. J. Polidoro, CONTAM User Guide and Program Documentation Version 3.4. doi: 10.6028/NIST.TN.1887r1.
38. R. W. Atkinson, B. K. Butland, H. R. Anderson, R. L. Maynard, Long-term concentrations of nitrogen dioxide and mortality. *Epidemiology* **29**, 460–472 (2018).
39. "National Ambient Air Quality Table" (2023); www.epa.gov/criteria-air-pollutants/naaqs-table.
40. World Health Organization Regional Office for Europe, "Guidelines for indoor air quality, selected pollutants" (2010); www.who.int/publications/i/item/9789289002134.
41. H. Zhao, W. R. Chan, W. W. Delp, H. Tang, I. S. Walker, B. C. Singer, Factors impacting range hood use in California houses and low-income apartments. *Int. J. Environ. Res. Public Health* **17**, 8870 (2020).
42. N. L. Nagda, M. D. Koontz, R. C. Fortmann, I. H. Billick, Prevalence, use, and effectiveness of range-exhaust fans. *Environ. Int.* **15**, 615–620 (1989).
43. S. C. Hill, L. D. Smoot, Modeling of nitrogen oxides formation and destruction in combustion systems. *Prog. Energy Combust. Sci.* **26**, 417–458 (2000).
44. Interactive Table Handbook of Chemistry and Physics 103rd Edition; https://hbcp-chemnetbase-com.stanford.idm.oclc.org/faces/contents/InteractiveTable.xhtml.
45. W. W. Delp, B. C. Singer, Performance assessment of U.S. residential cooking exhaust hoods. *Environ. Sci. Technol.* **46**, 6167–6173 (2012).
46. B. C. Singer, W. W. Delp, P. N. Price, M. G. Apte, Performance of installed cooking exhaust devices. *Indoor Air* **22**, 224–234 (2012).
47. World Health Organization, "Global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide" (2021); https://apps.who.int/iris/handle/10665/345329?locale-attribute=ar&s=.
48. U.S. Environmental Protection Agency, Report on the Environment (ROE) (2021); https://cfpub.epa.gov/roe/indicator.cfm?i=7.
49. Residential Indoor Air Quality Guideline: Nitrogen Dioxide - Canada.ca; www.canada.ca/en/health-canada/services/publications/healthy-living/residential-indoor-air-quality-guideline-nitrogen-dioxide.html#c4a.
50. R. Alotaibi, M. Bechle, J. D. Marshall, T. Ramani, J. Zietsman, M. J. Nieuwenhuijsen, H. Khreis, Traffic related air pollution and the burden of childhood asthma in the contiguous United States in 2000 and 2010. *Environ. Int.* **127**, 858–867 (2019).
51. T. Nurmagambetov, R. Kuwahara, P. Garbe, The economic burden of asthma in the United States, 2008-2013. *Ann. Am. Thorac. Soc.* **15**, 348–356 (2018).
52. Health Canada: Water and Air Quality Bureau, "Human health risk assessment for ambient nitrogen dioxide" (2016); https://publications.gc.ca/collections/collection_2016/sc-hc/H114-31-2016-eng.pdf.
53. S. Huang, H. Li, M. Wang, Y. Qian, K. Steenland, W. M. Caudle, Y. Liu, J. Sarnat, S. Papatheodorou, L. Shi, Long-term exposure to nitrogen dioxide and mortality: A systematic review and meta-analysis. *Sci. Total Environ.* **776**, 145968 (2021).
54. Centers for Disease Protection, Tobacco-Related Mortality (2020); www.cdc.gov/tobacco/data_statistics/fact_sheets/health_effects/tobacco_related_mortality/index.htm.
55. Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) | U.S. EPA; www.epa.gov/benmap.
56. Z. Merrin, P. W. Francisco, Unburned methane emissions from residential natural gas appliances. *Environ. Sci. Technol.* **53**, 5473–5482 (2019).
57. P. L. Jenkins, T. J. Phillips, E. J. Mulberg, S. P. Hui, Activity patterns of Californians: Use of and proximity to indoor pollutant sources. *Atmos. Environ. Part A* **26**, 2141–2148 (1992).
58. M. H. Garrett, M. A. Hooper, B. M. Hooper, M. J. Abramson, Respiratory symptoms in children and indoor exposure to nitrogen dioxide and gas stoves. *Am. J. Respir. Crit. Care Med.* **158**, 891–895 (2012).
59. C. F. Gould, M. L. Bejarano, B. De La Cuesta, D. W. Jack, S. B. Schlesinger, A. Valarezo, M. Burke, Climate and health benefits of a transition from gas to electric cooking. *Proc. Natl. Acad. Sci. U.S.A.* **120**, e2301061120 (2023).
60. World Health Organization, WHO global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide; www.who.int/publications/i/item/9789240034228.
61. J. J. Buonocore, S. Reka, D. Yang, C. Chang, A. Roy, T. Thompson, D. Lyon, R. McVay, D. Michanowicz, S. Arunachalam, Air pollution and health impacts of oil & gas production in the United States. *Environ. Res. Health* **1**, 021006 (2023).
62. B. Efron, Better bootstrap confidence intervals. *J. Am. Stat. Assoc.* **82**, 171–185 (1987).
63. K. Jung, J. Lee, V. Gupta, G. Cho, Comparison of bootstrap confidence interval methods for GSCA using a monte carlo simulation. *Front. Psychol.* **10**, 2215 (2019).
64. ASHRAE, *2021 ASHRAE Handbook Fundamentals* (2021); www.ashrae.org/technical-resources/ashrae-handbook/description-2021-ashrae-handbook-fundamentals.
65. OpenWeather Marketplace; https://home.openweathermap.org/history_bulks/new.
66. O. M. Lidwell, Air exchange through doorways. The effect of temperature difference, turbulence and ventilation flow. *J. Hyg.* **79**, 141–154 (1977).
67. A. K. Persily, A. Musser, D. D. Leber, A Collection of Homes to Represent the U.S. Housing Stock. [Preprint] (2008); www.nist.gov/publications/collection-homes-represent-us-housing-stock.
68. R. Hart, S. Selkowitz, C. Curcija, Thermal performance and potential annual energy impact of retrofit thin-glass triple-pane glazing in US residential buildings. *Build. Simul.* **12**, 79–86 (2019).
69. R. A. Winer, X. Qin, T. Harrington, J. Moorman, H. Zahran, Asthma incidence among children and adults: Findings from the Behavioral Risk Factor Surveillance system asthma call-back survey--United States, 2006–2008. *J. Asthma* **49**, 16–22 (2012).
70. A. Faustini, R. Rapp, F. Forastiere, Nitrogen dioxide and mortality: Review and meta-analysis of long-term studies. *Eur. Respir. J.* **44**, 744–753 (2014).
71. S. C. Anenberg, A. Mohegh, D. L. Goldberg, G. H. Kerr, M. Brauer, K. Burkart, P. Hystad, A. Larkin, S. Wozniak, L. Lamsal, Long-term trends in urban NO_2 concentrations and associated paediatric asthma incidence: Estimates from global datasets. *Lancet Planet. Health* **6**, e49–e58 (2022).
72. A. Mohegh, D. Goldberg, P. Achakulwisut, S. C. Anenberg, Sensitivity of estimated NO2-attributable pediatric asthma incidence to grid resolution and urbanicity. *Environ. Res. Lett.* **16**, 014019 (2020).
73. Centers for Disease Control, Child Current Asthma Prevalence and Weighted Number by State or Territory: BRFSS, Table C1 (2021); www.cdc.gov/asthma/brfss/2021/child/tablec1.html.
74. "Population Under Age 18 Declined Last Decade" (2021); www.census.gov/library/stories/2021/08/united-states-adult-population-grew-faster-than-nations-total-population-from-2010-to-2020.html.
75. M. A. Mansournia, D. G. Altman, Population attributable fraction. *BMJ* **360**, k757 (2018).
76. E. D. Lebel, D. R. Michanowicz, K. R. Bilsback, L. A. L. Hill, J. S. W. Goldman, J. K. Domen, J. M. Jaeger, A. Ruiz, S. B. C. Shonkoff, Composition, emissions, and air quality impacts of hazardous air pollutants in unburned natural gas from residential stoves in california. *Environ. Sci. Technol.* **56**, 15828–15838 (2022).
77. G. Hoek, R. M. Krishnan, R. Beelen, A. Peters, B. Ostro, B. Brunekreef, J. D. Kaufman, Long-term air pollution exposure and cardio-respiratory mortality: A review. *Environ. Health* **12**, 43 (2013).
78. ASTM, *D5157 Standard Guide for Statistical Evaluation of Indoor Air Quality Models*, https://www.astm.org/d5157-97r14.html.
79. V. Klug, A. Lobscheid, B. Singer, "*Cooking Appliance Use in California Homes*" (Berkeley, CA, United States, 2011); https://doi.org/10.2172/1050839.
80. G. Morrison, J. Cagle, G. Date, A national survey of window-opening behavior in United States homes. *Indoor Air* **32**, e12932 (2022).
81. National Centers for Environmental Information, "*Hourly Ground-Level Wind Speeds*", (2022), https://www.ncei.noaa.gov/access/data-search/normals-hourly-2006-2020?dataTypes=HLY-WIND-AVGSPD.

82. "*American Time Use Survey - 2021*" (2022); www.bls.gov/tus/data.htm.
83. N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, W. H. Engelmann, The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants. *J. Expo. Sci. Environ. Epidemiol.* **11**, 231–252 (2001).

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Utility Characteristics									RESIDENTIAL		
									Revenues	Sales	Customers
Data Year	Utility Number	Utility Name	Part	Service Type	Data Type O = Observed I = Imputed	State	Ownership	BA Code	Thousand Dollars	Megawatthours	Count
2022	5109	DTE Electric Company	A	Bundled	O	MI	Investor Owned	MISO	2,910,745.9	15,844,478	2,047,944
2022	5109	DTE Electric Company	C	Delivery	O	MI	Investor Owned	MISO	24.1	305	16

COMMERCIAL			INDUSTRIAL			TRANSPORTATION			TOTAL		
Revenues	Sales	Customers	Revenues	Sales	Customers	Revenues	Sales	Customers	Revenues	Sales	Customers
Thousand Dollars	Megawatthours	Count	Thousand Dollars	Megawatthours	Count	Thousand Dollars	Megawatthours	Count	Thousand Dollars	Megawatthours	Count
2,019,207.0	16,500,656	208,758	658,926.5	8,548,188	711	533.7	4,320	2	5,589,413.1	40,897,642	2,257,415
71,743.6	2,811,992	4,347	13,888.6	1,673,198	124	.	.	.	85,656.3	4,485,495	4,487

Utility Characteristics									RESIDENTIAL			
									Revenues	Sales	Customers	Revenues
Data Year	Utility Number	Utility Name	Part	Service Type	Data Type O = Observed I = Imputed	State	Ownership	BA Code	Thousand Dollars	Megawatthours	Count	Thousand Dollars
2022	15497	Puerto Rico Electric Pwr Authority	A	Bundled	O	PR	State	NA	1,823,195.0	6,419,574	1,370,811	2,332,860.0
2022	19879	Virgin Islands Water & Power Authority	A	Bundled	O	VI	State	NA	87,199.4	258,812	45,850	43,788.2
2022	40428	Guam Power Authority	A	Bundled	O	GU	State	NA	167,563.9	555,558	45,271	305,996.8
2022	40429	American Samoa Power Authority	A	Bundled	O	AS	State	NA	25,372.6	56,424	10,893	31,667.8
2022	57105	Commonwealth Utility Corporation	A	Bundled	O	MP	State	NA	25,079.1	94,566	12,770	37,702.1
2022	57313	Tesla Inc.	A	Bundled	O	PR	Behind the Meter	NA	0.0	0	0	201.0
2022	59579	Sunnova	A	Bundled	O	GU	Behind the Meter	NA	5,059.2	18,734	1,413	0.0
2022	59579	Sunnova	A	Bundled	O	PR	Behind the Meter	NA	68,257.0	276,245	33,822	0.0
2022	59647	Sunrun Inc.	A	Bundled	O	PR	Behind the Meter	NA	10,419.2	27,380	3,770	0.0
2022	60981	TerraForm US Energy Services, LLC	A	Bundled	O	PR	Behind the Meter	NA	0.0	0	0	118.0
2022	61098	Longroad Energy	A	Bundled	O	PR	Behind the Meter	NA	.	.	.	17.1
2022	99999	Adjustment 2022	A	Bundled	I	GU		NA	0.0	0	-1,413	0.0
2022	99999	Adjustment 2022	A	Bundled	I	PR		NA	0.0	0	-37,592	1,768.0

To calculate a state or the US total, sum Parts (A,B,C & D) for Revenue, but only Parts (A,B & D) for Sales and Customers.
To avoid double counting of customers, the aggregated customer counts for the states and US do not include the customer count for respondents with ownership code 'Behind the Meter'.
This group consists of Third Party Owners of rooftop solar systems.

COMMERCIAL		INDUSTRIAL			TRANSPORTATION			TOTAL		
Sales	Customers	Revenues	Sales	Customers	Revenues	Sales	Customers	Revenues	Sales	Customers
Megawatthours	Count	Thousand Dollars	Megawatthours	Count	Thousand Dollars	Megawatthours	Count	Thousand Dollars	Megawatthours	Count
7,495,422	127,739	505,081.0	1,768,396	589	0.0	0	0	4,661,136.0	15,683,392	1,499,139
101,485	7,524	95,359.1	261,772	2,292	.	.	.	226,346.7	622,069	55,666
984,602	7,602	.	.	.	.	.	.	473,560.7	1,540,160	52,873
70,418	1,575	10,834.7	24,745	4	.	.	.	67,875.1	151,587	12,472
163,706	4,195	0.0	0	0	0.0	0	0	62,781.2	258,272	16,965
4,834	12	0.0	0	0	0.0	0	0	201.0	4,834	12
0	0	0.0	0	0	0.0	0	0	5,059.2	18,734	1,413
0	0	0.0	0	0	0.0	0	0	68,257.0	276,245	33,822
0	0	0.0	0	0	0.0	0	0	10,419.2	27,380	3,770
731	5	0.0	0	0	0.0	0	0	118.0	731	5
101	2	.	.	.	.	.	.	17.1	101	2
0	0	0.0	0	0	0.0	0	0	0.0	0	-1,413
10,390	-17	0.0	0	0	0.0	0	0	1,768.0	10,390	-37,609

Utility Characteristics						Decoupled				Revenue Adjustment Method			
Data Year	Utility Number	Utility Name	Ownership	State	BA-Code	Residential	Commercial	Industrial	Transportation	Residential	Commercial	Industrial	Transportation
2022	604	City of Andalusia	Municipal	AL	SOCO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	963	Atlantic City Electric Co	Investor Owned	NJ	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	1167	Baltimore Gas & Electric Co	Investor Owned	MD	PJM	Yes	Yes	No	No	Automatic	Automatic		
2022	1179	Versant Power	Investor Owned	ME	ISNE	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	1179	Versant Power	Investor Owned	ME	NBSO	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	1764	Black Diamond Power Co	Investor Owned	WV	PJM	Yes	Yes			Automatic	Automatic		
2022	2651	Butler Rural Electric Coop Inc - (OH)	Cooperative	OH	PJM	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	2812	City of Calhoun - (GA)	Municipal	GA	SOCO	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	3240	Central Electric Coop Inc - (OR)	Cooperative	OR	BPAT	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	Proceeding
2022	3249	Central Hudson Gas & Elec Corp	Investor Owned	NY	NYIS	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	3542	Duke Energy Ohio Inc	Investor Owned	OH	PJM	Yes	No	No	No	Proceeding			
2022	3989	City of Colorado Springs - (CO)	Municipal	CO	WACM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	4003	City of Colton - (CA)	Municipal	CA	CISO	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	4110	Commonwealth Edison Co	Investor Owned	IL	PJM	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	4176	Connecticut Light & Power Co	Investor Owned	CT	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	4226	Consolidated Edison Co-NY Inc	Investor Owned	NY	NYIS	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	4296	Cookson Hills Elec Coop, Inc	Cooperative	OK	AECI	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	5027	Delmarva Power	Investor Owned	MD	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	5325	City of Douglas	Municipal	GA	SOCO	Yes	Yes			Automatic	Automatic		
2022	5336	City of Dover - (OH)	Municipal	OH	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	6374	Fitchburg Gas & Elec Light Co	Investor Owned	MA	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	7294	City of Glendale - (CA)	Municipal	CA	LDWP	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	7563	Grand Valley Power	Cooperative	CO	PSCO	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	8287	Hawaii Electric Light Co Inc	Investor Owned	HI	NA	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	9191	Idaho Power Co	Investor Owned	ID	IPCO	Yes	Yes	No	No	Proceeding	Proceeding		
2022	9246	Indian Electric Coop, Inc	Cooperative	OK	SWPP	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	10451	Kotzebue Electric Assn Inc	Cooperative	AK	NA	Yes	Yes			Automatic	Automatic		
2022	10668	Licking Rural Electric Inc	Cooperative	OH	PJM	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	10879	Lehi City Corporation	Municipal	UT	PACE	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	11171	Long Island Power Authority	State	NY	NYIS	Yes	Yes	No	Yes	Automatic	Automatic		Automatic
2022	11200	Lorain-Medina R E C, Inc	Cooperative	OH	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	11586	Town of Mansfield - (MA)	Municipal	MA	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	11804	Massachusetts Electric Co	Investor Owned	MA	ISNE	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	11843	Maui Electric Co Ltd	Investor Owned	HI	NA	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	12268	Medina Electric Coop, Inc	Cooperative	TX	ERCO	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	12351	City of Mesa - (AZ)	Municipal	AZ	WALC	Yes	Yes			Automatic	Automatic		
2022	12515	Midwest Electric, Inc	Cooperative	OH	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	12539	Midwest Electric Member Corp	Cooperative	NE	WACM	No	No	Yes	No			Automatic	
2022	13206	Nantucket Electric Co	Investor Owned	MA	ISNE	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	13214	The Narragansett Electric Co	Investor Owned	RI	ISNE	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	13314	Navajo Tribal Utility Authority	State	AZ	PACE	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	13314	Navajo Tribal Utility Authority	State	UT	PACE	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	13314	Navajo Tribal Utility Authority	State	NM	PACE	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	13511	New York State Elec & Gas Corp	Investor Owned	NY	NYIS	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	13573	Niagara Mohawk Power Corp.	Investor Owned	NY	NYIS	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	Proceeding
2022	13640	Northern Virginia Elec Coop	Cooperative	VA	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	13679	Town of North Attleborough - (MA)	Municipal	MA	ISNE	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	13693	North Central Elec Coop, Inc	Cooperative	OH	PJM	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	13762	Northern Neck Elec Coop, Inc	Cooperative	VA	PJM	Yes	Yes			Proceeding	Proceeding		
2022	13781	Northern States Power Co - Minnesota	Investor Owned	MN	MISO	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	14328	Pacific Gas & Electric Co.	Investor Owned	CA	CISO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	14354	PacifiCorp	Investor Owned	WA	PACW	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	14401	City of Palo Alto - (CA)	Municipal	CA	CISO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	14534	City of Pasadena - (CA)	Municipal	CA	CISO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	14537	Pascoag Utility District	Municipal	RI	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	14626	Pedernales Electric Coop, Inc	Cooperative	TX	ERCO	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	14839	City of Peru - (IN)	Municipal	IN	MISO	Yes	Yes	Yes		Proceeding	Proceeding	Proceeding	
2022	15248	Portland General Electric Co	Investor Owned	OR	PGE	Yes	Yes	No	No	Automatic	Automatic		

Utility Characteristics						Decoupled				Revenue Adjustment Method			
Data Year	Utility Number	Utility Name	Ownership	State	BA-Code	Residential	Commercial	Industrial	Transportation	Residential	Commercial	Industrial	Transportation
2022	15270	Potomac Electric Power Co	Investor Owned	MD	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	15270	Potomac Electric Power Co	Investor Owned	DC	PJM	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	15410	Prince George Electric Coop	Cooperative	VA	PJM	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	15466	Public Service Co of Colorado	Investor Owned	CO	PSCO	Yes	Yes	Yes	No	Proceeding	Proceeding	Proceeding	
2022	15477	Public Service Elec & Gas Co	Investor Owned	NJ	PJM	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	15500	Puget Sound Energy Inc	Investor Owned	WA	PSEI	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	16183	Rochester Gas & Electric Corp	Investor Owned	NY	NYIS	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	16572	Salt River Project	Political Subdivision	AZ	SRP	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	16609	San Diego Gas & Electric Co	Investor Owned	CA	CISO	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	17609	Southern California Edison Co	Investor Owned	CA	CISO	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	17612	Bear Valley Electric Service	Investor Owned	CA	CISO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	17637	Southern Maryland Elec Coop Inc	Cooperative	MD	PJM	Yes	Yes	No	No	Automatic	Automatic		
2022	19497	United Illuminating Co	Investor Owned	CT	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	19501	Union Rural Electric Coop, Inc	Cooperative	OH	PJM	No	No	Yes	No			Automatic	
2022	19547	Hawaiian Electric Co Inc	Investor Owned	HI	HECO	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	19603	USBIA-Mission Valley Power	Federal	MT	NWMT	Yes	Yes	Yes	No	Automatic	Automatic	Automatic	
2022	19896	City of Volga - (SD)	Municipal	SD	SWPP	Yes	Yes	Yes		Automatic	Automatic	Automatic	
2022	20169	Avista Corp	Investor Owned	WA	AVA	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	20169	Avista Corp	Investor Owned	MT	AVA	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	20169	Avista Corp	Investor Owned	ID	AVA	Yes	Yes	Yes	Yes	Automatic	Automatic	Automatic	Automatic
2022	24590	Unitil Energy Systems	Investor Owned	NH	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	26510	Liberty Utilities (Granite State Electri	Investor Owned	NH	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	38084	Great Lakes Energy Coop	Cooperative	MI	MISO	No	Yes	Yes			Automatic	Automatic	
2022	54913	NSTAR Electric Company	Investor Owned	MA	ISNE	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	56697	Ameren Illinois Company	Investor Owned	IL	MISO	Yes	Yes	Yes	Yes	Proceeding	Proceeding	Proceeding	Proceeding
2022	57483	Liberty Utilities	Investor Owned	CA	CISO	Yes	Yes	No	No	Proceeding	Proceeding		

STATE OF MICHIGAN

BEFORE THE MICHIGAN PUBLIC SERVICE COMMISSION

In the matter of the application of **DTE ELECTRIC COMPANY** for authority to increase its rates, amend its rate schedules and rules governing the distribution and supply of electric energy, and for miscellaneous accounting authority	Case No. U-21534 ALJ Sally Wallace

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PROOF OF SERVICE

I, Mark N. Templeton, certify that an electronic copy of the Accompanying Exhibits DAO-260 to DAO-270 (Part 2 of 4) for the Direct Testimony of Arjun Makhijani on Behalf of Soulardarity and We Want Green, Too was served on the following on July 26, 2024.

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The statements above are true to the best of my knowledge, information, and belief.

UNIVERSITY OF CHICAGO LAW SCHOOL
ABRAMS ENVIRONMENTAL LAW CLINIC
Counsel for Soulardarity and
We Want Green, Too

Date: July 26, 2024

Sincerely,

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