California Homelessness Data

Barriers, Methods, and Solutions for Local-Level Analysis

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Date: July 2025

Abstract

To monitor homelessness, state and federal agencies collect data through different systems that are not easily comparable. The U.S. Department of Housing and Urban Development (HUD) conducts annual Point-in-Time (PIT) counts, which estimate the number of people experiencing homelessness on a single night each January. Meanwhile, the U.S. Census Bureau gathers comprehensive population demographics through the decennial Census and the annual American Community Survey (ACS). However, these datasets rely on different definitions, geographic boundaries, and data collection timelines. This misalignment creates barriers to calculating accurate homelessness rates, which are critical for comparative analysis and evidence-based policymaking.

This study bridges that gap by integrating HUD's Point-in-Time counts with Census demographic data across California's metropolitan areas. Using geospatial analysis, it creates a combined dataset that calculates homelessness rates (% homeless) for each region alongside corresponding demographic characteristics. This integrated approach reveals significant geographic variation in homelessness rates and makes possible demographic analyses that were previously challenging due to fragmented data. The framework provides a replicable method for other regions to better understand local homelessness patterns. To accelerate further research, the dataset is being released through a Kaggle machine learning competition, inviting new insights into the factors that drive homelessness and helping inform better resource allocation.

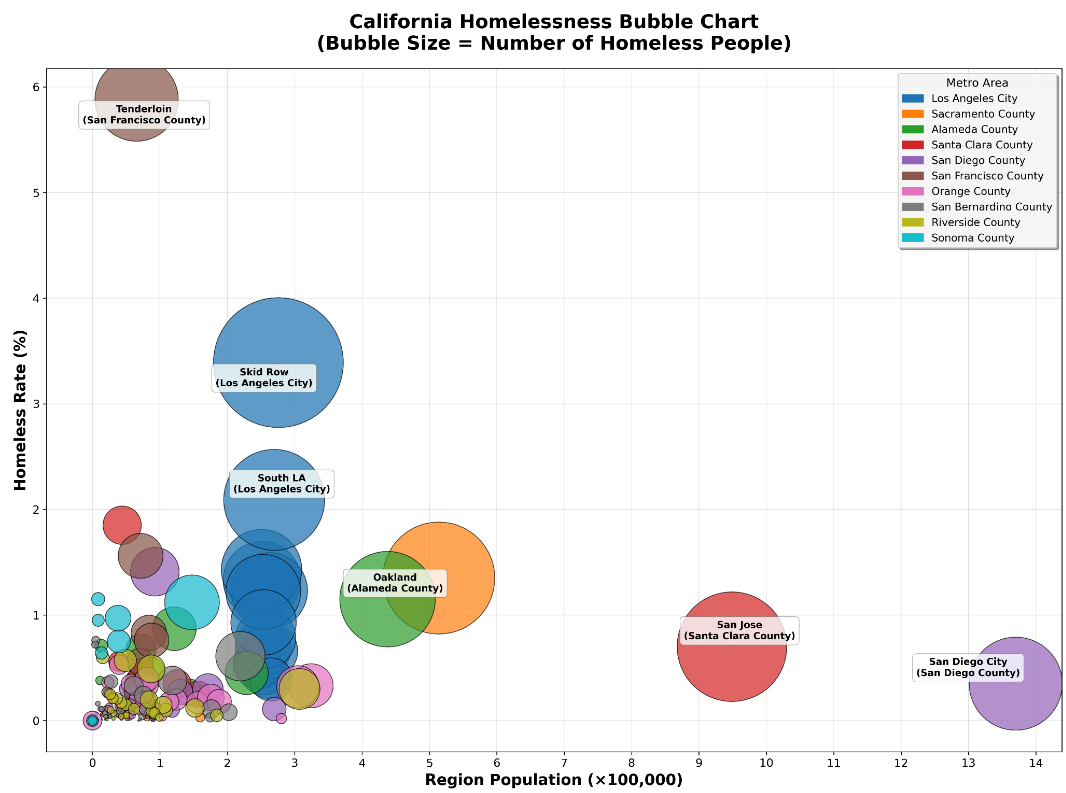

Figure 1. This plot highlights regional disparities in homelessness across California. Areas like Skid Row in Los Angeles and the Tenderloin in San Francisco stand out for both high homeless rates and large homeless populations. Other outliers such as South LA, Oakland, Sacramento, and San Jose also show concerning levels of homelessness, either in absolute numbers or as a percentage of the total population.

Introduction

Homelessness affects more than 187,000 people across California on any given night (HUD, 2024), making it both a profound human crisis and a persistent policy challenge. Billions in public spending flow into homelessness programs each year, yet answering basic questions — *which communities have the greatest need, which populations are most at risk, and whether interventions are working* — remains remarkably difficult.

Federal and local agencies do collect extensive data: annual Point-in-Time (PIT) counts estimate people experiencing homelessness, while the Census provides detailed population demographics. But these datasets use incompatible formats, different geographic boundaries, and inconsistent definitions. As a result, researchers cannot easily calculate what percentage of a community's population is homeless or detect demographic patterns that might guide prevention efforts.

The consequences of this fragmentation are stark. A recent audit of Los Angeles found that tracking $2.5 billion in homelessness spending was nearly impossible due to poor documentation and the lack of standardized data collection (Alvarez & Marsal, 2025). The human cost is even clearer: from 2021 to 2022, the all-cause mortality rate among people experiencing homelessness in Los Angeles County was nearly four times that of the general population (Los Angeles County Department of Public Health, 2024).

This study addresses that gap by integrating HUD PIT counts with Census demographic data across California's metropolitan regions. The resulting dataset enables standardized rate calculations, making it possible to compare local homelessness patterns and identify risk factors. To accelerate research progress, the dataset is being released through a Kaggle analysis competition, inviting data scientists to develop insights that can inform targeted prevention strategies and better resource allocation.

Data Infrastructure Barriers

Despite billions in annual spending on homelessness programs in California, basic questions about where and why people remain unhoused are surprisingly hard to answer. Federal guidelines do establish frameworks for counting affected populations, but multiple issues make this data either unavailable or unusable.

The system is fractured at multiple levels. First, key data is collected by separate federal agencies — HUD and the U.S. Census Bureau — using different definitions and timelines, with no shared framework to align their outputs. Second, requests for sub-county data are often passed between agencies without resolution, halting even basic analysis. Third, public releases usually stop at coarse regional summaries not aligned to Census tract definitions, making neighborhood-level rate calculations nearly impossible and turning policy evaluation into guesswork (LAist, 2023).

As an example, HUD requires counties to submit annual sheltered counts and unsheltered counts every other year (HUD PIT Count Methodology Guide, 2023). But while HUD collects detailed local submissions, there is no API for researchers to access this data at the tract or district level. Inquiries to HUD for sub-county data are typically redirected back to local agencies — even though HUD itself must, or certainly should, have this information in its systems. Direct requests to HUD for this information were not successful. As the U.S. Government Accountability Office notes, "HUD does not make available PIT count data below the CoC level. To obtain local-level data, users must contact individual CoCs" (U.S. Government Accountability Office [GAO], 2020).

Los Angeles, for all its flaws in record-keeping and program management (Alvarez & Marsal, 2025), does produce detailed, usable sub-county counts. The Los Angeles Homeless Services Authority (LAHSA) publishes results by City, Service Planning Area (SPA), and City Council District — a best-in-class example that deserves replication elsewhere.

Others fall far short. San Diego illustrates institutional deflection at its most frustrating. HUD referred data requests to the City, the City redirected them to the Regional Task Force on Homelessness (RTFH), and RTFH ultimately confirmed that sub-county PIT data were neither maintained nor published. To reconstruct historical totals, this project had to rely on archived reports retrieved via the Internet Archive's Wayback Machine — a workaround that underscores the broader inaccessibility of critical public data.

Sacramento stated that no historical city-level PIT data on sheltered homelessness were available, and no files were shared in response to formal records requests. While the county reported a total sheltered population of 2,614 to HUD, no breakdown by city or jurisdiction could be found. As a result, this project applied proportional allocation based on each region's share of the overall PIT count. Though approximate, this method provides reasonable local estimates in the absence of basic sub-county reporting — a gap that could have been addressed with minimal effort by local agencies.

In jurisdictions where PIT data exists, the structure is deeply flawed. The counts exclude critical risk factors like trauma, mental illness, or substance use — all well-documented drivers of homelessness (Leemis et al., 2022). They also rely on inconsistent, often biennial timelines, treating unsheltered homelessness as a phenomenon that can be measured only once every two years. For a crisis where people die on the streets, that level of delay is unacceptable.

These are not just technical gaps — they are structural and institutional failures that prevent the evidence-based policy needed to make progress on this important issue. This is a gap this project was specifically designed to address.

Methodology

Study Design and Geographic Scope

This study used a systematic approach to gather data from ten California counties, each selected for their substantial homeless populations. Data requests were submitted under the California Public Records Act, with an emphasis on obtaining machine-readable formats suitable for statistical analysis.

Data quality and availability varied widely across counties. Los Angeles provided the most comprehensive data, while Sacramento and San Diego posed the greatest challenges — requiring additional methods to fill gaps caused by incomplete or poorly documented records. This combination of missing, incomplete, and inconsistent data across counties made 2022 the most recent time period with information that could be reliably aligned statewide.

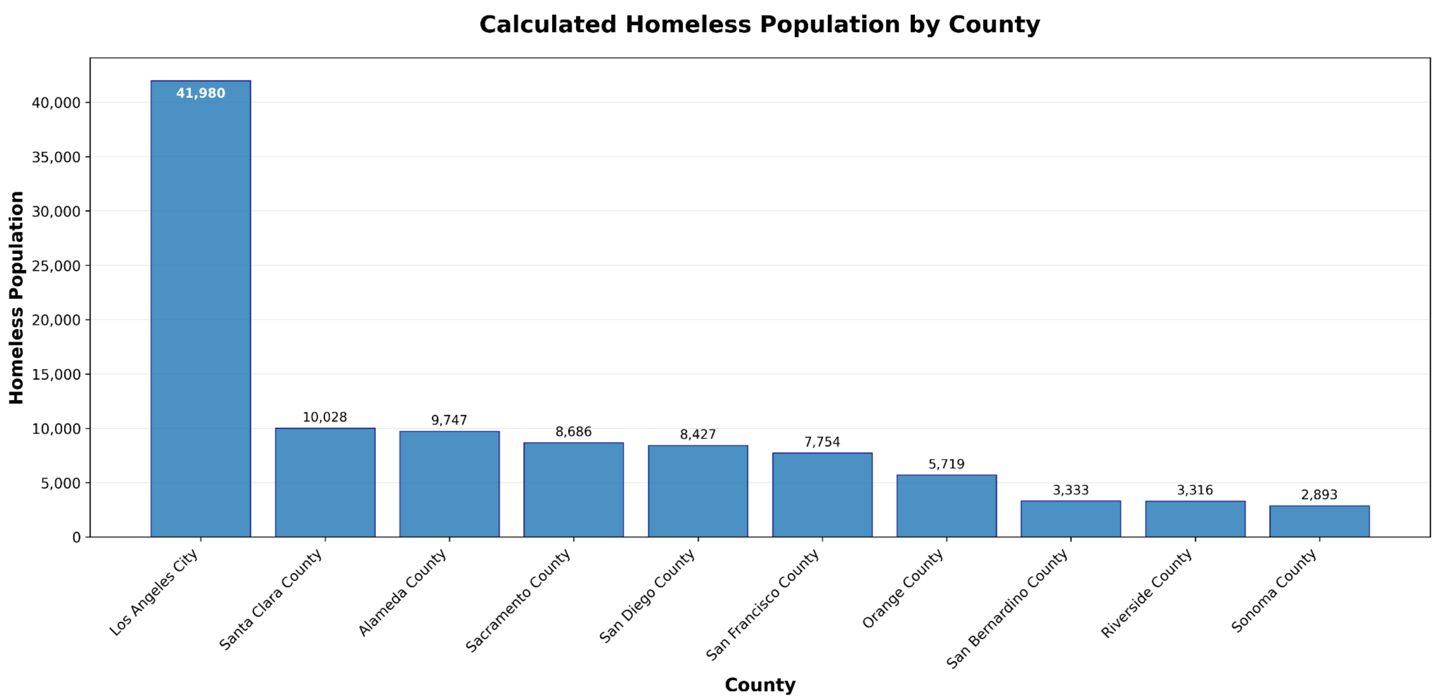

Figure 2. 2022 data was used based on the lack of more recent data across all regions.

Data Integration Framework

Beyond the administrative challenges of obtaining consistent data, the primary technical hurdle was reconciling the geographic boundaries used in HUD data with those used in Census demographic data. A mix of City Council Districts, and city boundaries were used, depending on the county, making it critical to ensure that the population denominators matched the exact areas where homeless data was available.

This process required:

1. Crosswalking local administrative boundaries to corresponding Census geographic units
2. Aligning the timing of Point-in-Time counts with the appropriate Census population estimates

Geographic Boundary Reconciliation

Aligning HUD Point-in-Time (PIT) homelessness counts with Census population data required a clear, replicable geospatial process to resolve mismatched boundaries. This process integrated HUD Continuum of Care (CoC) regions with Census Places and Tracts shapefiles, resulting in standardized geographic identifiers that accurately link PIT counts to population denominators.

Standardized Workflow

1. **Ingest HUD PIT data** to identify all incorporated cities, unincorporated areas, and special jurisdictions.
2. **Load and filter Census shapefiles** for Places and 2020 Census Tracts, restricted to each target county.
3. **Reproject shapefiles** to a common coordinate system (EPSG:3857) to enable spatial operations.
4. **Match HUD region names** to the `NAME` field in the Census Places shapefile.
5. **Generate representative points** guaranteed to lie inside the tract geometry.
6. **Assign tracts to places** via spatial join of representative points within city boundaries.
7. **Label unmatched tracts** as part of the corresponding unincorporated area.
8. **Aggregate ACS B01003 population** from tracts to each assigned region using `GEO_ID`.

This approach ensures that population denominators reflect the same local boundaries used to collect PIT counts — a critical requirement for calculating valid sub-county homelessness rates. In San Francisco and Los Angeles, city council districts were used instead of cities to more precisely delineate unique areas such as Skid Row and the Tenderloin.

A key design decision was to use representative points instead of geometric centroids when assigning tracts. Irregular tract geometries (e.g., narrow corridors or donut shapes) can cause centroids to fall outside boundaries, resulting in misclassified populations. Representative points eliminate this issue and ensure every tract is assigned accurately.

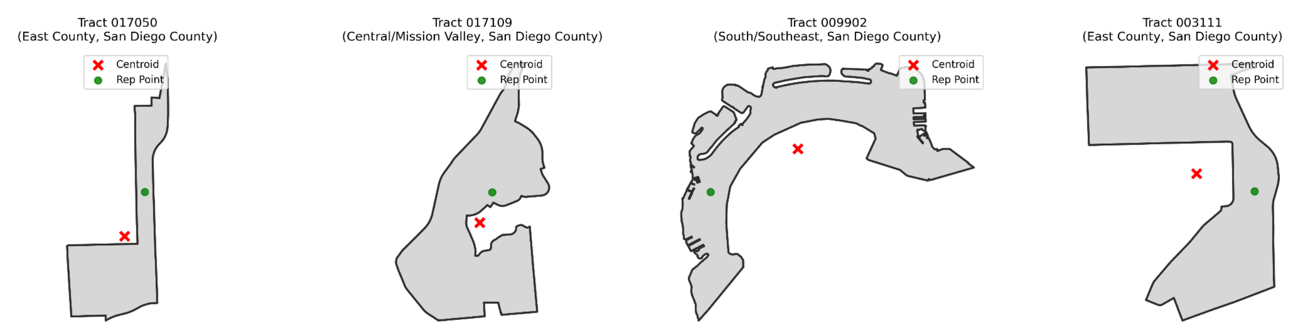

Figure 3. Irregular Census tracts in San Diego County.

Red X = centroid (outside); Green dot = representative point (inside).

Dataset Description

HUD Point-in-Time Data

The HUD Point-in-Time data provides critical information on the number of people experiencing homelessness, but it uses definitions and variables that do not fully align with publicly available Census data — for example, it includes behavioral health and trauma history that the Census does not publish. As a result, the integrated dataset provides homelessness counts converted to percent homeless per region, paired with corresponding Census demographic estimates. This approach makes it possible to analyze geographic variation and demographic patterns that would otherwise be challenging due to siloed data sources. This offers a comprehensive integrated view given the constraints of current public data sources.

Census Demographic Data

Census data provides the population denominators needed to calculate homelessness rates, along with detailed demographic characteristics from several key tables:

- **Table B01003 (ACS):** Total population (5-year estimates)
- **Table B01001 (ACS):** Detailed age and sex distribution
- **Table B21001 (ACS):** Veteran status for the civilian population age 18+
- **Table B18101 (ACS):** Disability status across six functional categories
- **Table B11003 (ACS):** Family structure and household composition
- **Table B15003 (ACS):** Education

Dataset Scale

- **Population Coverage:** +20 million residents across 10 metropolitan areas in California
- **Unique Census Tracts:** ~5k
- **Geographic Granularity:** ~200 sub-county administrative units
- **Feature Count:** ~200 demographic variables
- **Homeless Population Range:** From less than 0.03% to more than 3% of the local population

This level of detail supports robust demographic analysis and enables meaningful comparisons across communities.

Study Limitations

While this framework successfully integrates available public data sources, important analytical constraints remain. Research shows that behavioral health conditions and trauma exposure are critical risk factors for homelessness, with people experiencing homelessness facing substance use disorders, serious mental illness, and domestic violence at rates two to six times higher than the general population (Los Angeles Homeless Services Authority, 2020; SAMHSA, 2023; SAMHSA, 2024; Leemis et al., 2022). However, the Census does not provide this information in its publicly available data.

This creates an inherent “streetlight effect,” where demographic characteristics serve as proxies for unmeasurable behavioral health and trauma factors. As a result, demographic variables may show statistical associations with homelessness rates while representing downstream effects rather than direct causal mechanisms. This limitation constrains the explanatory power of demographic-based models but does not diminish the value of available data for understanding geographic distribution, targeting resources, and informing policy decisions.

Conclusion

This study presents a dataset that integrates Point-in-Time counts with Census demographic data to calculate homelessness rates across California’s metropolitan areas. The methodology addresses institutional data fragmentation through standardized geographic boundary reconciliation.

The resulting dataset enables evidence-based resource allocation and comparative analysis across more than ~200 sub-county regions representing +20 million residents. While demographic variables have inherent limitations compared to unmeasurable behavioral health factors, they remain the best available evidence for population-level homelessness analysis.

The framework provides a replicable template for other metropolitan areas facing similar data integration challenges. Through a Kaggle competition, we invite the data science community to develop explanatory analyses and tools that can advance our understanding of homelessness patterns and inform more effective policy responses.

Appendix: ACS B01001: Sex and Age

Brief Description

Population counts by sex and detailed age groups. Provides the foundation for demographic analysis with comprehensive age and sex breakdowns.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B01001_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

49 count variables from this table included in dataset

Key Variable Groups

- **B01001_001E**: Total population
- **B01001_002E**: Male population
- **B01001_003E-B01001_025E**: Male age groups (23 variables)
  - Under 5, 5-9, 10-14, 15-17, 18-19, 20, 21, 22-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-61, 62-64, 65-66, 67-69, 70-74, 75-79, 80-84, 85+
- **B01001_026E**: Female population
- **B01001_027E-B01001_049E**: Female age groups (23 variables)
  - Same age categories as males

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B01001

Appendix: ACS B11003: Families and Households

Brief Description

Household composition and family structure data. Breaks down households by family type and presence of children by age groups.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B11003_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

20 count variables from this table included in dataset

Key Variable Groups

- **B11003_001E**: Total households
- **B11003_002E**: Married-couple family households
- **B11003_003E-B11003_007E**: Married-couple families by children presence/age (5 variables)
    - With children under 18, under 6 only, 6-17 only, both age groups, no children
- **B11003_008E**: Other family households
- **B11003_009E-B11003_014E**: Male householder families by children presence/age (6 variables)
- **B11003_015E-B11003_020E**: Female householder families by children presence/age (6 variables)

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B11003

Appendix: ACS B18101: Disabilities

Brief Description

Disability status by sex and age groups. Covers civilian noninstitutionalized population with detailed breakdowns of disability presence across age ranges.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B18101_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

39 count variables from this table included in dataset

Key Variable Groups

- **B18101_001E**: Total civilian noninstitutionalized population
- **B18101_002E**: Male population
- **B18101_003E-B18101_020E**: Male by age and disability status (18 variables)
  - Age groups: Under 5, 5-17, 18-34, 35-64, 65-74, 75+
  - For each age group: Total, With disability, Without disability
- **B18101_021E**: Female population
- **B18101_022E-B18101_039E**: Female by age and disability status (18 variables)
  - Same age and disability structure as males

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B18101

Appendix: ACS B21001: Veteran Status

Brief Description

Veteran status by sex and age groups. Covers civilian population 18 years and over with detailed veteran/nonveteran breakdowns.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B21001_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

39 count variables from this table included in dataset

Key Variable Groups

- **B21001_001E**: Total civilian population 18 years and over
- **B21001_002E**: Veteran population
- **B21001_003E**: Nonveteran population
- **B21001_004E**: Male population 18+
- **B21001_005E-B21001_022E**: Male by veteran status and age groups (18 variables)
    - Age groups: 18-34, 35-54, 55-64, 65-74, 75+
    - For each age group: Total, Veteran, Nonveteran
- **B21001_023E**: Female population 18+
- **B21001_024E-B21001_039E**: Female by veteran status and age groups (16 variables)
    - Same age and veteran status structure as males

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B21001

Appendix: ACS B03002: Race and Hispanic Origin

Brief Description

Race and Hispanic/Latino ethnicity data. Treats race and ethnicity as independent measures - people can be counted in both a racial category AND as Hispanic/Latino.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B03002_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

21 count variables from this table included in dataset

Key Variable Groups

- **B03002_001E**: Total population
- **B03002_002E**: Not Hispanic or Latino (total)
- **B03002_003E-B03002_009E**: Not Hispanic or Latino by race (7 variables)
  - White alone, Black/African American alone, American Indian/Alaska Native alone, Asian alone, Native Hawaiian/Pacific Islander alone, Some other race alone, Two or more races
- **B03002_010E-B03002_011E**: Not Hispanic or Latino multiracial categories (2 variables)
- **B03002_012E**: Hispanic or Latino (total)
- **B03002_013E-B03002_021E**: Hispanic or Latino by race (9 variables)
  - Same racial categories as non-Hispanic groups

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B03002

Appendix: ACS B15003: Education

Brief Description

Educational attainment levels for adults. Covers population 25 years and over with detailed educational achievement categories from no schooling through doctorate degrees.

Survey Period

2018-2022 5-Year ACS Estimates

How this table can be identified

All variables begin with **B15003_** followed by a 3-digit sequence number and **E** (for estimate).

Dataset Variables

25 count variables from this table included in dataset

Key Variable Groups

- **B15003_001E**: Total population 25 years and over
- **B15003_002E-B15003_016E**: Elementary and secondary education (15 variables)
  - No schooling through 12th grade (detailed grade levels)
- **B15003_017E-B15003_018E**: High school completion (2 variables)
  - Regular high school diploma, GED or alternative credential
- **B15003_019E-B15003_021E**: Some college and associate degree (3 variables)
  - Some college less than 1 year, some college 1+ years no degree, associate degree
- **B15003_022E-B15003_025E**: Bachelor's degree and higher (4 variables)
  - Bachelor's degree, master's degree, professional degree, doctorate degree

Census Documentation

Variable definitions and friendly names: https://data.census.gov/table?q=B15003

Appendix: Denominator Options

Decisions on the base value to calculate rates will need to be made. Each METRO is divided into multiple REGIONs based on the source data. This creates an option for the analysis on the most usable basis.

1. METRO Approach

Group by METRO and sum B01001_001E to use as the denominator for any/all demographics if you wish to look at distributions at the METRO level.

2. REGION Approach

Group by REGION_CODE and sum B01001_001E to use as the denominator for any/all demographics if you wish to look at distributions at the REGION_CODE level.

Small Sample Issues

- Small denominators can produce unstable rates
- Consider setting minimum thresholds for reliable estimates
- Be cautious with percentages based on very small populations

Division by Zero

Decisions on the handling of Division by Zero will need to be made.

Race and Ethnicity Example

Some values will aggregate to greater than 100% of the total population. An example is when looking at RACE and Ethnicity. Data here treats them as independent measures.

Reference: https://www.census.gov/topics/population/race/about.html

Key concept: "Race and ethnicity are independent of each other" - people can be counted in both a racial category AND as Hispanic/Latino.

Resources

- **ACS Documentation**: https://www.census.gov/programs-surveys/acs/

Appendix: References

(APA 7th Edition Format)

Alvarez & Marsal. (2025). *Los Angeles Homeless Services Authority Financial and Performance Audit*. Alvarez & Marsal.

Anthropic. (2025). Claude (Version 4) [Large language model]. https://claude.ai

CalMatters. (2024, April 10). *California homelessness spending*. CalMatters. https://calmatters.org/housing/homelessness/2024/04/california-homelessness-spending/

Elgas, D. (2024). *Exploring the predictive power of socioeconomic data on homelessness in Los Angeles, CA*. Harvard University. https://medium.com/@davidelgas

Kreighbaum, A. (2024, May 16). *Audit finds flaws in LA's homeless services*. LAist. https://laist.com/news/housing-homelessness/audit-homeless-carter-lahsa

Leemis, R. W., Friar, N., Khatiwada, S., Chen, M. S., Kresnow, M., Smith, S. G., Caslin, S., & Basile, K. C. (2022). *The National Intimate Partner and Sexual Violence Survey: 2016/2017 Report on Intimate Partner Violence*. Centers for Disease Control and Prevention.

Los Angeles County Department of Public Health. (2024). *Mortality among People Experiencing Homelessness in Los Angeles County, 2021–2022*. Los Angeles County Department of Public Health.

Los Angeles Homeless Services Authority. (2020). *2020 Greater Los Angeles Homeless Count – City of Los Angeles Council District 1*. Los Angeles Homeless Services Authority.

Substance Abuse and Mental Health Services Administration. (2023). *Key Substance Use and Mental Health Indicators in the United States: Results from the 2023 National Survey on Drug Use and Health*. Center for Behavioral Health Statistics and Quality.

Substance Abuse and Mental Health Services Administration. (2024). *SAMHSA Releases Annual National Survey on Drug Use and Health*. Substance Abuse and Mental Health Services Administration.

U.S. Census Bureau. (2020). *2020 Census: Census counts people experiencing homelessness* [Fact sheet]. https://www.census.gov/content/dam/Census/library/factsheets/2020/dec/census-counts-homeless.pdf

U.S. Department of Housing and Urban Development. (2024). *The 2024 Annual Homelessness Assessment Report (AHAR) to Congress, Part 1: Point-in-Time Estimates of Homelessness in the U.S.* HUD Office of Community Planning and Development.

U.S. Department of Housing and Urban Development. (2023). *Point-in-Time Count Methodology Guide*. HUD Exchange. https://www.hudexchange.info/resources/documents/PIT-Count-Methodology-Guide.pdf

U.S. Government Accountability Office. (2020). *Homelessness: Better HUD Oversight of Data Collection Could Improve Estimates of Homeless Population* (GAO-20-433). https://www.gao.gov/products/gao-20-433

Appendix: Census Tract Assignments for small communities

To evaluate the feasibility of linking HUD Point-in-Time (PIT) homeless count regions—defined as cities, Census Designated Places (CDPs), or special areas—to 2020 Census Tracts for accurate population assignment and demographic analysis.

Data & Methods

- **Data Sources:** HUD PIT region definitions, 2020 TIGER/Line Census Tracts and Places, ACS tract and place-level data, and tract-to-PUMA crosswalks.
- **Primary Approach:** Spatial join of tract representative points within HUD region polygons (cities or places).
- **Fallback:** Use of CDP boundaries and population data when spatial tract assignment fails.
  Validation: Cross-check regions with tract and CDP coverage to identify unassignable areas.

Key Findings

- Most HUD PIT regions correspond to one or more Census tracts, enabling direct population linkage.
- Certain smaller or specialized CDPs (e.g., Lenwood, San Bernardino County) lack intersecting 2020 Census tracts.
- CDP-level data exist but do not provide tract-level GEOIDs, limiting integration with tract-based ACS features.
- These geographic mismatches necessitate explicit handling in population assignments.

Implications

- Regions without tract assignments should be flagged and assigned zero population for rate calculations.
- Researchers must document unassignable areas and consider alternative geographic methods when feasible.
- Transparency in linkage methodology enhances reproducibility and policy relevance.

Recommendations

- Prioritize spatial joins to tracts for population assignment.
- Use CDP data only as a secondary fallback, noting limitations.
- Clearly document and treat regions lacking tract matches separately.
- Monitor updates to geographic crosswalks for improved coverage.

Appendix: Source Files

```
================================================================================
1. ALAMEDA COUNTY
================================================================================
=== Homelessness Data ===
Reporting Agency: EveryOne Home (Alameda County CoC)
Agency URL: https://homelessness.acgov.org/
File URL:
https://homelessness.acgov.org/homelessness-assets/docs/reports/2022-Alameda-County-PIT-Report_9.2
2.22-FINAL-3.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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2. LOS ANGELES COUNTY
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=== Homelessness Data ===
Reporting Agency: Los Angeles Homeless Services Authority (LAHSA)
Agency URL: https://www.lahsa.org/
File URL: https://www.lahsa.org/documents?id=6532-countywide-geography-summary.pdf
Year: 2022 Point-in-Time Count
Note: City Council Districts used for additional detail.

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== Council District Boundaries ===
Reporting Agency: Los Angeles County GIS
Agency URL: https://egis-lacounty.hub.arcgis.com/
File URL:
https://public.gis.lacounty.gov/public/rest/services/LACounty_Dynamic/Political_Boundaries/MapServ
er/27
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022
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3. ORANGE COUNTY
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=== Homelessness Data ===
Reporting Agency: Orange County HMIS
Agency URL: https://ochmis.org/
File URL:
https://ochmis.org/wp-content/uploads/2022/05/2022-Pit-Data-Infographic-5.10.2022-Final.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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4. RIVERSIDE COUNTY
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=== Homelessness Data ===
Reporting Agency: Housing Authority of the County of Riverside
Agency URL: https://harivco.org/
File URL: https://kesq.b-cdn.net/2022/05/2022_Homeless_PITC.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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5. SACRAMENTO COUNTY
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=== Homelessness Data ===
Reporting Agency: Sacramento Steps Forward
Agency URL: https://sacramentostepsforward.org/
File URL: https://sacramentostepsforward.org/wp-content/uploads/2022/06/PIT-Report-2022.pdf
Year: 2022 Point-in-Time Count
Note: Sub-region totals required manual addition of HIC data to supplement PIT detail. 2-person discrepancy remains vs. HUD total (0.02% difference).

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018–2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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6. SAN BERNARDINO COUNTY
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=== Homelessness Data ===
Reporting Agency: San Bernardino County
Agency URL: https://main.sbcounty.gov/
File URL: https://www.sbcounty.gov/uploads/sbchp/SBC-2022-Homeless-Count-Report.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018–2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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7. SAN DIEGO COUNTY
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=== Homelessness Data ===
Reporting Agency: Regional Task Force on Homelessness (RTFH)
Agency URL: https://www.rtfhsd.org/
File URL:
https://www.rtfhsd.org/wp-content/uploads/2025/01/2022-San-Diego-Region-Cities-Sheltered-and-Unsheltered-Breakdown-FINAL_05182022.pdf
Year: 2022 Point-in-Time Count
Note: 16 cities plus unincorporated region used.

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018–2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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8. SAN FRANCISCO COUNTY
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=== Homelessness Data ===
Reporting Agency: SF Department of Homelessness & Supportive Housing (HSH)
Agency URL: https://hsh.sfgov.org/
File URL:
https://hsh.archive.sf.gov/wp-content/uploads/2022/08/2022-PIT-Count-Report-San-Francisco-Updated-8.19.22.pdf
Year: 2022 Point-in-Time Count
Note: Supervisorial Districts used for additional detail.

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018–2022 ACS 5-Year Estimates

=== Supervisorial District Boundaries ===
Reporting Agency: SF Department of Elections / DataSF
Agency URL: https://data.sfgov.org/
File URL: https://data.sfgov.org/Geographic-Locations/Supervisorial-Districts-2022/yjzx-k7si
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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9. SANTA CLARA COUNTY
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=== Homelessness Data ===
Reporting Agency: Santa Clara County Continuum of Care
Agency URL: https://www.santaclaracounty.gov/
File URL:
https://files.santaclaracounty.gov/exjcpb1571/migrated/2022%20PIT%20Report%20Santa%20Clara%20Count
y.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022

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10. SONOMA COUNTY
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=== Homelessness Data ===
Reporting Agency: Sonoma County Continuum of Care / County of Sonoma
Agency URL: https://sonomacounty.gov/
File URL:
https://sonomacounty.gov/Main%20County%20Site/Health%20and%20Human%20Services/Health%20Services/Do
cuments/Homelessness%20Services/Homeless%20Data/County%20of%20Sonoma%202022%20Point-in-Time%20Coun
t%20Results.pdf
Year: 2022 Point-in-Time Count

=== ACS Census Data ===
Reporting Agency: U.S. Census Bureau
Agency URL: https://www.census.gov
File URL: https://data.census.gov/table/ACSDT5Y2022.B01003
Year: 2018-2022 ACS 5-Year Estimates

=== City/Place Boundaries ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/PLACE/tl_2022_06_place.zip
Year: 2022

=== Census Tract Shapefiles ===
Reporting Agency: U.S. Census Bureau TIGER/Line
Agency URL: https://www.census.gov
File URL: https://www2.census.gov/geo/tiger/TIGER2022/TRACT/tl_2022_06_tract.zip
Year: 2022