Bridging Homelessness and Census Data: A CoC-to-Place Geographic Crosswalk

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Motivation

Homelessness Point-in-Time (PIT) counts and Housing Inventory Counts (HIC) are reported at the Continuum of Care (CoC) level, while Census data on housing and economic conditions are reported at the county and place level. We construct a crosswalk linking CoC codes to Census place FIPS codes, enabling researchers and policymakers to merge these two critical data sources at the CoC-level for every CoC in the nation.

Background

HUD's ∼400 CoCs are the primary geographic unit for homelessness data collection and service delivery. However, CoC boundaries do not consistently correspond to any standard Census geography. Historically, therefore, researchers have been forced to pool CoCs to match county boundaries.

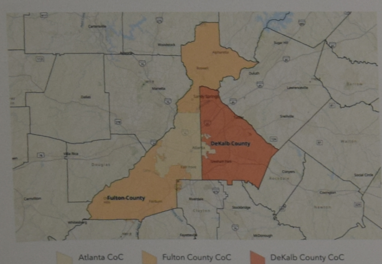


Figure 1:Atlanta CoC and county boundaries

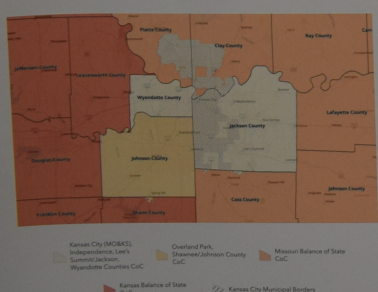


Figure 2:Kansas City CoC and county boundaries

The Crosswalk

Researchers have taken various approaches to overcome geographic complexity (see, for instance, concurrent work by Schachner and Gannon), but to my knowledge, there is currently no crosswalk that makes Census data available at the CoC level for every CoC in the U.S.

Manual inspection of each CoC's boundaries using HUD documentation reveals that **all CoC boundaries that do not align with Census county boundaries appear to be explained by Census place boundaries.** I construct the crosswalk by applying county- and place-level inclusions and exclusions to handle CoCs whose boundaries do not follow county lines. Each row represents one CoC-county-place match and contains:

- `coc_code` — HUD Continuum of Care identifier
- `state_fips` — State FIPS code
- `county_fips` — County FIPS code
- `place_fips` — Census place FIPS code

s_coc_code	state_fips	county_fips	county	place_fips	place	population
MO-604a	20	209	wyandotte	36000	kansas city city	155135
MO-604a	20	209	wyandotte	37975	lake quivira city	51
MO-604a	29	037	cass	38000	kansas city city	86
MO-604a	29	037	cass	41348	lees summit city	2708
MO-604a	29	047	clay	38000	kansas city city	140584
MO-604a	29	095	jackson	06652	blue springs city	59965
MO-604a	29	095	jackson	06670	blue summit cdp	1156
MO-604a	29	095	jackson	09424	buckner city	2914
MO-604a	29	095	jackson	28090	grain valley city	16271
MO-604a	29	095	jackson	28324	grandview city	26527
MO-604a	29	095	jackson	29494	greenwood city	5777
MO-604a	29	095	jackson	35000	independence city	121740
MO-604a	29	095	jackson	38000	kansas city city	315556

Figure 3:Kansas City CoC rows (partial)

Demonstration: Visualizing Per-Capita Homelessness

Unlike many other economic and demographic topics, even basic homelessness statistics have rarely been presented in per-capita terms below the state level because previously, it would have been challenging to measure the population of any CoC that does not happen to fall neatly within county lines. With the crosswalk in hand, PIT count data can now be merged with ACS place-level variables, facilitating novel research. In particular, I compute per capita homelessness at the CoC-level.

Count

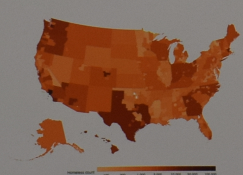


Figure 4:Heatmap: Log homeless count

Rank	CoC	State	Homeless Count	Per 100k
1	New York City	NY	140,134	1,652
2	Los Angeles	CA	75,308	768
3	Chicago	IL	18,836	695
4	Seattle	WA	16,868	738
5	Denver	CO	14,281	436
6	San Diego	CA	10,605	322
7	Santa Clara	CA	10,394	546
8	Alameda	CA	9,450	573
9	Phoenix	AZ	9,435	207
10	San Francisco	CA	8,323	1,002
11	Las Vegas	NV	7,906	339
12	Portland	OR	7,384	921
13	Orange County	CA	7,322	231
14	Sacramento	CA	6,615	415
15	Boston	MA	5,898	885
16	DC	DC	5,616	824
17	Philadelphia	PA	5,191	329
18	Stockton	CA	4,732	593
19	Honolulu	HI	4,497	449
20	Fresno	CA	4,305	366

Table 1:Top 20 CoCs by homeless count

Rate

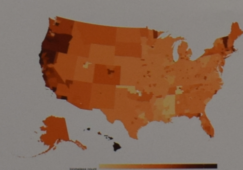


Figure 5:Heatmap: Log homeless per 100k

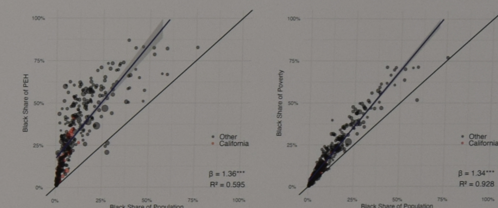
Rank	CoC	State	Homeless Count	Per 100k
1	New York City	NY	140,134	1,652
2	Humboldt	CA	1,573	1,169
3	Bristol County	MA	1,179	1,167
4	Lynn	MA	1,100	1,082
5	San Francisco	CA	8,323	1,002
6	Portland	OR	7,384	921
7	Lake	CA	604	886
8	Boston	MA	5,898	885
9	Mendocino	CA	774	858
10	Imperial	CA	1,508	837
11	DC	DC	5,616	824
12	Eugene	OR	3,085	803
13	Los Angeles	CA	75,308	768
14	Redding/N CA	CA	2,404	768
15	Seattle	WA	16,868	738
16	Santa Cruz	CA	1,850	698
17	Central	OR	1,799	698
18	Chicago	IL	18,836	695
19	Butte	CA	1,381	664
20	Springfield	MA	3,018	652

Table 2:Top 20 CoCs by homeless count

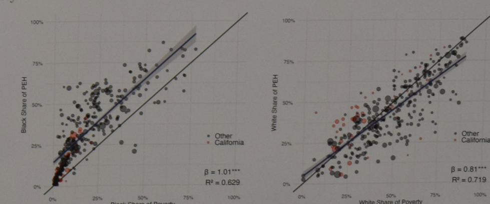
Utility in Research: Racial Disparities in Homelessness

This crosswalk also makes it possible to estimate relationships between homelessness, poverty, and other factors at a granular geographic level, capturing within-state heterogeneity and increasing statistical power. To illustrate this, I merge 2020-2024 ACS data with 2024 PIT counts and investigate how the relationship between poverty and homelessness differ by race.

As national statistics have long indicated, Black Americans experience homelessness at much higher rates than the broader U.S. population. I find that this is true in nearly every CoC (left). This may be partly attributable to the fact that Black Americans also experience poverty at higher rates than the broader population — again, this is the case in nearly every CoC (right).



With poverty and homelessness rates now available at the CoC level, however, it is possible to confirm that Black Americans experience homelessness at higher rates than other racial groups, even conditional on poverty.



Conclusions & Future Work

- The CoC-to-place crosswalk fills a longstanding gap in homelessness research and policy infrastructure
- Researchers can now link PIT counts to ACS housing, poverty, and labor market variables at the CoC level
- This also allows policymakers to obtain census data for their specific CoC, informing policy decisions
- We are in the process of linking the FBI's Uniform Crime Reports (UCR) dataset to this crosswalk, allowing us to analyze existing variables in conjunction with crime incidence at the CoC level
- Future work will modify the crosswalk to take into account CoC boundary changes, enabling longitudinal analysis and causal research

Acknowledgements

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