City-Defined Neighborhood Boundaries in the United States

Stephen Ansolabehere[1], Jacob R. Brown[2], Ryan D. Enos[1], Ben Shair[3], Tyler Simko[4], and David Sutton[1]

[1]Harvard University, Department of Government
[2]Boston University, Department of Political Science
[3]University of Rochester
[4]Princeton University, Department of Politics

ABSTRACT

Neighborhoods are frequently cited as impactful for social, economic, political, and health outcomes. Measuring neighborhoods, however, is challenging, as the definition of a neighborhood may change dramatically across places. Researchers lack widespread but locally-sourced data on neighborhoods, and instead often adopt widely available but arbitrary Census geographies as neighborhood proxies. Others invest in the collection of more precise definitions, but these types of data are hard to collect at scale. We address this tension between scale and precision by collecting, cleaning, and providing to researchers a new dataset of *city-defined neighborhoods*. Our data includes 206 of the largest cities in the United States, covering more than 77 million people. We combine these data with block-level Census demographic data and provide them along with open-source software to aid researchers in their use.

Introduction

Neighborhoods are the basic unit of analysis for many areas of social science. Examples include research on the social benefits of connected life in neighborhoods and communities (1; 2), intergenerational mobility and socioeconomic inequality (3; 4; 5), geographic and community sorting of individuals, crime (6; 7), the provision of public health and social services (e.g. 8), racial context and racial attitudes (9; 10), attitudes towards redistribution (11), and neighborhood effects on political behavior (12; 13; 14; 15).

Across this broad range of applications, measuring neighborhoods is a common research challenge. This measurement challenge arises because the term "neighborhood" has different meanings in different contexts. While neighborhoods are typically associated with particular geographic areas, neighborhoods are also "social constructions named and bounded differently by numerous and diverse individuals" structured by different perceptions between people (pg. 252 16) (quoted in (17)). More concretely, a Census Tract is a commonly deployed geographic unit representing a neighborhood in social science research. Yet, a 4,000 person (the target size for Census Tracts) tract in Manhattan may be more or less appropriate for capturing a Manhattan neighborhood than a 4,000 person Census Tract captures a neighborhood in Green Bay, Wisconsin. The extent to which neighborhoods form along different infrastructural or demographic boundaries likely varies across place as well. Complicating matters further, there may not be a common definition of neighborhoods even within the same city. Measurement and standardization concerns are recurring issues in the study of local politics more generally, given a lack of pre-existing centralized data on many subjects of interest for scholars (18; 19; 20).

This measurement problem appears in the study of neighborhoods when scholars seek to study multiple cities at the same time. When examining individual cities with well-defined historical and social neighborhoods, scholars often turn to local city-defined boundaries. For example, Sampson uses locally-defined neighborhoods in his work on Chicago (4). While local neighborhood definitions offer promising neighborhood definitions for place-based research that integrate local knowledge and context, local definitions are not centralized. Thus, researchers face a measurement problem when studying cities where neighborhoods are hard to find, or when studying multiple cities. Researchers generally address this measurement problem in one of two ways — (1) using administrative boundaries defined by the US Census Bureau, or (2) less commonly, by surveying subjective definitions of neighborhoods.

We argue these approaches both have limitations from a trade-off between *scale* and *precision*. The most common way to approximate neighborhoods relies on boundaries like Census Tracts, Census Block Groups, Census Voting Tabulation Districts (VTDs), and Postal Service ZIP Codes (ZIPs, ZCTAs). These layers are convenient for research at *scale* because they are universally defined by the Census Bureau and easy to download. However, they suffer from a lack of *precision* because they are defined for statistical reporting purposes, and do not necessarily correspond to the common meaning of a neighborhood as a local area of closely connected people, social activities, or economic activities. Alternatively, other research attempts to define neighborhoods using the subjective definitions that people provide when asked to draw, define, or otherwise describe their neighborhood (17; 21; 22; 23; 24; 25; 26). This research is informative about the connectedness of local areas and may offer better precision than administrative units, but require costly surveys that are difficult to scale to provide a national picture of neighborhoods in the United States.

In this paper, we address this tension between scale and precision by collecting, cleaning, and analyzing a new dataset of neighborhoods as defined by city governments. Our sample includes 20,635 neighborhoods for 206 of the largest cities in the United States (shown in Figure 1), encompassing more than 77,000,000 American residents. We attempted to acquire city-defined neighborhoods for each of the 336 cities in the United States with populations over 100,000 people as of 2022 through a combination of manual searches, direct contact with city officials, and open records requests. Our sampling frame thus includes the largest cities in the United States like New York, Los Angeles, and Chicago and more moderately sized cities like New Bedford, Massachusetts and Davenport, Iowa

We find that many major cities in the United States define neighborhoods for internal or external purposes. Often, these neighborhoods serve as the base layer for administrative city functions ranging from planning to parking to policing to schools. Many are historically rooted sub-communities defined by geographic features within a city or dating to the original incorporation of an area into the city. The data we collected further demonstrate that neighborhoods vary substantially in characteristics like population, area, and racial/ethnic diversity, both within and across cities.

We release two files for each city in the **City-Defined Neighborhood Dataset (CDND)**. First, we process and clean each neighborhood shapefile into a consistent format. Second, we combine these data on city-defined neighborhoods with 2020 Census Block demographic information. We demonstrate the utility of the **CDND** by comparing city-defined neighborhood definitions to commonly used proxies: Census Tracts, Block Groups, and Zip Codes. We use a series of comparisons and visualizations to demonstrate that city-defined neighborhoods are distinctive from these common neighborhood proxies. Comparisons of population and other demographics across and within cities further illustrate the potential for mismatch when relying on neighborhood proxies rather than our data.

The rest of the article proceeds as follows. First, we describe the data collection process for building a dataset of city-defined neighborhoods. Second, we present examples and summary statistics from the **CDND**. Third, we compare our city-defined neighborhoods to alternative neighborhood measures. We conclude with information on accessing the full dataset.

Building a Dataset of Neighborhoods

We rely on the expertise of local governments to collect neighborhood definitions. Many city governments define their own neighborhood boundaries. These neighborhoods are defined and used for various purposes, like planning and development, statistical reporting on public dashboards, and defining roles for public input via neighborhood associations. Even in cases where city governments do not have a single pre-specified purpose for neighborhood definitions, they often maintain maps of the boundaries of the city's neighborhoods to record what is commonly understood by city residents and officials as the distinctive areas of the city. Our data collection is thus motivated by asking cities directly to show us what are the neighborhoods in their municipalities, as this surveying is most likely to yield the best available data — locally sourced and officially maintained. This process means that we are capturing neighborhoods defined for official governmental purposes and often reflecting long-standing historical or sociological understandings that are meaningful to residents of the city. This process stands in contrast to alternative practices of overlaying Census or other geographies and assuming these reflect an underlying local reality.

For each city, we used a two-stage process to identify city-defined neighborhood boundaries. First, we searched websites of city and state offices for maps with designated neighborhoods. These searches included official websites of the city government or the cities' Geographic Information Systems (GIS) office, which often contained data on neighborhood boundaries in the form of a shapefile for use in GIS software. For example, Miami, Florida maintains a neighborhoods shapefile on their public "City of Miami GIS Open Data" portal alongside other datasets like trash routes and parcel maps.[1] Second, we contacted every city for which no map could be found in our initial searches. We started with an email or phone call and submitted formal records requests for cities that did not respond.

We differentiate between three different types of commonly available neighborhood definitions maintained by cities. First, we find boundaries of city-defined neighborhoods. These generally cover most or all land in the city and are the clearest representation of city-defined neighborhoods. Second, we find boundaries of neighborhood housing associations or neighborhood councils (NHAs). These are distinct from the first type in that they less frequently cover the entirety of the city, and are often for the specific use of citizen neighborhood engagement. However, we include NHAs as an alternative definition of neighborhoods, as local government officials often pointed to these as the most accurate neighborhood boundaries in the absence of city-defined neighborhoods. Therefore, in our data we include both of these types of boundaries as neighborhoods.

[1] The City of Miami, FL's Open Data portal is found here: `https://datahub-miamigis.opendata.arcgis.com/`

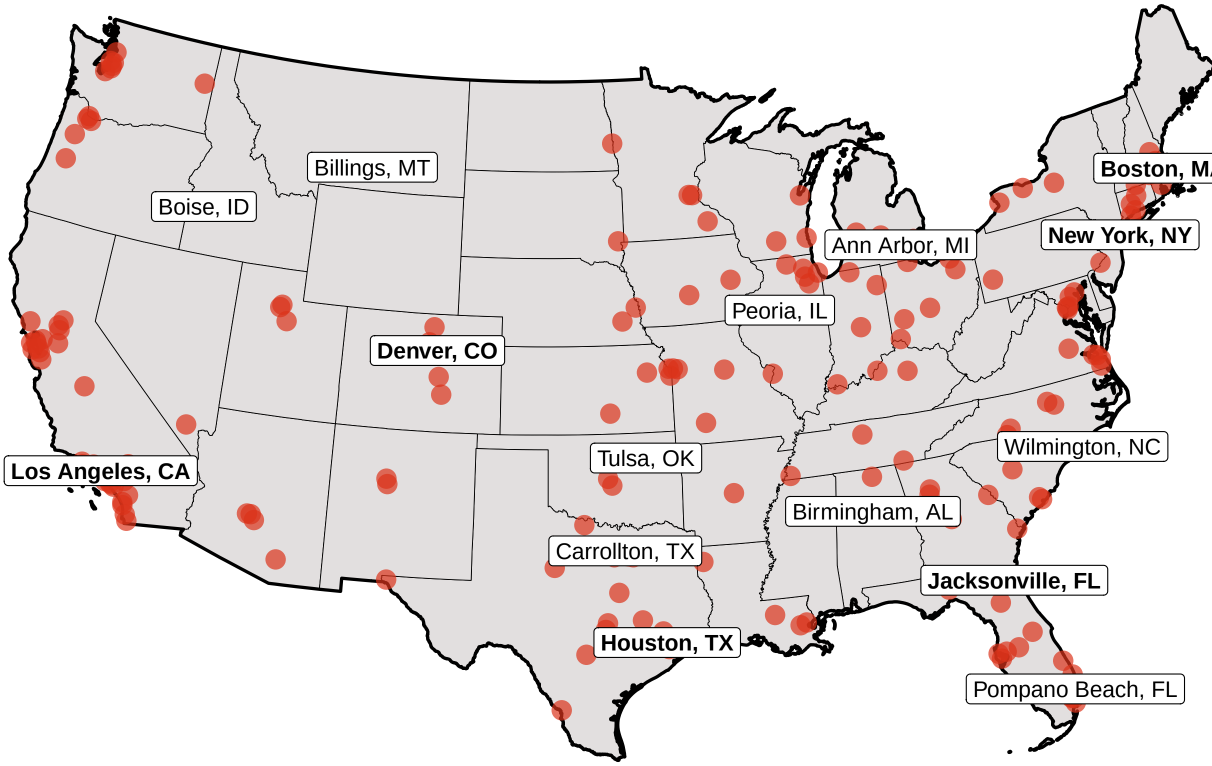

Figure 1. Neighborhoods Data Map This figure shows a map of the cities in our neighborhoods data. Each city is visualized as a red point. We label several example cities. Our sample includes both large and mid-sized cities: bold labels indicate the city is among the top 25 cities by population (though, note that the labels shown here are not exhaustive of the large cities in our sample), while other cities are shown in regular font. Anchorage, AK and Honolulu, HI are both included in the sample, though not visualized here.

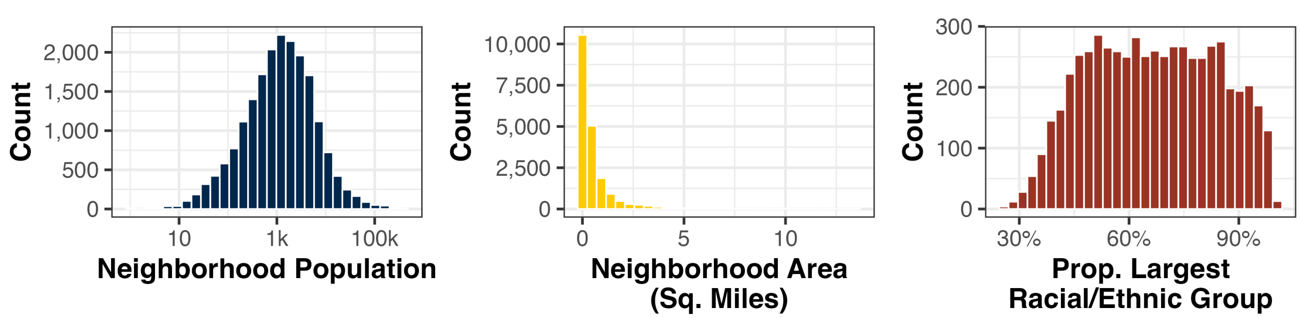

Figure 2. Neighborhoods and Sample Descriptives The histograms above demonstrate that our 25,213 sample neighborhoods vary widely across population, area, and racial composition. The left plot shows the total population in each neighborhood as reported by the 2020 Census, the middle column shows the number of square miles in each neighborhood, and the right column shows the proportion of the largest racial/ethnic group in each neighborhood (for neighborhoods with a total population of at least 500 Black, Hispanic, White, and Asian residents reported in the 2020 Census).

Table 1. Counts of neighborhood types across cities in the **CDND** for each of the 336 cities in our target sample.

	Cities	Neighborhoods	Pop.
Official neighborhoods	146	13,455	60,185,705
Neighborhood associations	60	7,180	16,840,405
Housing associations	41	-	7465576
No data	89	-	13,796,077

Third, we find boundaries of homeowner associations (HOAs), which are generally created by residential developers for real estate purposes. These boundaries are usually much smaller than neighborhoods or NHAs, and only cover select developments. In **CDND**, we also collect and release HOA data but note that these should be distinguished from city-defined neighborhoods. Table1 contains counts of total neighborhood, neighborhood housing associations, and homeowner association shapefiles provided in our data, and `city_list.csv` in the data release contains a list of all cities with fields marking which shapefiles are available for which cities.

Descriptive neighborhood statistics across the United States

We identified some form of city-defined neighborhood (either a neighborhood shapefile or a neighborhood housing association shapefile) map for 206 of our cities, either through our own research or direct contact with a city representative. These 206 cities contain 20,635 neighborhoods and cover over 77 million people. We release the geographic definition and demographic characteristics for each neighborhood (see below). 41 additional cities confirmed to us that they do not maintain any city-level definition of neighborhoods, but shared a shapefile of homeowners associations. The remaining 90 cities (out of the target 336 cities) either confirmed the city does not define neighborhoods in any capacity, or did not comply with our records request.

Figure 1 plots the cities in the **CDND**. Our sample contains cities in 45 states, and also includes Washington, DC. Given the selection criteria (cities with populations over 100,000 people) the cities in our sample are concentrated in denser and larger population states, but we still have high coverage across regions such as the Northeast, the South, the Sun Belt, the Midwest, and Pacific Northwest. Figure 2 shows our sample neighborhoods vary widely in population, area, and racial/ethnic composition. Neighborhoods across our sample have a median population of 1,125, but the data include some very large neighborhoods like New York City's Community Districts with more than 250,000 people. Similarly, the center histogram shows that most neighborhoods in the United States are less than a square mile in area.

Neighborhoods also vary drastically in racial / ethnic diversity. In the right histogram of Figure 2, we calculate a simple measure of racial diversity for each neighborhood in our sample. Specifically, we calculate the largest proportion of the neighborhood population represented by White, Black, Hispanic, or Asian residents by adding the group population for each Census block in the neighborhood. We calculate this by first performing a spatial merge between Census blocks and neighborhoods, and then aggregating Census block population counts for each racial group to the neighborhood level. Some neighborhoods primarily have residents from a single racial group: for example, Vine City in Atlanta, Georgia, borders Spelman and Morehouse Colleges and is over 85% Black. Other neighborhoods are more diverse.

Finally, we find that smaller cities are less likely than larger cities to define neighborhoods. Appendix Figure 6 visualizes this pattern across all cities in our sample. The largest several dozen cities in the United States all define neighborhoods in some form. However, the probability of having a city defined neighborhood generally decreases with population size. In our data collection, smaller cities were, on the whole, more elusive, and many of them were contacted directly through phone calls, emails, and public records requests. In these cases, we are confident in most cases that there was no official neighborhood map for the city.

Figure 3 offers Philadelphia, PA as an example of our collection efforts. The Planning Commission in Philadelphia maintains a "neighborhood" shapefile on the city's GIS site, shown in the map. These neighborhood units correspond to well-known areas in Philadelphia, like Fishtown, University City, and Germantown. Like many cities, Philadelphia's city government does not define universal "official" neighborhood boundaries used for all scenarios, often due to local contention over precise boundaries, shifting populations, and active development. Instead, the Planning Commission neighborhoods are defined as "general boundaries that historically have been in place around the city. They fall along the lines of development patterns, historic references and known names."[2]

Like our full sample, our data shows neighborhoods in Philadelphia vary in population, area, and racial / ethnic diversity. Philadelphia's 148 planning neighborhoods are slightly larger than our sample average as shown in the left histogram of Figure 3, with a median population of 8,304. Neighborhoods in Philadelphia are also generally less than 2 square miles. While

[2] Philadelphia Neighborhoods as defined by the Planning Commission are available from their GIS site here: https://m.arcgis.com/home/item.html?id=2ca56f18e3984d54a86f1fd6fb00e42d

Figure 3. **Philadelphia Neighborhoods and Sample Descriptives** The top map shows 148 Philadelphia neighborhoods as defined by the Planning Commission, with three notable neighborhood labeled. The white areas of the map are places within Census Place limits that are not assigned to a particular neighborhood, such as the Northeast Philadelphia Airport near the top of the map. The histograms demonstrate that Philadelphia's 148 planning neighborhoods vary widely across the same dimensions shown in Figure 2. The left column shows the total population in each neighborhood as reported by the 2020 Census, the middle column shows the number of square miles in each neighborhood, and the right column shows the proportion of the largest racial/ethnic group in each neighborhood, among the Black, Hispanic, White, and Asian populations.

Philadelphia neighborhoods are more racially/ethnically homogeneous than our sample average, some neighborhoods are quite diverse. For example, in Philadelphia's Holmesburg neighborhood, the population is barely majority White; Black and Hispanic residents each comprise about 20% of the population, and nearly 5% of the population is Asian.

Data Records

The **CDND** contains two types of data records. For each city, we release (1) a pre-processed shapefile including the neighborhood geometries and (2) a Census-block level dataset that includes spatially merged neighborhoods and 2020 Census demographics. Our pre-processing ensures that each neighborhood file includes valid neighborhood geometries. For example, several cities include neighborhoods in other cities in the neighborhood file they provided us, which we remove. Other cities often define a "no neighborhood" spatial layer, which we redefine as missing.

For each city, we also release a second file that includes neighborhood geometries merged to 2020 Census-block level data. We include the following Census geographic and demographic data using (27): a set of Census identifiers (the block-level 'GEOID', identifiers for the state, county, place, and tract), population counts for both total population and voting age population (total population, and separately for White, Black, Hispanic, American Indian and Alaska Native (AIAN), Asian, Native Hawaiian and Other Pacific Islander (NHPI), two or more races, and Other).

Finally, when a city reported a Homeowners Associations (HOA), we include the raw file. We release these separately, and do not merge HOAs into our block-level data, because HOAs are private organizations and not officially defined by the city government. Nonetheless, we include HOA shapefile data in **CDND** due to their potential for use in a wide variety of research questions (28; 29).

Technical Validation

Finally, we demonstrate the utility of our data by comparing our city-defined neighborhoods to other common proxies of neighborhoods: Census Block Groups, Census Tracts, and Zip Code Tabulation Areas. For Philadelphia, Appendix Figure 4 shows that these four ways of operationalizing neighborhoods differ in several ways. First, they have vastly different scales: while tracts are one of the most commonly used neighborhood proxies, Philadelphia's Planning Neighborhoods are generally larger. Second, Philadelphia's Planning Neighborhoods make clear that not all areas of cities contain a neighborhood definition. For example, the Northeast Philadelphia Airport is not assigned to a neighborhood by the city government.

This intuition that neighborhood proxies can produce different estimates of desired quantities holds across our entire sample. In Figure 5, we compare aggregate statistics for logged population size (top panel), land area (middle panel), and percent Black population (bottom panel) for neighborhoods in **CDND** against Census Tracts, Block Groups, and ZCTAs. The results show that even straightforward questions like "what is the average neighborhood population" in a given city can differ drastically depending on how neighborhoods are operationalized. Further, city-defined neighborhoods and Census geographies are only weakly correlated for area and total population.

Code availability

All code and data for the **CDND** are available on our Harvard Dataverse page: **https://doi.org/10.7910/DVN/02NP1O**.

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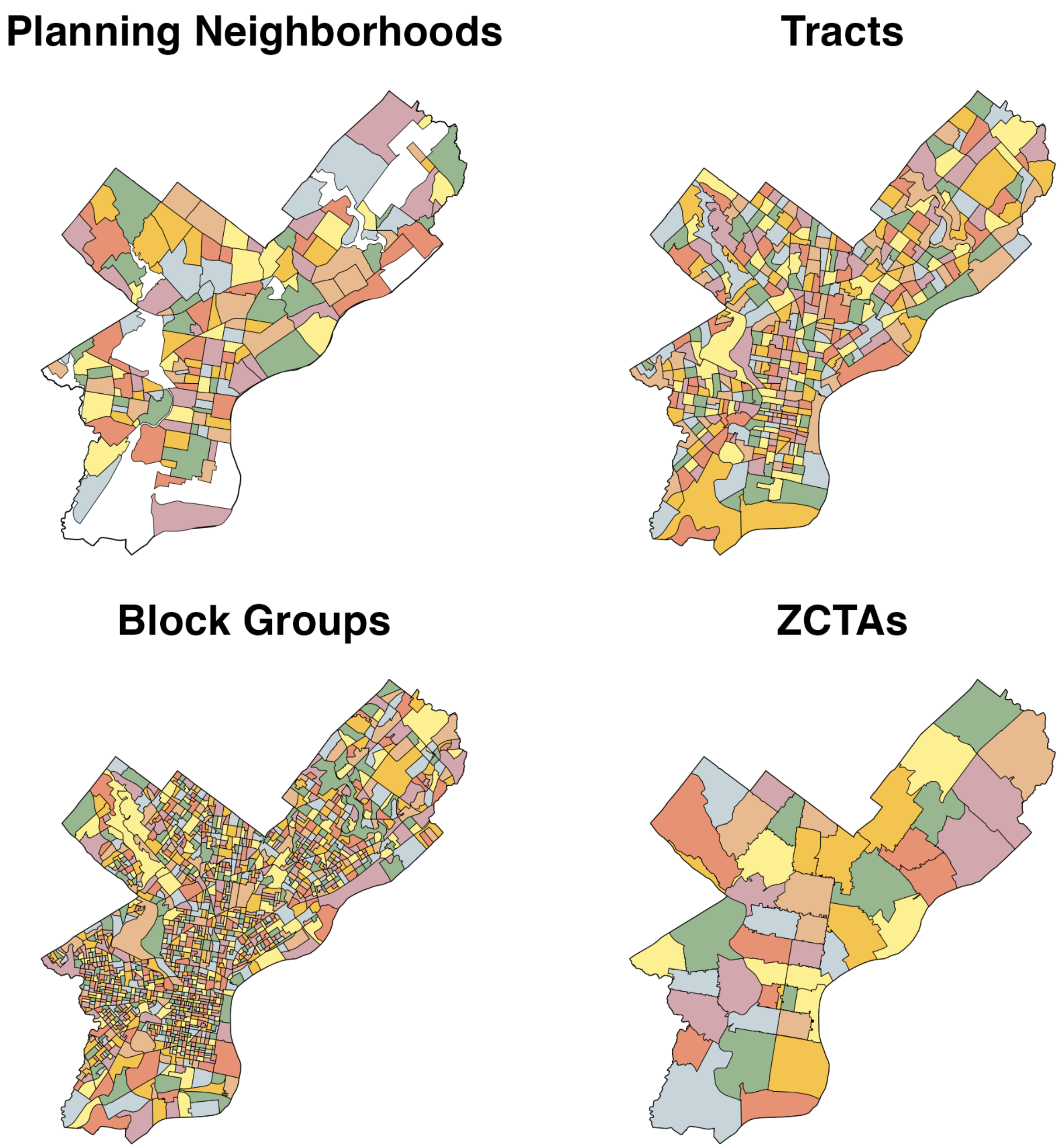

Figure 4. **Four Ways to Define Neighborhoods in Philadelphia** This figure shows how four common ways to define neighborhoods can drastically differ. Here, we compare Philadelphia's planning neighborhoods from our sample along with three different Census geographies commonly used by researchers and policymakers: tracts, block groups, and Zip Code Tabulation Areas (ZCTAs, a geographic approximation of postal ZIP codes created by the US Census).

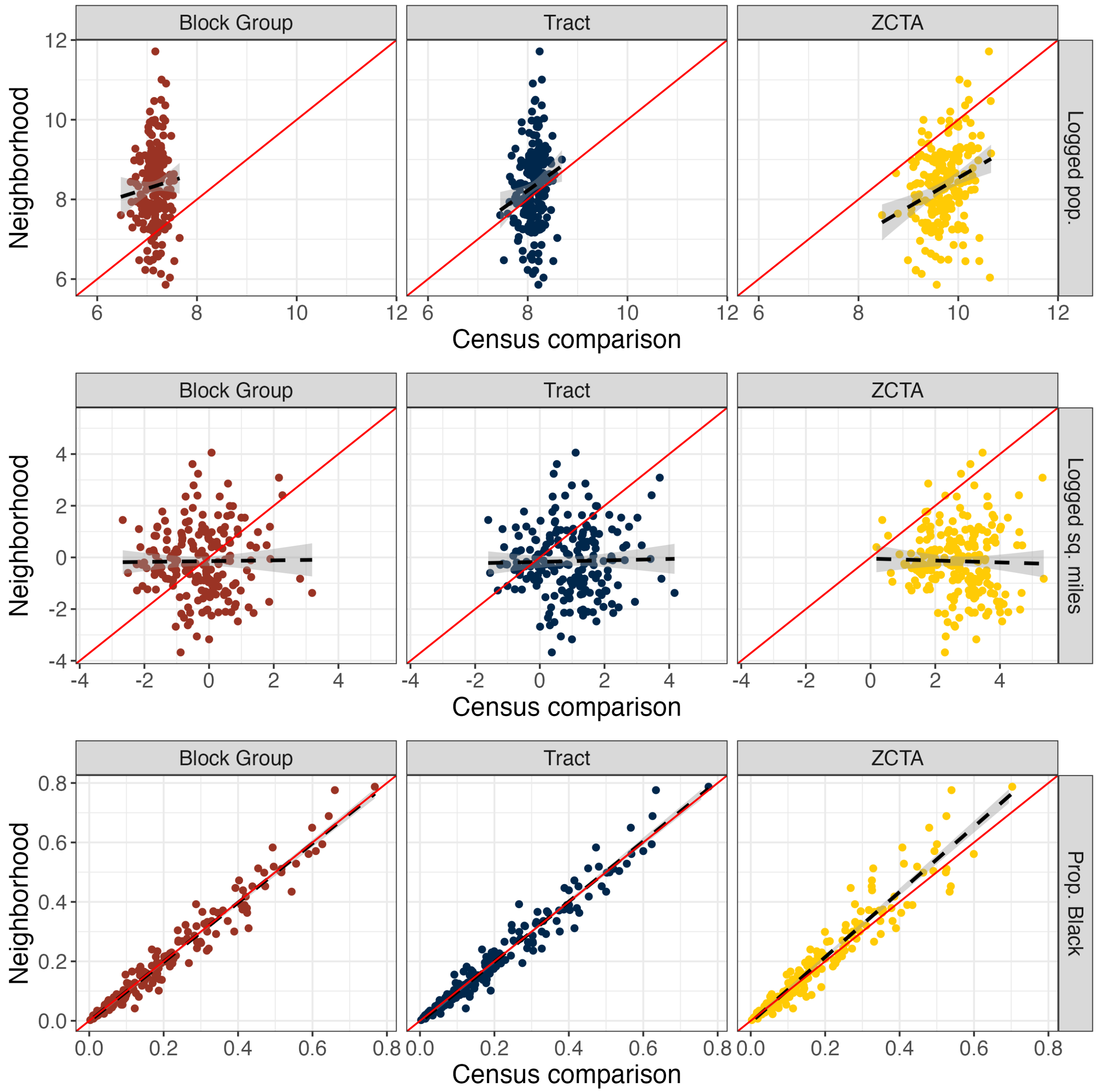

Figure 5. Demographic comparisons of neighborhoods and Census geographies. Figure plots city-level averages of various statistics against city-level averages of the same statistics for Census geographies ZCTAs, Tracts, and Block Groups. We show comparisons for neighborhood population (top panel), land area in square miles (middle panel), and the proportion of the population that is White (bottom panel). Average population and land area are logged to remove skewness for visualization.

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Author contributions statement

J.B., B.S., T.S., and D.S. collected all data. J.B., T.S., and D.S analyzed the data. All authors conceived the study, wrote the manuscript, and reviewed the manuscript.

Additional information

To include, in this order: **Accession codes** (where applicable); **Competing interests** (mandatory statement).

The corresponding author is responsible for submitting a competing interests statement on behalf of all authors of the paper. This statement must be included in the submitted article file.

Appendix

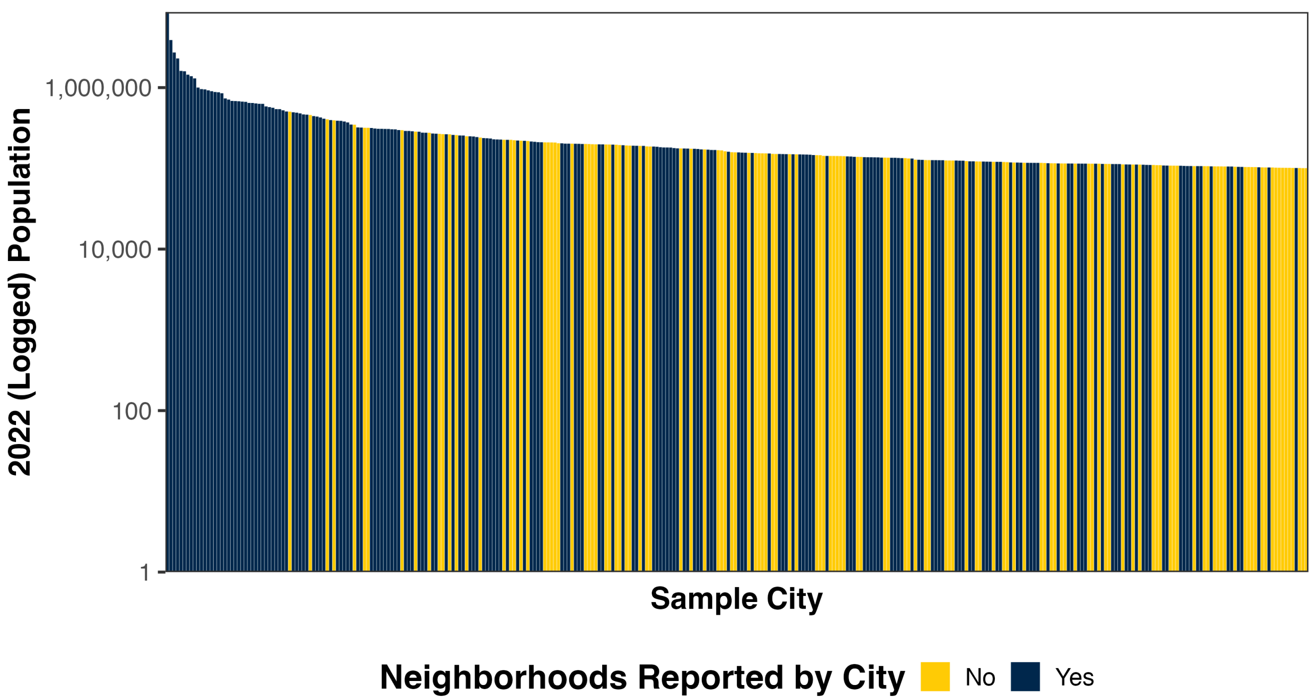

Figure 6. Neighborhood Reporting for Sample Cities This plot shows the population of all cities in our sample, where the columns are colored by whether the city reported a neighborhood shapefile to us (blue) or not (maize). Cities that did not report a neighborhood are not necessarily “missing," as they often confirmed that the city does not define any neighborhood definition.

Table 2. List of cities, 1-120

	City	Pop	NBHD	NHA	HOA
1	New York, NY	8,622,467	Yes	No	No
2	Los Angeles, CA	3,881,041	Yes	Yes	No
3	Chicago, IL	2,721,914	Yes	No	No
4	Houston, TX	2,296,253	Yes	Yes	No
5	Phoenix, AZ	1,609,456	Yes	Yes	No
6	Philadelphia, PA	1,593,208	Yes	No	No
7	San Antonio, TX	1,445,662	No	Yes	No
8	San Diego, CA	1,383,987	Yes	No	No
9	Dallas, TX	1,300,642	No	Yes	No
10	San Jose, CA	1,001,176	Yes	No	No
11	Austin, TX	958,202	Yes	No	No
12	Jacksonville, FL	950,203	Yes	No	No
13	Fort Worth, TX	924,663	No	Yes	No
14	Columbus, OH	902,449	Yes	No	No
15	Indianapolis, IN	882,006	Yes	No	No
16	Charlotte, NC	875,045	Yes	No	No
17	San Francisco, CA	851,036	Yes	No	No
18	Seattle, WA	734,603	Yes	No	No
19	Denver, CO	710,800	Yes	No	No
20	Nashville, TN	684,103	Yes	Yes	No
21	Oklahoma City, OK	681,088	No	Yes	No
22	El Paso, TX	677,181	Yes	Yes	No
23	Washington, DC	670,587	Yes	No	No
24	Boston, MA	665,945	Yes	No	No
25	Portland, OR	646,101	Yes	No	No
26	Las Vegas, NV	644,835	No	Yes	Yes
27	Detroit, MI	636,787	Yes	No	No
28	Memphis, TN	630,027	No	Yes	No
29	Louisville, KY	629,176	Yes	No	No
30	Baltimore, MD	584,548	Yes	Yes	No
31	Milwaukee, WI	573,299	Yes	No	No
32	Albuquerque, NM	562,551	No	Yes	No
33	Fresno, CA	541,528	Yes	No	No
34	Tucson, AZ	541,033	Yes	Yes	No
35	Sacramento, CA	523,600	Yes	Yes	No
36	Kansas City, MO	505,958	Yes	No	No
37	Mesa, AZ	503,390	No	No	Yes
38	Atlanta, GA	494,838	Yes	Yes	No
39	Omaha, NE	489,201	No	Yes	No
40	Colorado Springs, CO	479,612	Yes	No	No
41	Raleigh, NC	465,517	No	Yes	No
42	Long Beach, CA	462,293	Yes	No	No
43	Virginia Beach, VA	457,900	No	No	Yes
44	Miami, FL	443,665	Yes	No	No
45	Oakland, CA	437,825	Yes	No	No
46	Minneapolis, MN	426,877	Yes	No	No
47	Tulsa, OK	411,938	No	Yes	No
48	Bakersfield, CA	404,321	No	No	No
49	Wichita, KS	395,951	No	Yes	No
50	Arlington, TX	393,469	No	No	Yes
51	Tampa, FL	388,768	No	Yes	No
52	Aurora, CO	387,349	Yes	Yes	Yes
53	New Orleans, LA	380,408	Yes	No	No
54	Cleveland, OH	370,365	Yes	No	No
55	Honolulu, HI	348,547	Yes	No	No
56	Anaheim, CA	347,111	No	No	Yes
57	Lexington, KY	321,276	No	Yes	No
58	Stockton, CA	320,030	Yes	No	No
59	Henderson, NV	318,063	No	No	Yes
60	Corpus Christi, TX	317,804	No	No	Yes
61	Riverside, CA	316,076	Yes	No	No
62	Santa Ana, CA	311,379	No	Yes	No
63	Cincinnati, OH	308,870	Yes	No	No
64	St Paul, MN	308,806	Yes	No	No
65	Orlando, FL	307,738	Yes	Yes	No
66	Newark, NJ	307,355	Yes	No	No
67	Irvine, CA	304,527	Yes	No	No
68	Pittsburgh, PA	303,843	Yes	No	No
69	St Louis, MO	298,018	Yes	No	No
70	Greensboro, NC	297,202	No	No	No
71	Anchorage, AK	290,674	Yes	No	No
72	Lincoln, NE	290,531	No	Yes	No
73	Jersey City, NJ	287,899	Yes	No	No
74	Plano, TX	284,948	No	No	Yes
75	Durham, NC	284,094	Yes	No	No
76	Buffalo, NY	276,688	Yes	No	No
77	Chula Vista, CA	276,103	Yes	No	No
78	Chandler, AZ	275,618	No	No	No
79	Toledo, OH	269,962	Yes	Yes	No
80	Madison, WI	268,516	No	Yes	No
81	Gilbert, AZ	267,267	No	No	No
82	Reno, NV	265,196	No	No	Yes
83	Fort Wayne, IN	264,514	No	Yes	No
84	North Las Vegas, NV	264,022	No	No	No
85	St Petersburg, FL	259,343	No	Yes	Yes
86	Lubbock, TX	258,190	No	No	Yes
87	Laredo, TX	255,293	Yes	No	No
88	Irving, TX	254,962	No	Yes	No
89	Winston Salem, NC	249,571	No	No	No
90	Chesapeake, VA	249,377	Yes	No	No
91	Glendale, AZ	248,083	No	Yes	Yes
92	Garland, TX	244,026	No	Yes	No
93	Scottsdale, AZ	240,537	No	No	Yes
94	Norfolk, VA	236,973	Yes	No	No
95	Arlington, VA	235,845	Yes	No	No
96	Boise, ID	234,192	No	Yes	No
97	Fremont, CA	228,795	Yes	No	No
98	Spokane, WA	227,922	Yes	No	No
99	Richmond, VA	227,171	Yes	No	No
100	Santa Clarita, CA	225,850	No	No	No
101	Baton Rouge, LA	225,500	Yes	Yes	No
102	Enterprise, NV	225,461	No	No	No
103	Hialeah, FL	222,996	No	No	No
104	San Bernardino, CA	221,041	No	Yes	No
105	Spring Valley, NV	220,114	No	No	No
106	Tacoma, WA	219,234	Yes	No	No
107	Modesto, CA	218,308	No	No	No
108	Huntsville, AL	215,025	No	Yes	No
109	Des Moines, IA	213,164	No	Yes	No
110	Rochester, NY	210,992	No	Yes	No
111	Port St Lucie, FL	210,520	Yes	No	No
112	Yonkers, NY	209,780	No	No	No
113	Moreno Valley, CA	209,578	No	No	No
114	Fontana, CA	209,279	No	No	No
115	Fayetteville, NC	208,697	No	No	No
116	Columbus, GA	204,572	No	No	No
117	Worcester, MA	204,191	No	Yes	No
118	Oxnard, CA	202,279	Yes	No	No
119	Little Rock, AR	202,218	No	Yes	No
120	Frisco, TX	202,075	No	No	No

Table 3. List of cities, 121-240

	City	Pop	NBHD	NHA	HOA
121	Augusta, GA	201,615	Yes	No	No
122	Salt Lake City, UT	201,269	No	Yes	No
123	Birmingham, AL	200,431	Yes	No	No
124	Amarillo, TX	200,360	No	No	No
125	Montgomery, AL	199,819	No	No	No
126	Cape Coral, FL	198,912	No	No	Yes
127	Sunrise Manor, NV	198,325	No	No	No
128	Tallahassee, FL	198,259	No	Yes	Yes
129	Grand Rapids, MI	198,096	No	Yes	No
130	Huntington Beach, CA	197,481	No	No	No
131	Grand Prairie, TX	197,279	No	No	Yes
132	Overland Park, KS	196,676	Yes	No	No
133	Mc Kinney, TX	196,160	No	No	No
134	Glendale, CA	194,512	No	No	No
135	Sioux Falls, SD	193,401	No	Yes	No
136	Knoxville, TN	191,857	No	No	No
137	Peoria, AZ	191,292	No	No	Yes
138	Vancouver, WA	190,700	No	Yes	No
139	Akron, OH	190,273	Yes	No	No
140	Paradise, NV	189,733	No	No	No
141	Providence, RI	189,715	Yes	No	No
142	Brownsville, TX	186,999	No	No	No
143	Mobile, AL	186,316	No	No	No
144	Shreveport, LA	186,183	Yes	No	No
145	Newport News, VA	185,118	Yes	No	No
146	Fort Lauderdale, FL	182,673	Yes	No	No
147	Aurora, IL	181,405	Yes	Yes	No
148	Chattanooga, TN	181,288	No	Yes	No
149	Tempe, AZ	181,005	No	Yes	No
150	Santa Rosa, CA	178,221	Yes	No	No
151	Eugene, OR	176,755	Yes	No	No
152	Ontario, CA	176,326	No	No	No
153	Elk Grove, CA	176,105	No	Yes	No
154	Salem, OR	175,754	No	Yes	No
155	Cary, NC	174,880	No	No	Yes
156	Rancho Cucamonga, CA	174,696	Yes	No	No
157	Oceanside, CA	173,722	Yes	No	No
158	Garden Grove, CA	171,637	Yes	No	No
159	Lancaster, CA	171,465	No	No	No
160	Pembroke Pines, FL	170,472	Yes	No	No
161	Springfield, MO	168,873	Yes	No	No
162	Fort Collins, CO	168,758	Yes	No	No
163	Clarksville, TN	167,882	No	No	Yes
164	Palmdale, CA	166,895	No	No	No
165	Salinas, CA	162,783	No	No	No
166	Hayward, CA	160,602	Yes	No	No
167	Corona, CA	158,346	No	No	Yes
168	Paterson, NJ	157,864	No	No	No
169	Alexandria, VA	157,594	Yes	No	No
170	Macon, GA	156,554	Yes	No	No
171	Lakewood, CO	156,149	Yes	No	No
172	Kansas, KS	155,438	No	No	No
173	Springfield, MA	155,305	Yes	No	No
174	Sunnyvale, CA	154,573	No	No	No
175	Killeen, TX	153,708	No	No	No
176	Murfreesboro, TN	153,487	No	No	No
177	Jackson, MS	153,271	No	No	No
178	Hollywood, FL	152,764	Yes	No	No
179	Escondido, CA	151,114	No	No	No
180	Pasadena, TX	150,620	No	No	No

	City	Pop	NBHD	NHA	HOA
181	Bellevue, WA	150,606	Yes	Yes	No
182	Joliet, IL	150,221	Yes	No	No
183	Charleston, SC	149,960	No	Yes	No
184	Pomona, CA	149,831	No	No	No
185	Mesquite, TX	149,439	Yes	No	No
186	Naperville, IL	149,089	No	No	Yes
187	Roseville, CA	148,879	No	Yes	No
188	Bridgeport, CT	148,470	Yes	No	No
189	Rockford, IL	148,173	No	Yes	No
190	Savannah, GA	147,583	Yes	Yes	No
191	Syracuse, NY	146,134	Yes	No	No
192	Surprise, AZ	145,591	No	No	Yes
193	Torrance, CA	145,454	No	No	Yes
194	Mc Allen, TX	142,722	No	No	No
195	Gainesville, FL	142,414	Yes	No	No
196	Fullerton, CA	142,280	No	No	No
197	Denton, TX	142,262	No	No	Yes
198	Olathe, KS	142,114	No	No	No
199	Thornton, CO	141,799	No	No	No
200	Visalia, CA	141,466	No	No	Yes
201	Waco, TX	140,545	No	Yes	No
202	Metairie, LA	140,046	Yes	No	No
203	West Valley City, UT	138,868	Yes	No	No
204	Orange, CA	138,728	No	No	Yes
205	Warren, MI	138,588	No	No	No
206	Pasadena, CA	137,554	No	Yes	No
207	Dayton, OH	137,305	Yes	No	No
208	Hampton, VA	137,217	Yes	No	No
209	Cedar Rapids, IA	136,929	No	Yes	No
210	Columbia, SC	136,754	No	Yes	No
211	New Haven, CT	135,736	Yes	No	No
212	Elizabeth, NJ	135,665	No	No	No
213	Stamford, CT	135,413	No	No	No
214	Kent, WA	135,169	Yes	Yes	No
215	Miramar, FL	135,158	Yes	No	No
216	Victorville, CA	134,417	Yes	No	No
217	Coral Springs, FL	133,801	Yes	No	No
218	Sterling Heights, MI	133,744	No	No	No
219	Midland, TX	132,490	No	No	No
220	Carrollton, TX	132,284	Yes	No	No
221	Santa Clara, CA	128,058	No	No	No
222	Norman, OK	127,701	Yes	No	No
223	Fargo, ND	127,319	Yes	No	No
224	Athens, GA	126,672	No	No	No
225	Thousand Oaks, CA	126,532	No	No	Yes
226	Topeka, KS	126,431	No	Yes	No
227	Abilene, TX	126,356	Yes	Yes	No
228	Columbia, MO	126,172	No	Yes	No
229	Simi Valley, CA	126,153	No	Yes	No
230	Allentown, PA	125,292	No	No	No
231	Vallejo, CA	125,132	No	No	No
232	Lewisville, TX	125,028	No	No	No
233	Concord, CA	125,007	Yes	No	No
234	Pearland, TX	124,478	Yes	No	No
235	Lehigh Acres, FL	124,440	Yes	No	No
236	Arvada, CO	123,066	No	No	Yes
237	Independence, MO	122,218	Yes	No	No
238	Ann Arbor, MI	122,216	Yes	Yes	No
239	Lafayette, LA	121,706	No	No	Yes
240	Palm Bay, FL	121,513	No	No	No

Table 4. List of cities, 241-336

	City	Pop	NBHD	NHA	HOA
241	Berkeley, CA	121,385	Yes	No	No
242	Hartford, CT	121,057	Yes	No	No
243	Rochester, MN	120,848	No	Yes	No
244	Clovis, CA	120,607	No	No	No
245	Round Rock, TX	120,465	Yes	No	No
246	College Station, TX	120,451	No	Yes	No
247	Meridian, ID	119,872	No	No	No
248	Fairfield, CA	119,420	No	No	No
249	Woodlands Township, TX	118,402	Yes	No	No
250	Richardson, TX	118,063	No	No	Yes
251	Cambridge, MA	117,962	Yes	No	No
252	West Palm Beach, FL	117,588	No	Yes	No
253	East Los Angeles, CA	117,222	No	No	No
254	Billings, MT	117,093	Yes	Yes	No
255	Clearwater, FL	116,984	No	Yes	No
256	Wilmington, NC	116,933	Yes	No	No
257	Evansville, IN	116,906	No	Yes	No
258	Spring Hill, FL	116,882	No	No	No
259	West Jordan, UT	116,383	No	No	Yes
260	North Charleston, SC	115,755	Yes	No	No
261	Richmond, CA	115,619	No	No	No
262	Westminster, CO	115,502	No	No	Yes
263	Manchester, NH	115,037	Yes	No	No
264	Antioch, CA	115,016	No	No	Yes
265	Brandon, FL	114,923	No	No	No
266	Carlsbad, CA	114,745	Yes	No	No
267	Lowell, MA	114,737	Yes	No	No
268	Beaumont, TX	114,573	No	No	No
269	Waterbury, CT	114,480	Yes	No	No
270	Lakeland, FL	114,404	Yes	No	No
271	Provo, UT	114,400	Yes	No	No
272	Broken Arrow, OK	114,237	No	No	Yes
273	Springfield, IL	114,214	No	No	No
274	Elgin, IL	114,190	No	Yes	No
275	High Point, NC	114,120	No	No	No
276	Gresham, OR	113,525	No	Yes	No
277	League City, TX	113,469	No	No	No
278	Odessa, TX	113,353	No	No	Yes
279	Peoria, IL	113,054	Yes	No	No
280	Downey, CA	113,052	Yes	No	No
281	Lansing, MI	112,986	No	Yes	No
282	Murrieta, CA	111,899	No	No	No
283	Pompano Beach, FL	111,790	Yes	No	No
284	Miami Gardens, FL	111,618	Yes	No	No
285	Costa Mesa, CA	111,490	No	No	No
286	Pueblo, CO	111,430	Yes	No	No
287	Las Cruces, NM	111,273	No	No	Yes
288	Everett, WA	110,847	Yes	No	No
289	Ventura, CA	110,358	Yes	No	No
290	Temecula, CA	110,114	Yes	No	Yes
291	Sugar Land, TX	110,077	No	No	Yes
292	El Monte, CA	109,543	No	No	No
293	Santa Maria, CA	109,543	No	No	No
294	Dearborn, MI	108,414	Yes	Yes	No
295	West Covina, CA	108,173	Yes	No	No
296	Sparks, NV	108,025	No	No	Yes
297	Greeley, CO	107,949	No	No	Yes
298	South Fulton, GA	107,865	No	No	Yes
299	Centennial, CO	107,702	No	Yes	No
300	Sandy Springs, GA	107,221	No	Yes	Yes

	City	Pop	NBHD	NHA	HOA
301	Green Bay, WI	106,846	No	Yes	No
302	Inglewood, CA	106,806	Yes	No	No
303	Hillsboro, OR	106,612	No	No	No
304	Columbia, MD	106,600	Yes	No	No
305	Boulder, CO	106,598	Yes	No	No
306	Tyler, TX	106,440	No	No	Yes
307	Burbank, CA	106,389	No	No	No
308	Davie, FL	105,821	Yes	No	No
309	Tuscaloosa, AL	105,797	No	No	No
310	El Cajon, CA	105,721	No	No	No
311	Jurupa Valley, CA	105,672	No	No	No
312	Allen, TX	105,444	No	No	Yes
313	Renton, WA	105,355	Yes	No	No
314	Concord, NC	105,335	Yes	No	No
315	Brockton, MA	104,713	No	No	No
316	Rio Rancho, NM	104,351	No	Yes	No
317	San Mateo, CA	104,165	Yes	No	No
318	Rialto, CA	103,873	No	No	No
319	Spokane Valley, WA	103,761	No	No	No
320	Menifee, CA	103,680	No	No	Yes
321	Daly, CA	103,648	No	No	No
322	South Bend, IN	103,084	No	Yes	No
323	Chico, CA	102,790	No	No	No
324	Nampa, ID	102,598	No	No	No
325	Wichita Falls, TX	102,482	Yes	No	No
326	Riverview, FL	102,467	No	No	No
327	Norwalk, CA	101,893	No	No	No
328	Lees Summit, MO	101,728	No	No	Yes
329	Vacaville, CA	101,631	No	No	No
330	Highlands Ranch, CO	101,514	No	No	No
331	Davenport, IA	101,448	No	No	Yes
332	San Tan Valley, AZ	101,207	No	No	No
333	Quincy, MA	100,981	Yes	No	No
334	Edinburg, TX	100,964	No	No	No
335	Lynn, MA	100,653	No	No	No
336	New Bedford, MA	100,620	No	No	No