The Spatial Structure of US Metropolitan Employment:

New Insights from LODES Data

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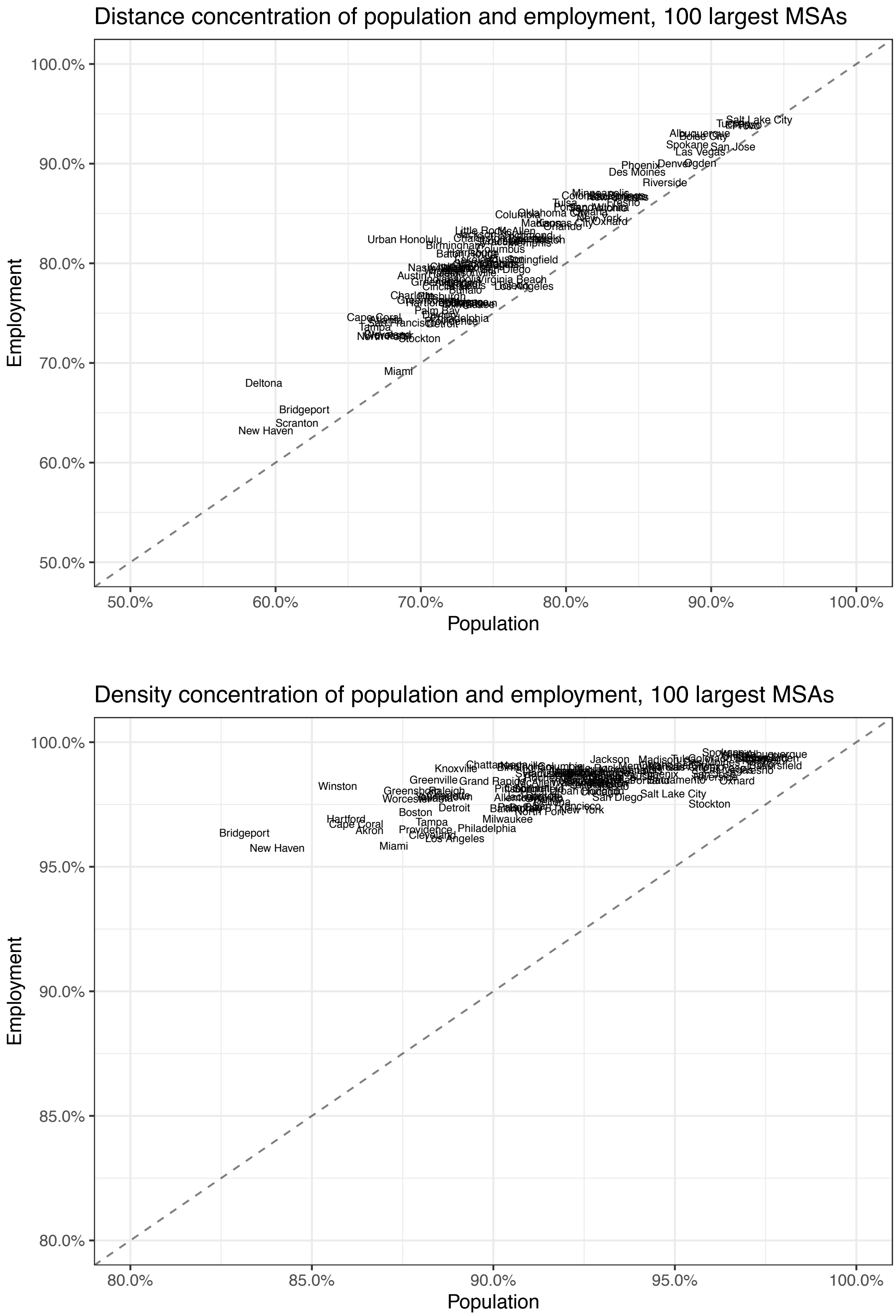
Supplementary Material

Distance and density concentration of employment and residents in the 100 largest MSAs

Figure 2 in the main text demonstrated that jobs in the Boston MSA are not more centralized but are more spatially concentrated than residents. To quantify this finding and extended it to the remainder of the 100 largest MSAs, I calculate the area under each of the curves in Figure 2 and the equivalent curves for each MSA. Figure S1 plots these “distance concentration” and “density concentration” indexes for each MSA. The dashed lines in each panel denote where the points would fall if employment and population were distributed similarly. As shown in the top panel, in terms of distance concentration most metros are similar to Boston in that jobs are a bit, but not much, more centralized than residents. This pattern conforms to that noted by Wheaton (2004) and Glaeser and Kahn (2001). However, as shown in the bottom panel, in terms of density concentration, employment in every metro is much more spatially concentrated than population. This suggests that it is incorrect to describe jobs and people as similarly distributed throughout metro areas.

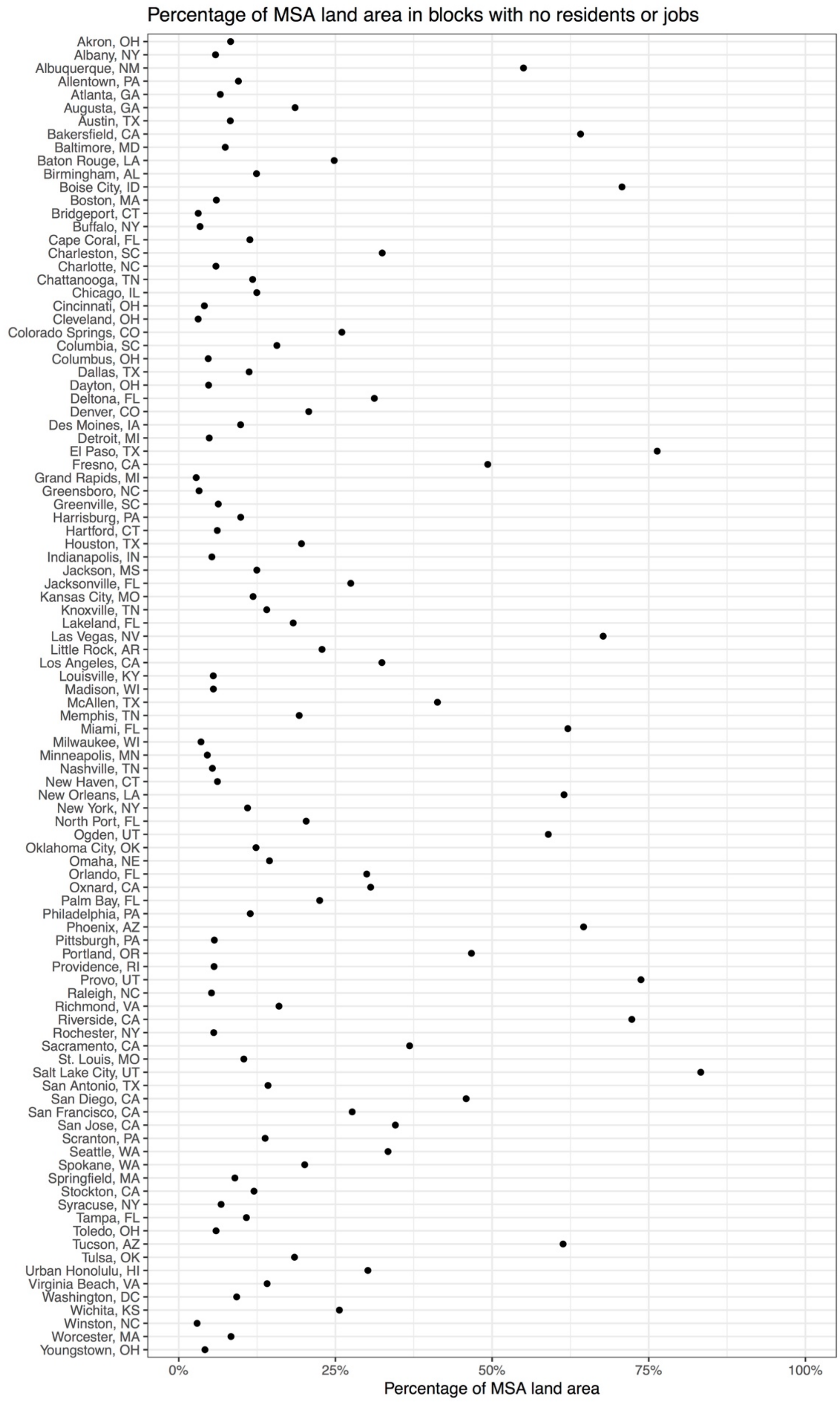
Figure S1. Distance (top) and density (bottom) concentration indices for population and employment, 100 largest MSAs.



Built land area by MSA

Metropolitan Statistical Areas are defined using counties, and US counties containing cities sometimes also contain large areas of uninhabitable land. To account for this inconsistency I use the “built land area,” defined as the land area of all blocks with at least one job or resident, rather than total land area when conducting area comparisons. Figure S2 plots the percentage of total land in each MSA that is unbuilt.

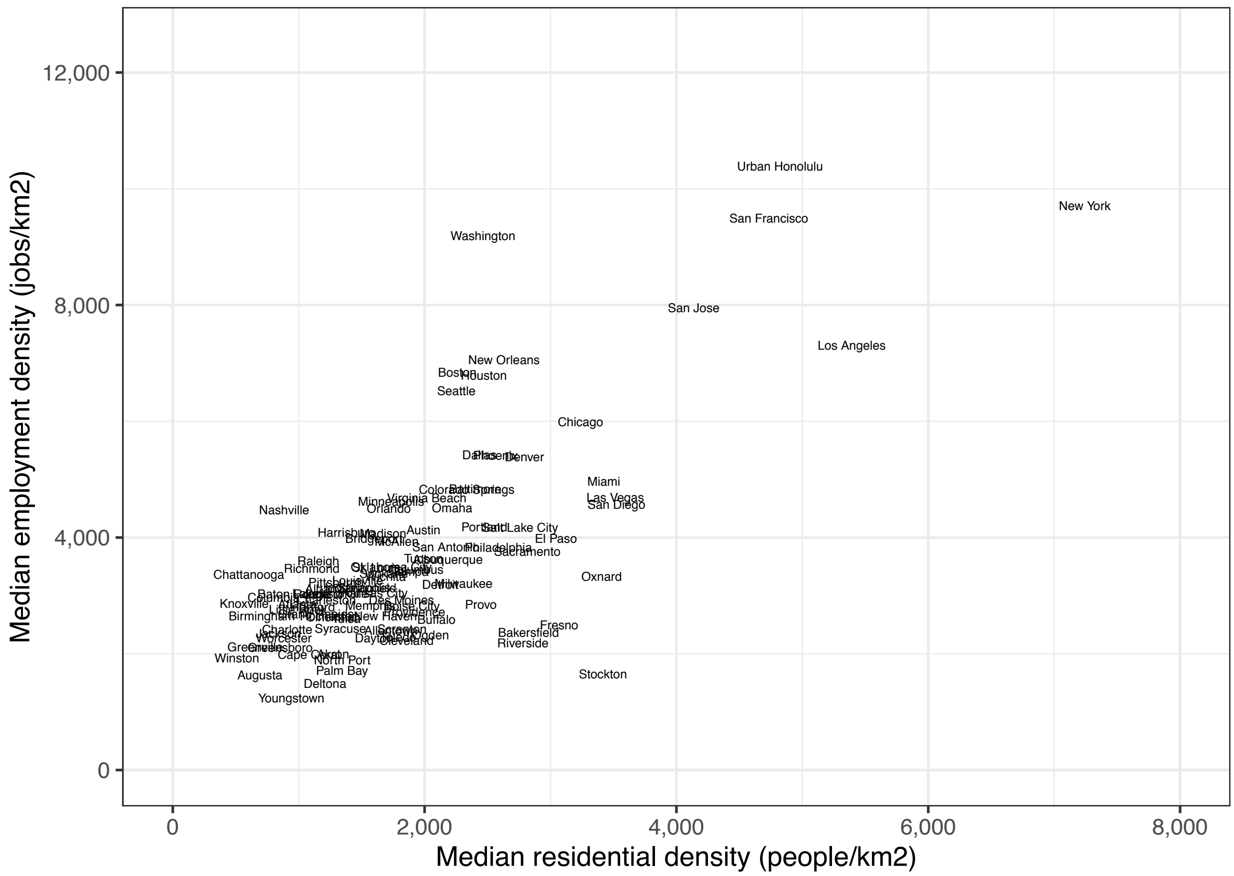
Figure S2. Unbuilt land area as a proportion of total land area, 100 largest MSAs.



Correlation between residential and employment densities

The consistent spatial allocation of jobs and land across cities is striking given the extreme variation in population and employment density among the largest 100 MSAs. As Figure 1 in the main text indicates, American cities vary enormously in the density at which they are constructed. Yet the patterns in Figure 3 suggest that while the absolute level of density may vary between San Francisco and Birmingham, the relative density of employment and population must be similar across metros. This consistent relationship is shown in Figure S3, which plots the median residential and employment density for each MSA. Median residential density varies by a factor of 14 across the 100 largest MSAs, while median employment density varies by a factor of 8. But the median employment and population densities are highly correlated ($r = 0.72$). While certain outliers may have relatively dense employment and sparse residences (as in Washington DC), or dense residences and sparse employment (as in Stockton, CA), for the most part the densities of employment and residences vary together.

Figure S3. Median residential and population density, 100 largest MSAs.



Specification choices in the business district identification algorithm

The business district identification algorithm I introduce has two global parameters: the distance buffer below which nearby blocks will be counted as adjacent, and the ratio of jobs to people above which blocks are determined to be employment areas. There is no theoretical basis for favoring a particular value of either parameter. With each, a less restrictive value will increase the likelihood of grouping employment blocks into sprawling, internally varied districts, while a more restrictive value may result in splintering nearby blocks of similar character into multiple districts. Perhaps more concerning, in some cases the buffer that appears to make the most sense for downtown areas may result in the fragmentation of suburban business districts, especially those built on opposite sides of interstate highways. These cases are not difficult to diagnose and correct visually, so should not inhibit the use of these methods among practitioners working in individual metro areas, but they may cause difficulty in comparative studies.

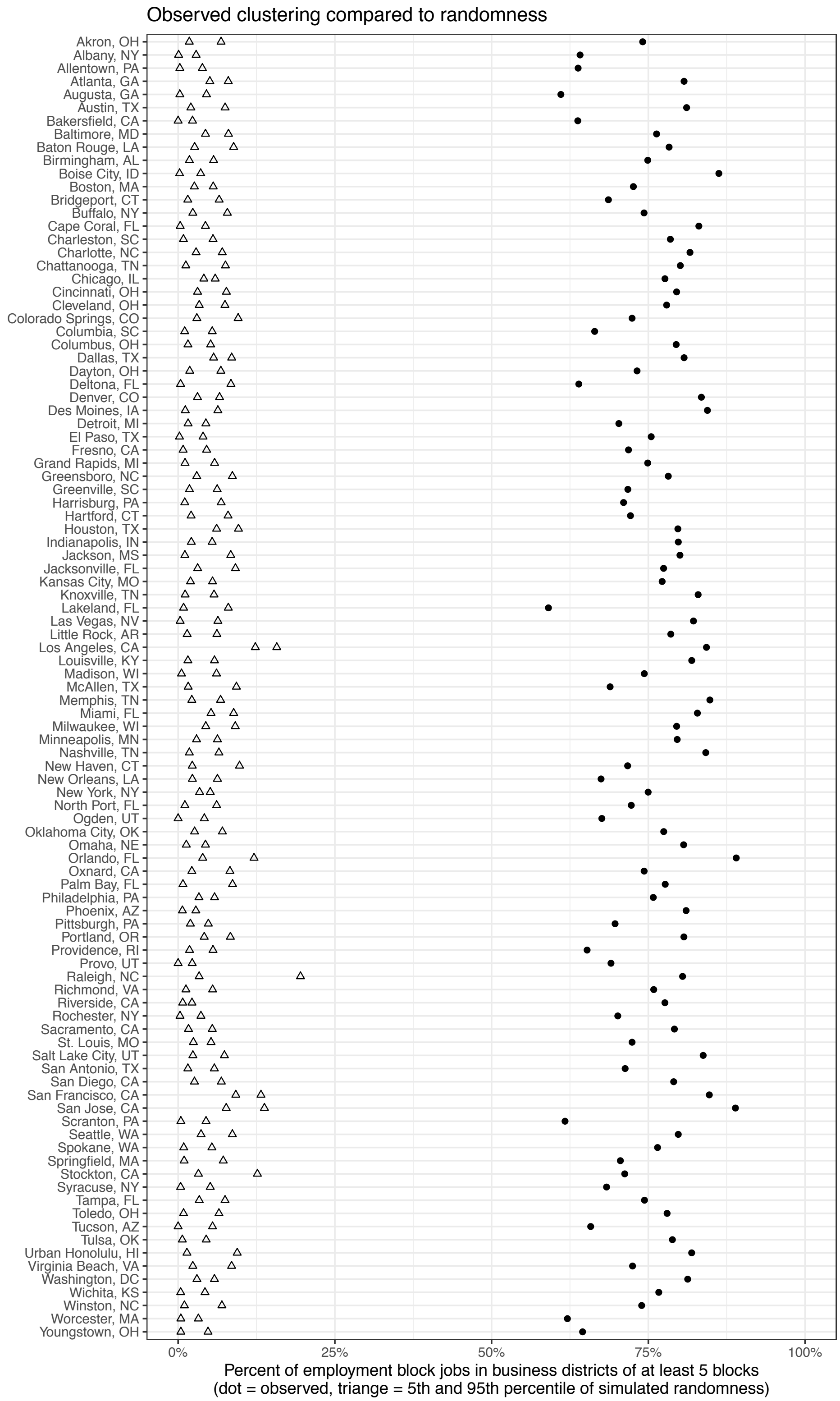
To empirically determine which set of parameters results in the best delineation of business districts I run the identification algorithm using all combinations of distance buffers of 0, 15, 20, and 25 meters and ratio thresholds of 100%, 150%, 200%, and 250%. The extent to which heterogeneous blocks are grouped into the same business districts is measured using the coefficient of variation of both block area and employment density within each business district, averaged for each MSA weighting by the number of jobs in that district. To measure the extent to which nearby blocks are not being incorporated into the same business district I calculate the number of "near misses," additional jobs that would be added to each business district by expanding the buffer to 50 meters. I again take the average weighted by the number of jobs in each district. Changing the buffer size involves a direct tradeoff between internal diversity and near misses. Increasing the relative threshold decreases internal diversity without increasing the proportion of near misses, but at the cost of fewer overall jobs in employment areas. In the primary analysis I use cutoffs of 200% and 15 meters as they are intuitively appealing and near the middle on both outcome measures.

One possible way to reduce the number of sprawling, internally varied districts without increasing the number of near misses may be to adopt certain features of the DBSCAN algorithm for cluster detection in points (Ester et al., 1996). DBSCAN reduces the likelihood of "bridge" points that connect two otherwise distinct clusters. Initial trials of an adaptation of the DBSCAN algorithm, which first classifies employment blocks as "clustered" if they border at least three other employment blocks and "non-clustered" if they do not, then groups contiguous clustered points together into business districts, and then adds any non-clustered employment blocks that adjoin a core business district, appear promising. Future work should investigate the optimal parameters for this algorithm and compare it to the algorithm introduced in the main text.

Observed clustering compared to expected clustering under randomness

To evaluate the probability that the employment clustering I observe occurs simply due to random chance, I run simulations in which I randomly reshuffle employment across the blocks of each MSA 100 times, re-apply the clustering algorithm, and re-compute the fraction of employment in clustered business districts. Results are presented in Figure S4. In all cases, the observed fraction of jobs in clusters of more than five contiguous employment blocks is many times higher than that obtained via random shuffling. In the median MSA, the 95^{th} percentile of the random draws puts 6.3% of employment block jobs in clusters of more than five blocks, while the median observed value is 76.7%. No MSA has an observed value below 59.1%, and the 95^{th} percentile of the random reshuffling is never greater than 19.5%.

Figure S4. Observed clustering compared to expected clustering under randomness, largest 100 MSAs.

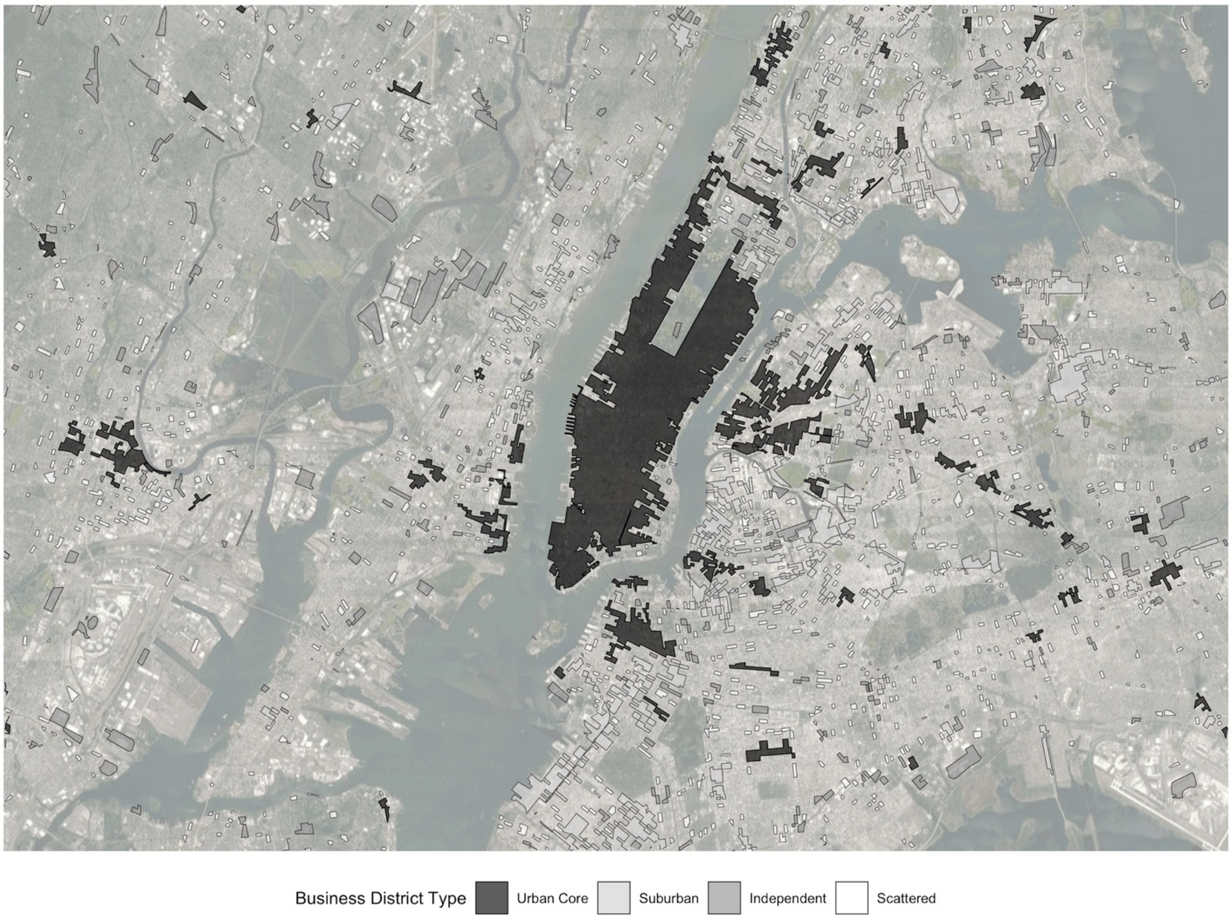


Comparison of business districts identified using the employment-population ratio with those identified using an employment density threshold.

In this paper I use the employment to population ratio as the core statistic for defining business districts. Most previous work (e.g. Giuliano and Small, 1991; McMillen, 2001) has used employment density alone. Here I show how the business districts identified using my algorithm differ from those that would be identified using previous approaches. Figure S5 shows the business districts identified in the New York MSA using the density threshold approach of Giuliano and Small (1991), the most widely used method of identifying employment subcenters. The density threshold is set at one half the density of the median job (9,710 jobs per square km in New York city), which results in 62.0% of all MSA jobs being assigned to business districts, compared to 70.6% using the employment to population ratio.

A few clear differences stand out between Figure S5 and Figure 4 of the main text. First, the business district at the center of Manhattan identified using the density threshold method is much, much larger than that identified by my algorithm: in addition to Midtown and Downtown, it encompasses the entire island below Central Park, along with much of the upper east and west sides. As I argue in the main text, this seems to conflate dense yet primarily residential areas with true business districts. At the same time, many lower density areas that nonetheless are still major employment centers, such as the Meadowlands in New Jersey, are not identified as subcenters using the density threshold method. In some cases, adjacent blocks with similar land uses fall onto either side of the density cutoff, resulting in fragmented business districts. This again stands out in the industrial areas of Northern New Jersey, where fewer than half of the blocks meet the employment density threshold and those that do are split across several different subcenters. In contrast, the approach introduced by this paper, as shown in Figure 4 in the main text, is able to consistently identify large areas of adjacent industrial land use as part of the same employment center.

Figure S5. Employment subcenters in the New York MSA as identified using the density threshold approach of Giuliano and Small (1991).



The distribution of business districts within and across cities.

The fact that the business districts identified by my algorithm are collections of blocks rather than single points allows for their size and characteristics to be quantified precisely. This allows for comparisons of business districts both within and across cities.

As an example of the type of within-city comparisons that are possible using this method, Figures S6 and S7 map business districts in the Denver and Atlanta metro areas. Each business district is indicated by a circle that is proportional in size to its total employment. This allows a quick visual investigation of the employment landscape in each city. In Denver, downtown is immediately recognizable as a major concentration of jobs. But there are also large job centers in the suburbs, most notably in the Denver Tech Center in the southeastern portion of the metro area and in the industrial area northeast of downtown. Employment in Atlanta shows a similar pattern: there are clear centers in Downtown and Midtown Atlanta, as well as similarly sized business districts near the airport and in Perimeter Center. Analogous maps for all 100 MSAs, as well as maps in the style of Figure 4 of the main text, are available on the author's website.

Table S1 provides summary statistics of business districts across all 100 MSAs, giving the total employment, the percentage of jobs in employment blocks, and the percentage of jobs in the single largest business district for each MSA. It also provides a count of the number of large business districts with at least 20,000 jobs. Table S2 provides a brief illustration of the potential for cross-MSA comparisons, which previous methods of subcenter identification have not allowed. It provides summary statistics for the 20 largest business districts in the whole country, showing, for instance, that Midtown Manhattan has just over twice as many jobs as the Chicago Loop. Most of the 20 largest business districts are traditional urban cores, but a few very large suburban business districts exist in places like San Jose, Orlando, and Las Vegas.

Figure S6. Business districts of the Denver, CO, MSA.

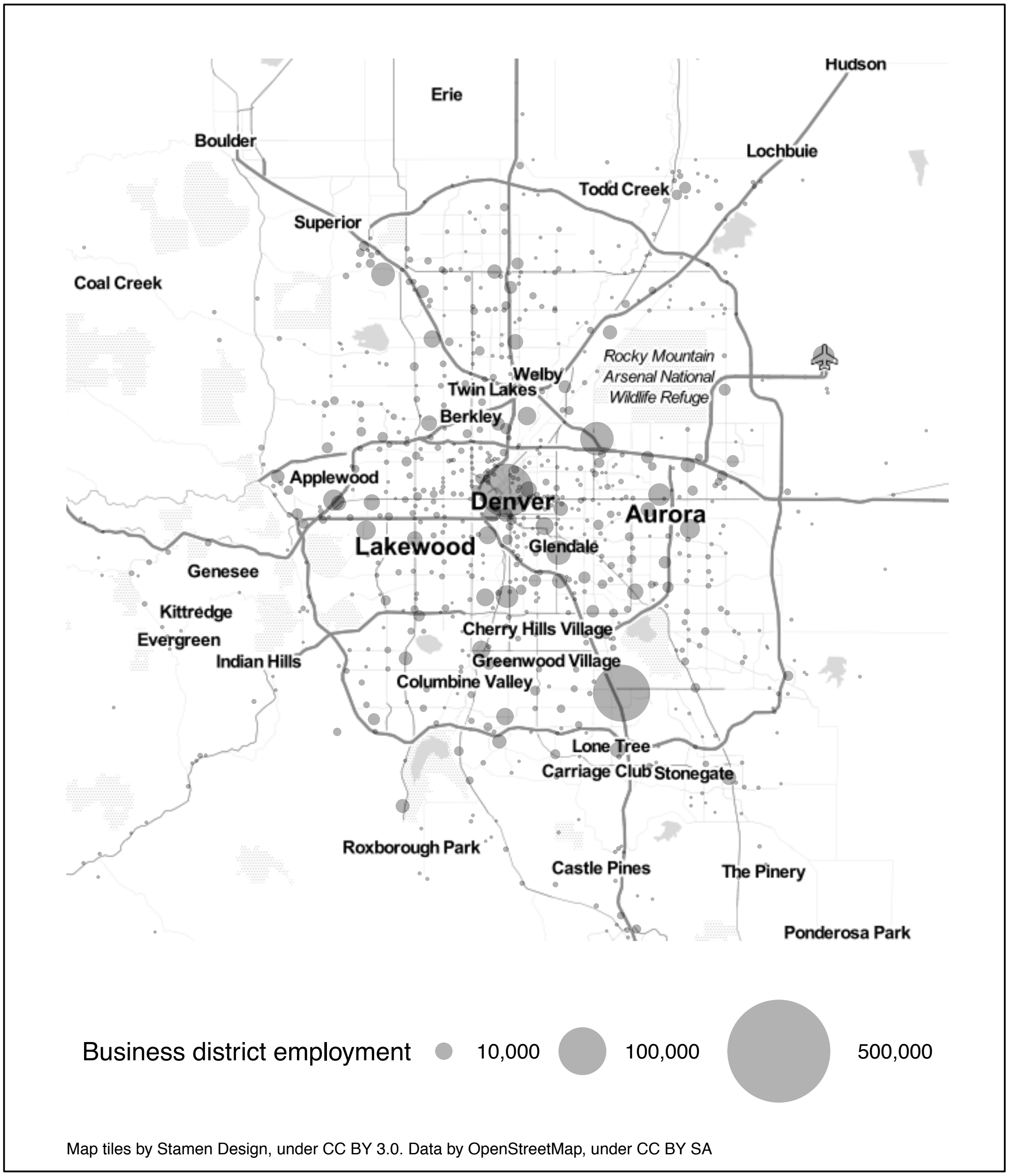


Figure S7. Business districts of the Atlanta, GA, MSA.

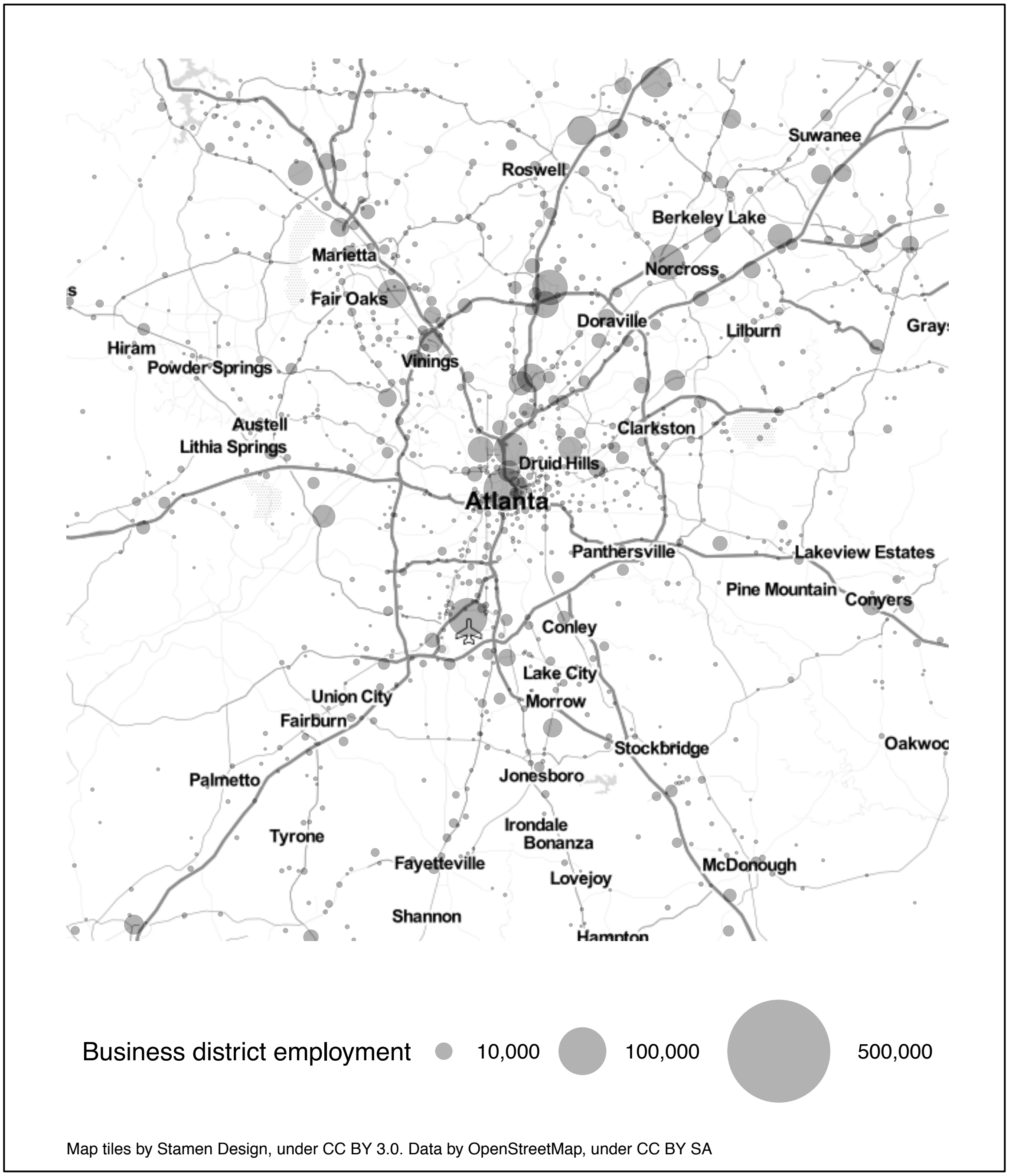


Table S1. Summary statistics of business districts by MSA.

MSA	Total primary jobs	% jobs in employment blocks	% jobs in largest BD	Number of BDs with > 1% of total employment	Number of BDs with > 20,000 jobs
Akron, OH	300,877	75.5%	11.7%	14	1
Albany-Schenectady-Troy, NY	398,723	73.7%	8.3%	14	1
Albuquerque, NM	349,220	78.2%	11.7%	11	4
Allentown-Bethlehem-Easton, PA-NJ	317,282	74.6%	8.3%	15	2
Atlanta-Sandy Springs-Roswell, GA	2,289,559	74.7%	3.6%	14	16
Augusta-Richmond County, GA-SC	195,773	72.6%	15.3%	10	1
Austin-Round Rock, TX	837,815	76.6%	14.7%	14	7
Bakersfield, CA	256,558	75.3%	9.0%	12	1
Baltimore-Columbia-Towson, MD	1,174,337	75.9%	8.5%	10	6
Baton Rouge, LA	358,274	75.2%	11.1%	14	4
Birmingham-Hoover, AL	465,748	79.7%	12.0%	11	1
Boise City, ID	267,193	76.3%	14.2%	13	2
Boston-Cambridge-Newton, MA-NH	2,270,359	76.5%	11.6%	7	8
Bridgeport-Stamford-Norwalk, CT	392,755	70.2%	6.1%	17	1
Buffalo-Cheektowaga-Niagara Falls, NY	512,191	71.8%	8.8%	11	2
Cape Coral-Fort Myers, FL	200,457	69.6%	23.9%	9	1
Charleston-North Charleston, SC	284,237	77.9%	8.1%	15	2
Charlotte-Concord-Gastonia, NC-SC	1,019,607	75.7%	11.5%	11	5
Chattanooga, TN-GA	217,564	81.8%	15.7%	16	1
Chicago-Naperville-Elgin, IL-IN-WI	3,941,399	82.2%	10.5%	5	18
Cincinnati, OH-KY-IN	936,346	74.3%	10.1%	13	4
Cleveland-Elyria, OH	923,212	71.1%	10.8%	12	4
Colorado Springs, CO	227,807	81.8%	7.9%	13	0
Columbia, SC	344,414	79.7%	13.3%	17	1
Columbus, OH	908,715	79.0%	8.2%	17	5
Dallas-Fort Worth-Arlington, TX	2,976,134	83.4%	4.5%	13	19
Dayton, OH	329,014	74.1%	10.3%	11	3
Deltona-Daytona Beach-Ormond Beach, FL	166,265	66.6%	12.3%	16	1
Denver-Aurora-Lakewood, CO	1,241,803	81.6%	11.7%	11	5
Des Moines-West Des Moines, IA	314,698	78.7%	14.5%	14	2
Detroit-Warren-Dearborn, MI	1,694,360	77.7%	3.1%	11	8
El Paso, TX	297,785	78.8%	13.2%	15	2
Fresno, CA	309,281	73.1%	11.0%	14	1
Grand Rapids-Wyoming, MI	473,900	79.3%	10.4%	14	3
Greensboro-High Point, NC	322,192	76.5%	14.4%	19	1
Greenville-Anderson-Mauldin, SC	355,563	78.3%	7.7%	16	2
Harrisburg-Carlisle, PA	307,509	81.8%	8.4%	17	2
Hartford-West Hartford-East Hartford, CT	573,250	74.9%	7.7%	18	1
Houston-The Woodlands-Sugar Land, TX	2,621,068	81.5%	5.4%	11	16
Indianapolis-Carmel-Anderson, IN	914,130	81.4%	8.9%	14	7
Jackson, MS	246,712	81.3%	14.7%	15	3
Jacksonville, FL	606,997	76.8%	6.5%	18	2
Kansas City, MO-KS	934,346	79.3%	7.1%	11	5
Knoxville, TN	344,295	81.6%	17.1%	13	2
Lakeland-Winter Haven, FL	198,764	76.2%	7.0%	19	0
Las Vegas-Henderson-Paradise, NV	801,445	81.1%	29.9%	12	4
Little Rock-North Little Rock-Conway, AR	315,076	77.7%	13.4%	17	1
Los Angeles-Long Beach-Anaheim, CA	5,158,903	77.1%	5.9%	14	31
Louisville/Jefferson County, KY-IN	566,865	78.3%	10.7%	13	3
Madison, WI	337,000	79.3%	7.1%	16	2

Table S1. (continued)

MSA	Total primary jobs	% jobs in employment blocks	% jobs in largest BD	Number of BDs with > 1% of total employment	Number of BDs with > 20,000 jobs
McAllen-Edinburg-Mission, TX	215,034	74.3%	16.0%	16	1
Memphis, TN-MS-AR	544,749	83.6%	17.5%	15	3
Miami-Fort Lauderdale-West Palm Beach, FL	2,134,529	75.5%	7.7%	14	14
Milwaukee-Waukesha-West Allis, WI	762,926	78.9%	9.4%	16	4
Minneapolis-St. Paul-Bloomington, MN-WI	1,663,594	79.3%	7.9%	11	9
Nashville-Davidson--Murfreesboro--Franklin, TN	800,399	80.3%	19.3%	19	3
New Haven-Milford, CT	341,645	69.8%	11.1%	13	2
New Orleans-Metairie, LA	501,938	79.9%	12.4%	11	2
New York-Newark-Jersey City, NY-NJ-PA	7,757,625	70.6%	14.3%	2	29
North Port-Sarasota-Bradenton, FL	235,803	69.3%	6.7%	15	0
Ogden-Clearfield, UT	198,643	71.1%	10.4%	13	1
Oklahoma City, OK	558,429	80.1%	8.7%	17	3
Omaha-Council Bluffs, NE-IA	423,515	83.6%	9.5%	14	5
Orlando-Kissimmee-Sanford, FL	1,047,886	80.8%	23.2%	11	7
Oxnard-Thousand Oaks-Ventura, CA	274,598	74.1%	12.4%	14	2
Palm Bay-Melbourne-Titusville, FL	177,907	71.3%	19.7%	11	1
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2,496,512	73.9%	7.7%	6	10
Phoenix-Mesa-Scottsdale, AZ	1,712,283	81.7%	10.7%	13	12
Pittsburgh, PA	1,027,620	72.8%	6.9%	8	3
Portland-Vancouver-Hillsboro, OR-WA	1,001,149	74.6%	9.3%	14	7
Providence-Warwick, RI-MA	619,581	66.8%	3.8%	13	1
Provo-Orem, UT	178,636	70.3%	8.5%	20	0
Raleigh, NC	586,261	79.1%	17.3%	16	3
Richmond, VA	556,100	80.3%	9.0%	14	3
Riverside-San Bernardino-Ontario, CA	1,175,398	72.1%	12.6%	11	8
Rochester, NY	463,541	71.8%	6.5%	15	3
Sacramento--Roseville--Arden-Arcade, CA	823,710	75.4%	11.5%	11	4
St. Louis, MO-IL	1,199,137	76.9%	6.3%	9	6
Salt Lake City, UT	588,890	78.9%	16.6%	13	5
San Antonio-New Braunfels, TX	842,774	75.5%	7.1%	10	4
San Diego-Carlsbad, CA	1,203,195	76.2%	8.6%	16	5
San Francisco-Oakland-Hayward, CA	1,961,015	76.6%	16.0%	13	12
San Jose-Sunnyvale-Santa Clara, CA	907,027	80.1%	30.5%	12	4
Scranton--Wilkes-Barre--Hazleton, PA	226,383	73.3%	8.7%	15	0
Seattle-Tacoma-Bellevue, WA	1,575,849	77.8%	14.2%	13	9
Spokane-Spokane Valley, WA	204,323	76.4%	14.8%	14	1
Springfield, MA	235,002	69.6%	12.9%	12	1
Stockton-Lodi, CA	196,777	66.9%	5.6%	16	0
Syracuse, NY	274,967	71.9%	19.6%	7	2
Tampa-St. Petersburg-Clearwater, FL	1,098,070	75.4%	9.1%	10	5
Toledo, OH	263,897	75.7%	7.3%	21	0
Tucson, AZ	324,296	75.2%	7.3%	15	1
Tulsa, OK	414,419	78.9%	15.4%	12	2
Urban Honolulu, HI	346,022	74.5%	28.2%	8	3
Virginia Beach-Norfolk-Newport News, VA-NC	641,086	77.4%	5.4%	13	3
Washington-Arlington-Alexandria, DC-VA-MD-WV	2,657,171	77.6%	13.5%	10	15
Wichita, KS	274,121	79.6%	16.3%	11	1
Winston-Salem, NC	230,220	74.3%	12.3%	13	2
Worcester, MA-CT	335,686	67.4%	8.3%	9	1
Youngstown-Warren-Boardman, OH-PA	202,799	65.3%	6.3%	14	0

Table S2. Summary statistics of the 20 largest business districts in the US.

Business district name	MSA	Total employment	Resdential population	Land Area (sq. km)	Count of blocks	Type
Midtown Manhattan	New York	1,112,861	65,143	7.0	431	Urban core
Chicago Loop	Chicago	413,306	8,685	4.9	425	Urban core
Downtown Washington DC	Washington	359,459	8,210	9.9	388	Urban core
Lower Manhattan	New York	330,343	19,220	2.4	250	Urban core
Downtown San Francsico	San Francisco	314,206	8,964	4.9	372	Urban core
Downtown LA	Los Angeles	303,711	6,693	21.8	676	Urban core
Northern San Jose	San Jose	276,294	4,273	73.0	602	Suburban
Downtown Boston/Back Bay	Boston	263,831	10,492	2.8	248	Urban core
Southern Orlando	Orlando	243,343	3,886	88.8	360	Suburban
Las Vegas Strip	Las Vegas	239,982	2,094	29.3	204	Suburban
Downtown Seattle	Seattle	223,859	6,633	16.6	554	Urban core
Center City Philadelphia	Philadelphia	191,284	5,315	2.2	216	Urban core
Downtown Phoenix/Airport	Phoenix	183,040	2,643	70.1	461	Suburban
Western Miami industrial zone	Miami	165,205	1,626	81.3	483	Suburban
Downtown Nashville	Nashville	154,835	4,668	13.3	506	Urban core
Ontario industrial area	Riverside	148,672	1,919	92.9	365	Suburban
Colorado Tech Center	Denver	144,961	2,388	35.4	232	Suburban
Downtown Houston	Houston	142,729	868	3.0	267	Urban core
North Dallas	Dallas	134,872	1,437	19.3	287	Suburban
Downtown Minneapolis	Minneapolis	131,837	3,408	5.4	194	Urban core

Distribution of jobs across business district categories

Jobs are unevenly distributed across business district categories. Table S3 shows the fraction of jobs, residents, and built land area falling into each business district category across all 100 MSAs. The vast majority of land area and residents are found in residential areas, while a plurality of jobs are found in suburban strips, the second largest number are found in urban cores, and the rest are close to evenly split across the remaining categories.

Table S3. Overall breakdown of area, jobs, and population, 100 largest MSAs.

Category	Land Area		Jobs		Population		Blocks	
	Square km	%	Count	%	Count	%	Count	%
Residential	708,205	88.1%	9,012,242	10.4%	188,587,285	92.5%	2,517,614	85.1%
Mixed	44,022	5.5%	11,040,647	12.8%	11,499,521	5.6%	134,027	4.5%
Urban core	882	0.1%	13,891,345	16.1%	447,957	0.2%	30,372	1.0%
Suburban strip	23,748	3.0%	37,692,925	43.7%	1,937,480	1.0%	172,389	5.8%
Independent	4,094	0.5%	8,696,659	10.1%	639,172	0.3%	14,456	0.5%
Scattered	23,163	2.9%	5,947,074	6.9%	743,431	0.4%	91,200	3.1%
Total	**804,114**	**100%**	**86,280,892**	**100%**	**203,854,846**	**100%**	**2,960,058**	**100%**

The national distributions conceal substantial variation in these proportions across MSAs. Figure S8 plots the breakdown of MSA employment into the various categories. Cities besides New York that have at least 25% of their overall employment in traditional urban cores include Honolulu, Houston, New Orleans, San Francisco, Washington, DC, and Jackson, MS. 24 further cities, including Boston, Atlanta, Nashville, Seattle, and Chicago, have over 15% of their employment in urban cores. These cities have important downtowns, and many are considered exemplars of urbanism, but at the metro scale suburban employment clearly dominates. On the other end of the spectrum, Fresno, CA, Ogden, UT, and Palm Bay, FL have no urban cores that meet the 10,000 jobs/square km threshold, while 16 other cities have fewer than 5% of their jobs in traditional urban cores.

Figure S9 plots the same distributions using business districts identified based on employment density alone, as in Figure S5. The largest differences from Figure S8 are the larger fraction of jobs assigned to residential areas and the smaller fraction of jobs in suburban business districts. This conforms to the patterns shown in Figure S5, where areas that are identified as large contiguous suburban business districts by my algorithm are split into smaller, fragmented employment centers with higher densities and residential/non-subcenter blocks.

Figure S8. Breakdown of employment by block type and business district category, 100 largest MSAs.

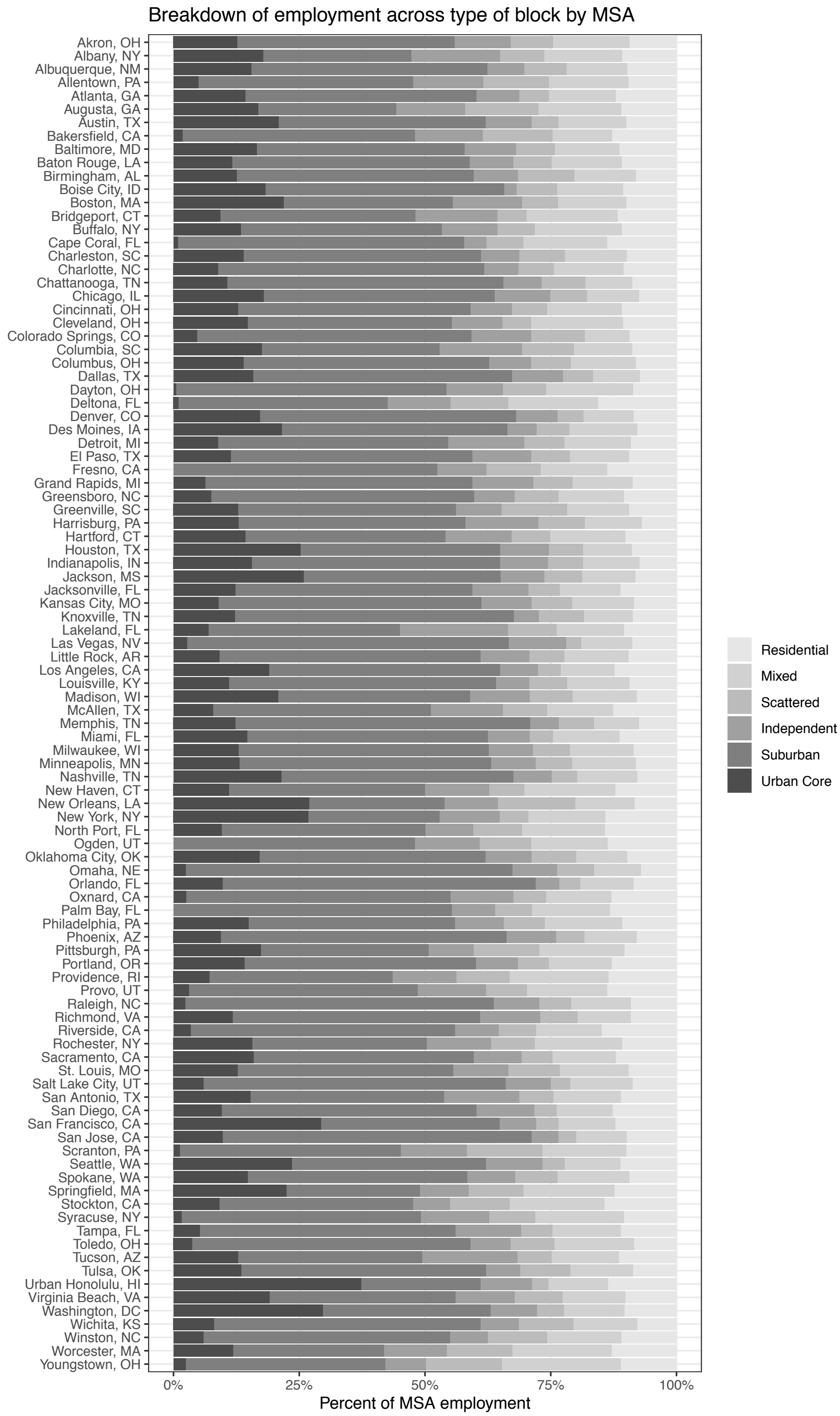
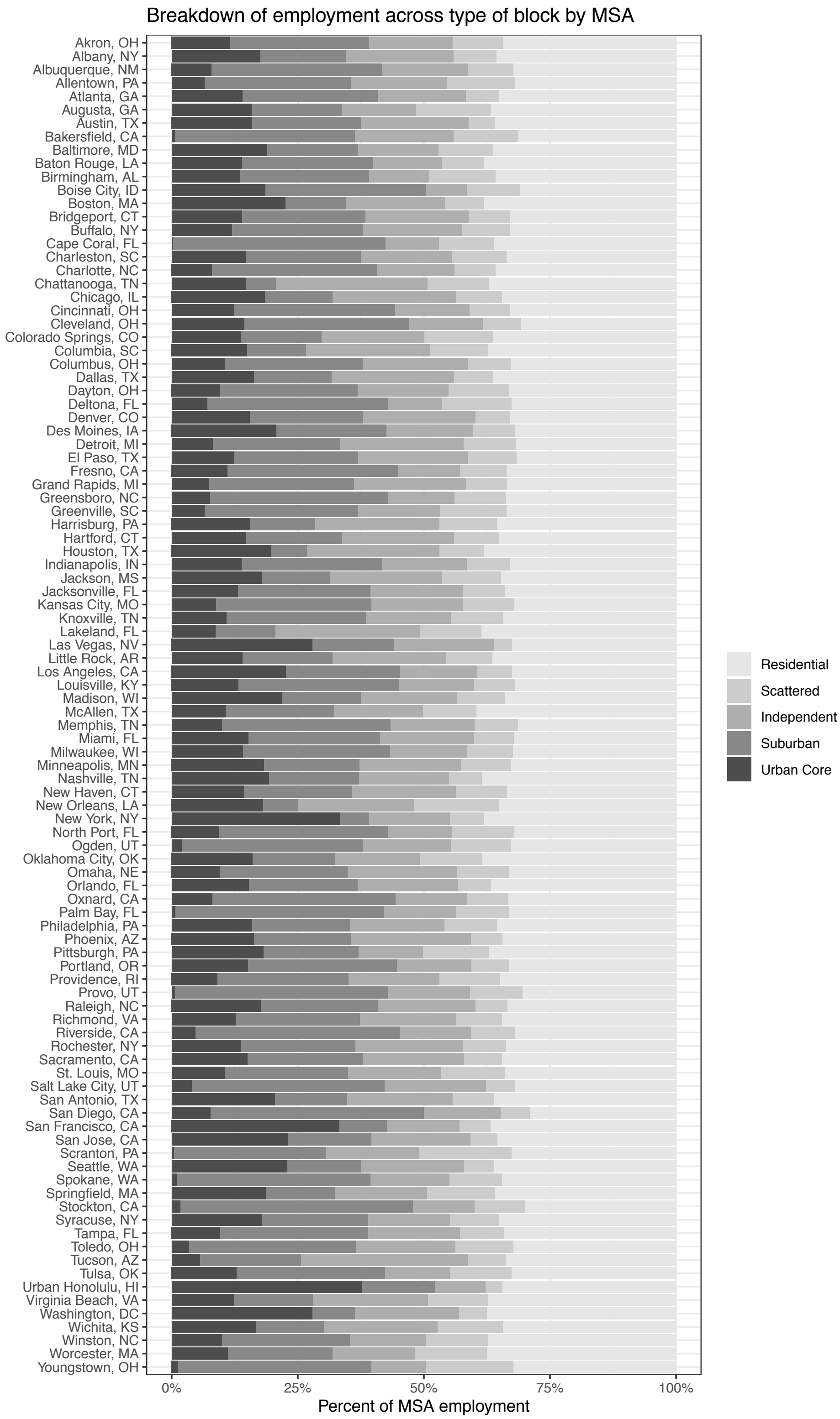


Figure S9. Breakdown of employment by block type and business district category, top 100 MSAs. Business districts are defined using the density threshold method (Giuliano and Small, 1991), with the density threshold set at 50% of the density of the median job in each MSA.



Identification of CBDs and comparison to CBDs identified by Google Maps

The presence of urban core business districts in almost every major city provides a scalable and replicable way to identify city centers for the purposes of urban geographic analysis. Many theoretical and empirical attempts to understand metropolitan structure have been undertaken in reference to a Central Business District or other central point. But systematically defining and identifying such places has proven difficult. In many cases scholars have had to resort to ad hoc or manually created CBD definitions, which are both not scalable and difficult to characterize. A large number of papers rely on a table produced from the 1982 Economic Census, which identified the tract or tracts containing the Central Business District of metro areas of 50,000 or more people (e.g. Baum-Snow, 2007; Glaeser and Kahn, 2001; Ottensmann, 2016). However, these estimates are more than 30 years old, they exist only for cities that met the size threshold in 1982 and also chose to participate, and they were constructed in part via a survey of local leaders, a method that is difficult to replicate (Glaeser and Kahn, 2004; U.S. Bureau of the Census, 1983). An alternative approach has been to use the location of City Hall (Ottensmann, 2016) or a prominent commercial building (Haughwout et al., 2008). Recently there have been promising attempts to identify city centers using Volunteered Geographic Information (Hollenstein and Purves, 2010; Sun et al., 2016; Yu et al., 2015).

The urban core business districts identified here provide a systematic and transparent method of identifying the CBD or city center. The largest urban core business district is labeled the Central Business District, and its employment-weighted centroid is the point from which distances are measured. If a metro has no urban core district with at least 1% of overall employment, the single largest business district of any type is used instead. This constraint applies in seven cities. This approach provides a single, rigorous way of determining the CBD of any metro area that is easy to update and based solely on current employment data.

The CBDs identified using this approach closely match intuitive and inspection-based conceptions of the center of town, but they emerge entirely and consistently from the employment data. As a proxy for the intuitive centers of each metro area, I compare the CBDs identified here to the locations returned by the Google Maps API as the center of the largest principal city of each MSA. Google is a common source of geographic information among both academics and the public, but it is notoriously opaque. For instance, although Google Maps returns specific coordinates for each MSA, it provides no information about how it determines these coordinates. Importantly, while the coordinates almost always have a clear intuitive interpretation, that interpretation is different in different cities. In Atlanta, the coordinates are those of the Georgia State Capitol. In New York City, they are New York City Hall, while in Los Angeles they point to the LAPD headquarters. In Austin, Texas, they point to the Frost Bank Tower, a prominent office building and the fifth tallest building in the city (but about half a mile south of the state capitol and the same distance east of city hall). In Madison, Wisconsin, they are the intersection of Park Street and University Avenue, in the eastern part of the UW-Madison campus and about a mile from the Wisconsin State Capitol and Madison City Hall. The coordinates for Toledo, Ohio, are the center of the intersection between Erie Street and Madison Street, just west of the main skyscraper district. In some cities, like Chicago, Detroit, and Tampa, Florida, the coordinates appear to approximate the center of the main business district, but do not fall directly onto a particular building or street intersection.

Each of the locations returned by Google Maps makes some sense in its local context, but the apparent justification differs from city to city, with no obvious rationale for the variation.

This makes it impossible to replicate the analysis done by Google, or to justify it beyond simply appealing to Google's expertise and widespread usage. Google coordinates may also change at any time without warning—for instance, over the course of preparing this manuscript, the coordinates returned by Google for the centers of the Portland, Oregon, and Winston-Salem, North Carolina, MSAs moved roughly 1.5 miles southwest and 0.9 miles northwest respectively. For all of these reasons, the Google Maps coordinates, while readily available and intuitively appealing, are not ideal for use by social scientists. The CBD coordinates identified by my algorithm offer a transparent, consistent, and replicable alternative. In 80 of the 100 MSAs I study the CBD identified using my algorithm and that identified by Google are less than two miles apart, and in at least eight of the discrepancies the location selected by the algorithm is arguably closer to the true city center than that identified by Google.[1] A full list of the CBD coordinates for each of the 100 largest MSAs as identified using this algorithm and from Google Maps is presented in Table S4. CBD coordinates generated with this method for the remaining 817 Core Based Statistical Areas, all 2013 Combined Statistical Areas, and all 1990 Commuting Zones are available on the author's website.

[1] For instance, the algorithm used here identifies Midtown Manhattan as the CBD of the New York MSA, while Google Maps returns downtown Manhattan, consistent with the historic development of the city. In polycentric MSAs such as Virginia Beach, VA, Bridgeport, CT, and several metro areas in Florida, the largest business districts are in cities that are not the most populous of the MSA (the largest business district in the Virginia Beach MSA is downtown Norfolk, while that in the Bridgeport MSA is downtown Stamford).

Table S4. Comparison of CBDs identified via algorithm with those identified via Google Maps.

MSA FIPS Code	MSA Name	City Center - CBD Algorithm		City Center - Google		Distance (miles)
		Latitude	Longitude	Latitude	Longitude	
10420	Akron, OH	41.0791191	-81.5183238	41.0814447	-81.5190053	0.16
10580	Albany, NY	42.6540835	-73.7522704	42.6525793	-73.7562317	0.23
10740	Albuquerque, NM	35.0887396	-106.6499396	35.0843859	-106.6504220	0.30
10900	Allentown, PA	40.6021959	-75.4719724	40.6022939	-75.4714098	0.03
12060	Atlanta, GA	33.7568566	-84.3896577	33.7489954	-84.3879824	0.55
12260	Augusta, GA	33.4728461	-81.9822198	33.4734978	-82.0105148	1.63
12420	Austin, TX	30.2739241	-97.7428213	30.2671530	-97.7430608	0.47
12540	Bakersfield, CA	35.4505325	-119.0372456	35.3732921	-119.0187125	5.44
12580	Baltimore, MD	39.2915901	-76.6101805	39.2903848	-76.6121893	0.14
12940	Baton Rouge, LA	30.4518149	-91.1863776	30.4514677	-91.1871466	0.05
13820	Birmingham, AL	33.5117923	-86.8054730	33.5185892	-86.8103567	0.55
14260	Boise City, ID	43.6146911	-116.1999461	43.6150186	-116.2023137	0.12
14460	Boston, MA	42.3546685	-71.0643721	42.3600825	-71.0588801	0.47
14860	Bridgeport, CT	41.0532807	-73.5390715	41.1792258	-73.1894384	20.20
15380	Buffalo, NY	42.8899323	-78.8731515	42.8864468	-78.8783689	0.36
15980	Cape Coral, FL	26.6147925	-81.8638695	26.5628537	-81.9495331	6.40
16700	Charleston, SC	32.7845182	-79.9490589	32.7764749	-79.9310512	1.19
16740	Charlotte, NC	35.2249242	-80.8428142	35.2270869	-80.8431267	0.15
16860	Chattanooga, TN	35.0716069	-85.1493709	35.0456297	-85.3096801	9.25
16980	Chicago, IL	41.8841062	-87.6311106	41.8781136	-87.6297982	0.42
17140	Cincinnati, OH	39.1029172	-84.5113858	39.1031182	-84.5120196	0.04
17460	Cleveland, OH	41.5024397	-81.6843395	41.4993200	-81.6943605	0.56
17820	Colorado Springs, CO	38.8400469	-104.7990842	38.8338816	-104.8213634	1.27
17900	Columbia, SC	34.0050942	-81.0324942	34.0007104	-81.0348144	0.33
18140	Columbus, OH	39.9629117	-82.9990397	39.9611755	-82.9987942	0.12
19100	Dallas, TX	32.8221781	-96.8470597	32.7766642	-96.7969879	4.29
19380	Dayton, OH	39.7682910	-84.1838775	39.7589478	-84.1916069	0.77
19660	Deltona, FL	29.1964541	-81.0667108	28.9005446	-81.2636738	23.68
19740	Denver, CO	39.7457924	-104.9907150	39.7392358	-104.9902510	0.45
19780	Des Moines, IA	41.5863795	-93.6291937	41.5868353	-93.6249593	0.22
19820	Detroit, MI	42.3320846	-83.0481600	42.3314270	-83.0457538	0.13
21340	El Paso, TX	31.7608403	-106.3556520	31.7618778	-106.4850217	7.61
23420	Fresno, CA	36.7366411	-119.7860999	36.7377981	-119.7871247	0.10
24340	Grand Rapids, MI	42.9668958	-85.6683283	42.9633599	-85.6680863	0.24
24660	Greensboro, NC	36.0738792	-79.7919238	36.0726354	-79.7919754	0.09
24860	Greenville, SC	34.8481412	-82.3991116	34.8526176	-82.3940104	0.42
25420	Harrisburg, PA	40.2629557	-76.8822532	40.2731911	-76.8867008	0.75
25540	Hartford, CT	41.7622838	-72.6735724	41.7658043	-72.6733723	0.24
26420	Houston, TX	29.7555211	-95.3674842	29.7604267	-95.3698028	0.37
26900	Indianapolis, IN	39.7686268	-86.1579611	39.7684030	-86.1580680	0.02
27140	Jackson, MS	32.2998557	-90.1867155	32.2987573	-90.1848103	0.13
27260	Jacksonville, FL	30.3172856	-81.6560366	30.3321838	-81.6556510	1.03
28140	Kansas City, MO	39.1009754	-94.5824315	39.0997265	-94.5785667	0.22
28940	Knoxville, TN	35.9632687	-83.9177657	35.9606384	-83.9207392	0.25
29460	Lakeland, FL	28.0420490	-81.9555894	28.0394654	-81.9498042	0.40
29820	Las Vegas, NV	36.1697272	-115.1411682	36.1699412	-115.1398296	0.08
30780	Little Rock, AR	34.7485384	-92.3201719	34.7464809	-92.2895948	1.74
31080	Los Angeles, CA	34.0415830	-118.2469825	34.0522342	-118.2436849	0.76
31140	Louisville, KY	38.2520934	-85.7603499	38.2526647	-85.7584557	0.11
31540	Madison, WI	43.0753727	-89.3807482	43.0730517	-89.4012302	1.05

Table S4. (continued)

MSA FIPS Code	MSA Name	City Center - CBD Algorithm		City Center - Google		Distance (miles)
		Latitude	Longitude	Latitude	Longitude	
32580	McAllen, TX	26.2154399	-98.2277797	26.2034071	-98.2300124	0.84
32820	Memphis, TN	35.1442288	-90.0451529	35.1495343	-90.0489801	0.43
33100	Miami, FL	25.7745852	-80.1900838	25.7616798	-80.1917902	0.90
33340	Milwaukee, WI	43.0408733	-87.9048863	43.0389025	-87.9064736	0.16
33460	Minneapolis, MN	44.9779832	-93.2681413	44.9777530	-93.2650108	0.15
34980	Nashville, TN	36.1460712	-86.7881076	36.1626638	-86.7816016	1.20
35300	New Haven, CT	41.3102981	-72.9250419	41.3082740	-72.9278835	0.20
35380	New Orleans, LA	29.9517093	-90.0711571	29.9510658	-90.0715323	0.05
35620	New York, NY	40.7537208	-73.9837555	40.7127753	-74.0059728	3.06
35840	North Port, FL	27.4945002	-82.5647708	27.0442240	-82.2359254	37.13
36260	Ogden, UT	41.2320487	-111.9790193	41.2230000	-111.9738304	0.68
36420	Oklahoma City, OK	35.4704618	-97.5176331	35.4675602	-97.5164276	0.21
36540	Omaha, NE	41.2581650	-95.9617668	41.2565369	-95.9345034	1.42
36740	Orlando, FL	28.5418901	-81.3758209	28.5383355	-81.3792365	0.32
37100	Oxnard, CA	34.2293562	-119.1741933	34.1975048	-119.1770516	2.21
37340	Palm Bay, FL	28.0952901	-80.6434117	28.0344621	-80.5886646	5.37
37980	Philadelphia, PA	39.9521938	-75.1629820	39.9525839	-75.1652215	0.12
38060	Phoenix, AZ	33.4977915	-112.0550440	33.4483771	-112.0740373	3.59
38300	Pittsburgh, PA	40.4436906	-79.9957771	40.4406248	-79.9958864	0.21
38900	Portland, OR	45.5234135	-122.6847872	45.5051064	-122.6750261	1.35
39300	Providence, RI	41.8106575	-71.4083538	41.8239891	-71.4128343	0.95
39340	Provo, UT	40.2337733	-111.6596180	40.2338438	-111.6585337	0.06
39580	Raleigh, NC	35.7844340	-78.5869623	35.7795897	-78.6381787	2.89
40060	Richmond, VA	37.5410761	-77.4364153	37.5407246	-77.4360481	0.03
40140	Riverside, CA	33.9783704	-117.3753880	33.9806005	-117.3754942	0.15
40380	Rochester, NY	43.1227472	-77.6231720	43.1565779	-77.6088465	2.45
40900	Sacramento, CA	38.5765556	-121.4934921	38.5815719	-121.4943996	0.35
41180	St. Louis, MO	38.6299874	-90.2080335	38.6270025	-90.1994042	0.51
41620	Salt Lake City, UT	40.6701062	-111.8465484	40.7607793	-111.8910474	6.69
41700	San Antonio, TX	29.4270469	-98.4919237	29.4241219	-98.4936282	0.23
41740	San Diego, CA	32.7224040	-117.1717349	32.7157380	-117.1610838	0.77
41860	San Francisco, CA	37.7882419	-122.4036342	37.7749295	-122.4194155	1.26
41940	San Jose, CA	37.3344936	-121.8895766	37.3382082	-121.8863286	0.31
42540	Scranton, PA	41.2703270	-75.8894958	41.4089690	-75.6624122	15.20
42660	Seattle, WA	47.5988779	-122.3338337	47.6062095	-122.3320708	0.51
44060	Spokane, WA	47.6564541	-117.4172540	47.6587802	-117.4260465	0.44
44140	Springfield, MA	42.1126320	-72.5796336	42.1014831	-72.5898110	0.93
44700	Stockton, CA	37.9544790	-121.2876333	37.9577016	-121.2907796	0.28
45060	Syracuse, NY	43.0480832	-76.1342110	43.0481221	-76.1474244	0.67
45300	Tampa, FL	27.9484263	-82.4567779	27.9505750	-82.4571776	0.15
45780	Toledo, OH	41.6917216	-83.5210388	41.6528052	-83.5378674	2.83
46060	Tucson, AZ	32.2228232	-110.9722744	32.2226066	-110.9747108	0.14
46140	Tulsa, OK	36.1512403	-95.9905966	36.1539816	-95.9927750	0.23
46520	Urban Honolulu, HI	21.3041100	-157.8564523	21.2765308	-157.8257819	2.75
47260	Virginia Beach, VA	36.8512070	-76.2879618	36.8529263	-75.9779850	17.16
47900	Washington, DC	38.9000080	-77.0289278	38.9071923	-77.0368707	0.66
48620	Wichita, KS	37.6239754	-97.2852333	37.6871761	-97.3300530	5.01
49180	Winston, NC	36.0925883	-80.2660134	36.1039642	-80.2544350	1.02
49340	Worcester, MA	42.2681073	-71.7998920	42.2625932	-71.8022934	0.40
49660	Youngstown, OH	41.1141260	-80.6578884	41.0997803	-80.6495194	1.08

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