The Census Place Project: A Method for Geolocating Unstructured Place Names

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Researchers use microdata to study the economic development of the United States and the causal effects of historical policies. Much of this research focuses on county- and state-level patterns and policies because comprehensive sub-county data is not consistently available. We describe a new method that geocodes and standardizes the towns and cities of residence for individuals and households in decennial census microdata from 1790–1940. We release public crosswalks linking individuals and households to consistently-defined place names, longitude-latitude pairs, counties, and states. Our method dramatically increases the number of individuals and households assigned to a sub-county location relative to standard publicly available data: we geocode an average of 83% of the individuals and households in 1790–1940 census microdata, compared to 23% in widely-used crosswalks. In years with individual-level microdata (1850–1940), our average match rate is 94% relative to 33% in widely-used crosswalks. To illustrate the value of our crosswalks, we measure place-level population growth across the United States between 1870 and 1940 at a sub-county level, confirming predictions of Zipf's Law and Gibrat's Law for large cities but rejecting similar predictions for small towns. We describe how our approach can be used to accurately geocode other historical datasets.

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1 Introduction

The public release of full-count decennial census microdata from 1790-1940 has increased the quantity and quality of research studying trends and policies in the United States during these periods. Much of this work uses state- or county-level data (e.g., Aaronson and Mazumder, 2011; Donaldson and Hornbeck, 2016; Desmet and Rappaport, 2017) or focuses on a small number of counties or large cities where researchers have detailed sub-county microdata (e.g., Michaels, Rauch, and Redding, 2012; Shertzer, Walsh, and Logan, 2016; Brooks and Lutz, 2019; Fishback et. al, 2020; Aaronson, Hartley, Mazumder, 2021). One reason for this geographic focus is data availability: commonly-used historical datasets only consistently identify states, counties, and large cities. However, states and counties cover broad geographic areas and contain important heterogeneity in demographics, policies, and access to local amenities; while larger cities can be systematically different from their smaller peers. In this paper, we use a new method to construct consistent measures of place for U.S. residents in the 1790—1940 decennial censuses. We create a crosswalk that allows researchers using public or restricted decennial census microdata to link respondents to consistently defined sub-county locations.[1]

To construct these links, we clean and analyze raw place names from census manuscripts corresponding to cities and townships. After we identify all unique places within a given decade of census microdata, we iterate through the strings to identify a standardized location name and latitude/longitude. To do this, we match strings to geocoded places in NHGIS historical place point files, GNIS place files, and Google Maps.[2] When location strings are not reported or found, we are often able to exploit the existence of nearby enumeration districts to impute an accurate sub-county location. After we perform these steps for every census year in our sample, we standardize place names and locations across years to make our locations temporally consistent.

[1]We define a sub-county location as any location at a finer geography than county borders, not official Census sub-county areas.

[2]For more details about NHGIS place point files, see Manson et al. (2021). For more details about the GNIS place files, see United States Geological Survey (2021).

Relative to publicly available datasets, we map many more people to sub-county locations. We match an average of 83% of the individuals and households in 1790−1940 census microdata to the longitudes and latitudes of their cities and towns of residence, compared to 23% in currently widely-used crosswalks. In years with individual-level microdata (1850−1940), our average match rate is 94% relative to 33% in widely-used crosswalks. In 1870 (the year where we obtain our best match rate), we geocode 99.1% of individuals relative to 19% in public crosswalks.

We highlight the value of our new place data with two applications. First, we take the 69,393 unique geocoded places from our census microdata crosswalks covering 1790-1940 and we iteratively cluster these places into 42,133 consistently-defined places over time. Our clustering approach is informed by the closeness and size of neighboring places and addresses the fuzziness of fixed place definitions both over time and across borders. Our clusters account for shifting place borders, annexations, subsumed suburbs, and ghost towns. We include these clusters as variables in our crosswalks, providing other researchers with a data-driven definition of local metropolitan areas.

Next, we link our clusters to census microdata and create granular measures of place-level population growth over time. We show that our clustered places consistently follow Zipf's Law and Gibrat's Law for large cities in historical time periods, matching predictions from theory and modern-day empirical contexts (e.g., Gabaix 1999; Ioannides and Overman 2003; Giesen and Sudekum, 2011). We also find sharp deviations from Zipf's Law and Gibrat's Law for small places. To the best of our knowledge, we are the first to document these patterns for smaller places across the entire U.S. in a historical context, since prior historical work focuses only on large cities, county-level patterns (eg. Desmet and Rappaport, 2017), or a small subset of states with high-quality sub-county data (Michaels, Rauch, and Redding, 2012).[3]

Our work builds on past efforts to digitize, standardize, and improve the usability of the complete count census files. In particular, IPUMS staff have standardized large portions of the histor-

[3]For a review of prior historical work on city growth rates in a historical context, embedded in a larger discussion of historical urban economics, see Hanlon and Heblich (2021).

ical census enumeration sheets and created variables for many common fields that researchers commonly use (Ruggles et. al, 2021). Public IPUMS data generally identifies only larger cities, though the effective city-size thresholds vary over time.[4] Our approach is informed by efforts like the Census Linking Project, which provides public census data users a crosswalk that allows them to link census respondents across time, a process that otherwise would require access to restricted census data (Abramitzky, Boustan, and Rashid, 2020).

Many papers (including our own prior work) use raw census strings to define sub-county areas that are smaller than IPUMS-provided cities for subsets of the historical censuses.[5] For example, Karger (2021) and Berkes and Nencka (2021) develop string cleaning methods to identify small cities and towns that had Carnegie libraries in the early 1900s. Michaels, Rauch, and Redding (2012) standardize sub-county areas in the 1880 census and link these areas to 2000 data to study long-run trends in population dynamics.[6] Nagy (2020) standardizes cities in the 1790 to 1860 censuses to study city formation and the effects of transportation infrastructure. Feigenbaum and Gross (2021) clean city names with more than 2,000 people from 1910 to 1940 to track information on telephone operators. Otterstrom, Price, and Van Leeuwen (2021) use linked census records from 1900–1940 to measure changes in city population size for the 1,000 largest cities in 1900. Connolly (2021) digitizes locations in the 1920 census to study the impact of two-year colleges on children's adult outcomes. To our knowledge, we are the first to standardize raw location strings for the universe of all available full-count census data, allowing us to use information *across* census years to improve the accuracy of matches. Moreover, we identify additional sub-county locations for observations with missing or uninformative strings by relying on nearby, sequentially numbered enumeration districts. Finally, by releasing our crosswalks and associ-

[4]See the IPUMS documentation for a detailed description of the IPUMS CITY variable, which is the primary temporally consistent source of sub-county place information in publicly available Census microdata. We describe the IPUMS standardization more fully and compare our mapping to theirs in Section 3.1. For 1940, IPUMS recently released a more comprehensive city variable that captures more (but not all) of the locations that we geocode. This variable is named PLACENHG in the public 1940 data and is constructed using NHGIS place files.

[5]It would be difficult to highlight every paper that used sub-county historical variation. In this section, we highlight a number of illustrative examples.

[6]These areas are also used in Hodgson (2018) to study the effects of the railroad on population growth.

ated time-consistent clusters, we give all researchers the ability to study sub-county trends and policies while reducing duplicated effort in the research community.

Relative to publicly released census data, our added value is highest when studying rural areas or smaller locations adjacent to nearby cities. By contrast, we do not attempt to geocode *within-city* locations like addresses or neighborhoods, which are the subject of recent valuable exercises focused on larger cities (e.g., Logan et. al 2011, Shertzer, Walsh and Logan, 2016; Fishback et. al, 2020; Brooks and Lutz, 2019; Aaronson, Hartley, Mazumder, 2020). Sub-city geocoding requires historically accurate street layouts, which makes it difficult to apply to smaller or rural areas. In recent work, Ferrara, Testa, and Zhou (2022) construct population-based crosswalks of countries and congressional districts using backward-looking population projections. Our work complements their contribution: we focus on matching individuals to geocoded places using contemporaneous location information, allowing researchers to use individual microdata to measure area characteristics. We do not attempt to model the entire geographic population distribution.[7]

While our focus is historical U.S censuses, our methods apply more broadly. Our publicly-accessible programs provide a consistent and automatic methodological approach to geocoding and clustering townships, cities, and unincorporated places. We hope that these methods will be useful in other contexts where researchers need to assign geocodes to historical documents that contain location strings. For example, U.S patents include the city, state, and county of inventors, and birth certificates often include detailed birth locations. Our methods provide an easily applicable framework for geocoding locations in these documents.

The rest of the paper is structured as followed: in Section 2 we discuss our geocoding procedure. In Section 3 we compare our geocode coverage to existing census data and show an illustrative example of how to use our data. In Section 4 we discuss how to implement our method in other applications which involve sub-county data. In Section 5 we conclude.

[7] Ferrara, Testa, and Zhou (2022) discuss both the benefits and limits of their approach in Section 4 of their paper.

2 Method

In this section, we describe the method that we use to geocode the historical censuses. We discuss our approach with reference to the information available in in the US census, though as we discuss in Section 4 many of the steps below will be similar for any data involving historical locations.

We begin by identifying all the geographic information available in IPUMS' raw decennial census data from 1790–1940. These variables represent raw text strings and in some cases IPUMS-standardized place names. The data includes between one and six raw location strings each year along with contemporary county and state identifiers.[8] These text strings are sometimes broad (eg. "New York City"), but often contain granular information about places (eg. "District 83, Beebe Volborg").

We clean the text strings by applying a standardized set of criteria, described in more detail in our Data Appendix. To summarize these steps, we standardize common prefixes, remove punctuation, remove common words (like "justice ward" or "courthouse"), and standardize cardinal directions when they refer to an explicit quadrant of a town or city. For example, the text string "Precinct 10, Aubrey [30] & Precinct 6, South Side [11]" is cleaned into the location "Aubrey."

Next, we attempt to geocode all of our clean place names in several steps, relying on historical spatial databases from IPUMS National Historical Geographic Information System (NHGIS) and The Geographic Names Information System (GNIS). NHGIS contains the locations of incorporated and unincorporated places used by the U.S. Census Bureau from 1900 onward. GNIS is the U.S. Board on Geographic Names' consistent database of places, maintained by the federal government. We iterate over the raw census location strings, starting with the most granular place name and then using less granular place names if we cannot make a match.

For 1900–1940, we take each cleaned census place and its associated county in historical data, and we look for the most similarly named place in NHGIS that is in the correct historical county.In most cases, we use county and state maps corresponding to the relevant census year. However,

[8] For a full list of the variables we use, see our Data Appendix.

we have a penultimate round of matching that uses 1910 counties as our reference geography. The standardized census data uses some county or state names before they were official (e.g., West Virginia in 1860). This additional step reduces false negative matches. We require that the census and NHGIS strings have a match score of 0.95 to identify accurate matches.[9] If we cannot find a match, we then perform the same search within the GNIS place data, looking for matches to different feature types, ranging from populated places to post offices and valleys. For any unmatched census places after this step, we search NHGIS and then GNIS for place names in the correct county that have an edit-distance of 1 with our census place. Finally, we remove cardinal directions and look again for places in the NHGIS and GNIS files with a match score of 0.95.

Our strategy for geocoding the 1790−1880 census years is similar to our process for 1900-1940. However, since NHGIS historical place points are not available before 1900, we only use the GNIS place file to match census strings to place names. Otherwise, we use identical approaches.

Once we have initial geocodes for all census years from the NHGIS and GNIS files, we complete four final steps to increase match rates and standardize geocodes. First, we impute coordinates for places in enumeration districts when another named place within that enumeration district was successfully geocoded. Second, we impute coordinates for enumeration districts that are numerically between two successfully geocoded, nearby enumeration districts. Third, we search Google Maps for all unmatched places. We use the Google Maps latitude and longitude if it falls within the correct historical census county. Lastly, we compare across census years and standardize the spelling of matched place names and the exact coordinates of each place. This standardizes small perturbations in the reported coordinates of places across NHGIS, GNIS, and Google Maps. In our crosswalks, we include flags that indicate at which step each match is made, so that researchers can exclude these imputed matches as desired. The Data Appendix includes more details on all of these steps.

After this procedure, there are 708,928 unique census year -by- cleaned location observations

[9] The match score is calculated using the string-matching process of the fuzzywuzzy library in Python. It combines several methods for calculating a measure of 'distance' between potential strings, normalizing by string length.

that we extract from the raw census data. Of those year-place observations, we fail to geocode 42,155 places (6% of the total number). 390,913 places (55%) match to NHGIS places in our first attempt, and an additional 198,491 (28%) match to the most common types of GNIS places in our first attempt. 14,690 (2%) match to NHGIS and GNIS places using slight variation in fuzziness of match requirements, and an additional 54,403 (8%) match through our two enumeration district imputation steps. By ensuring time-consistency of identically-named place names across census years, we geocode an additional 7,357 (1%) of places. And lastly, we geocode 919 (0.2%) of places using Google Maps.

Our final crosswalks create consistent longitudes and latitudes of each person's town, city, or unincorporated place of residence. To increase the usability of our crosswalks, we also assign modern-day county and state identifiers to each geocoded place. This provides a consistent measure of county and state of residence for all geocoded observations. Our crosswalks provide an accurate and consistent way to identify the county of residence for the vast majority of U.S. residents, complementing recently-constructed spatial harmonizations of changing county borders over time (Hornbeck, 2010; Perlman, 2014; Ferrara, Testa, and Zhou, 2022).

3 Results and Application

3.1 Geocoding Rates

In this subsection, we describe the coverage of our geocoded data across decades and compare our match rates to existing public data. In all years, our match rates allow researchers to observe more sub-county locations relative to previously available sources. To see this, we calculate the share of observations in public census data that can be geocoded using extracts from IPUMS. In particular, we compare our cities to observations with non-missing IPUMS standardized city variables "CITY" or (for 1940 only) "PLACENHG."

We show our match rate comparison in Figure 1, which plots the percent of census observations with valid sub-county locations across years, for both our crosswalks and publicly available IPUMS data. We successfully match 56-99 percent of observations to a sub-county location, depending on the census year. Our match rate generally increases over time, particularly when the census moves to the collection of individual-level data in 1850. Match rates surpass 91% in all years from 1860–1940.[10] Our match rate differs across years due to the various methods that censuses used to collect information on geographical locations. For example, the 1870 census has significantly more geographical digitized information relative to prior years. In most cases, our failure to link a sub-county location to a valid latitude and longitude occurs when there is *no* geographical information beyond county recorded on an enumeration district and we have limited information on adjoining enumeration districts.[11]

3.2 Example: Waukesha County

To illustrate the value of our data and approach, consider Waukesha County in Wisconsin. Today, Waukesha County is Wisconsin's third-largest county by population and covers 581 square miles. The county is geographically diverse: its eastern portion is an extended suburb of Milwaukee and is heavily commercialized with manufacturing and service industries, while the western and southern portions are rural and contain significant farmland.

In 1930, Waukesha County had 52,000 people. In publicly available 1930 census data, the only available sub-county location is the county seat, Waukesha.[12] In 1930, the city of Waukesha contained roughly 35% of the county population, leaving 65% of the city lacking a valid sub-county location. By contrast, we assign *100%* of the 1930 Waukesha County population to a valid

[10] An observation is a household in 1790-1840. Starting in 1850, an observation is a person. We focus on census *observations* and not the count of people throughout this paper because the decennial population censuses did not collect information about the slave population in all years.

[11] Conceptually, it is possible to map these places manually by consulting the original enumeration district maps, as is done by Connolly (2021) for a set of 1920 cities. Unfortunately, since enumeration district boundaries change over time, this procedure would need to be repeated for every decade in our sample. These unnamed locations tend to be small rural areas.

[12] This location starts to be identified in the public census microdata from IPUMS in 1900. Before this, there is no city identified in this county in the public census data.

sub-county location.[13]

In Figure 2, we illustrate the coverage of our geocoded 1930 places using a map of modern-day Waukesha County locations. The city of Waukesha—framed in black—is the only sub-county 1930 location in public census data. By contrast, all of the cities highlighted in blue are also included in our new geolocated place data. This includes extremely small locations in 1930—for instance, Wales had only 123 residents, while Dousman had 256 residents. Figure 2 highlights that our new data shows the geographic diversity of Waukesha County. Even in 1930, the jobs and industries of the eastern portions of the county were changing and becoming more industrialized relative to the more rural parts of the county. With our location data linked to publicly-available IPUMS data, researchers can observe and study the persistence of these within-county differences throughout history.

3.3 Clustering

While our place-level longitude-latitude mappings are comprehensive, these places are not defined consistently over time. To address this limitation, we use an iterative density-clustering approach to map our 69,393 unique locations across the 150 year period of 1790–1940 to a smaller set of 42,133 consistently-defined places. While most places are distinct and not combined in this step, larger cities like Atlanta, Pittsburgh, and Chicago have borders that expand over time as they merge with other towns and experience high levels of in-migration. Our method captures these expanding borders, allowing us to consistently measure features of these cities over time.[14]

[13] Our match rates for this example are similar if we focus on other census years with individual microdata. In 1940, IPUMS data also captures some of these sub-county locations with their newly constructed "PLACENHG" variable.

[14] We cluster places consistently over time so that researchers can use our cluster identifiers to track city growth, shrinking urban borders, mergers, and annexation. For example, in 1907 Pittsburgh annexed nearby Allegheny City against the wishes of a majority of Allegheny residents who, in repeated referenda, rejected the annexation attempt. The annexation was forced on Allegheny by Pennsylvania, whose legislators passed a law allowing a majority of the combined voters from Pittsburgh and Allegheny City to determine the results of the annexation, even if a majority of the voters in the targeted city (Allegheny City) rejected the annexation attempt. For more discussion of this and related annexations, see Lonich (1993). Researchers interested in the distinction between Pittsburgh and Allegheny City can use our data to differentiate those two places in years where the places were enumerated distinctly. But as the cities merged, the definition of Pittsburgh and Allegheny became amorphous, and our clusters provide a

We iteratively cluster any neighboring places that are within three miles of each other within census years and across census years. We also cluster together any two places i and j that are within $100 * K_{cluster} * max\{sharepop_i, sharepop_i\}$ miles of each other, where $sharepop_i$ is the fraction of the population in decennial census data that we map to place i across all years (1790–1940), assigning equal weight to each year. For our main results, we rely on a constant $K_{cluster}$ of 5. This choice of clustering allows large cities to be combined with more of their suburbs. For example, Chicago contains roughly 2.5% of the people in decennial census microdata from 1790-1940. When $K_{cluster} = 5$, Chicago will be close neighbors with any smaller place within 12.5 miles of it. We cluster places consistently over time by defining each cluster to be the connected component of all close neighbors for each place.

In Figure 3, we map all of our consistently defined places. We color each cluster to reflect close neighbors. Our individually-geocoded places reflect the geographic distribution of people in the United States from 1790–1940, highlighting the densely populated New England corridor. Our clusters show consistently-defined metropolitan areas that can spread across state and county borders. We include these cluster definitions in our crosswalks so that other researchers can use them.

To further show the value of our clusters, in Figure 4 we focus on four representative states across different census regions and highlight the individual geocoded places, our consistently-defined clusters, and the five largest clusters in each state. The top left panel shows that our clustering combines the Birmingham, Alabama suburbs into one cluster. In the top right panel, Miami and Tampa Bay, Florida are combined into distinct clusters with their nearby suburbs. In the bottom panels, the dense west coast of Oregon is clustered into a small number of metropolitan areas. In Pennsylvania, Pittsburgh and Philadelphia form distinct clusters.[15]

In Figure 5, we show the same four states with modern-day county borders. These maps show the value of our geocoded places to researchers hoping to analyze spatial variation in access

time-consistent approach to measuring the number and type of people living in the Pittsburgh area over time.

[15]Figures A1–A4 show full-page versions of these state-level figures for easy readability.

to policies or spatial outcomes in a historical setting. We geocode an average of 23 places per modern-day county in the U.S. This granular classification of locations gives researchers the tools to analyze distance-based access to local programs, within-county border discontinuity designs, and urban/rural migration patterns within counties.[16]

Our preferred value of $K_{cluster}$ in the above specifications is 5 because that allows large cities to subsume close suburbs, but it maintains the geographic distinctness of nearby small places. We also provide alternative clusters for different values of $K_{cluster}$ so that researchers can choose that clustering that best fit their analysis based on the level of geographical variation in which they are interested. In Figure 6, we show our clusters for Washington with two levels of aggregation: $K_{cluster} = 5$ and $K_{cluster} = 500$. With the less aggressive level of aggregation, Seattle and Everett (29 miles away from each other) form distinct clusters with their respective surrounding suburbs and nearby towns. With more aggressive clustering ($K_{cluster} = 500$), the Seattle and Everett clusters merge and become one larger Seattle metropolitan area and the Spokane cluster absorbs more nearby towns.

3.4 Population Dynamics

To showcase our new crosswalks, we use our preferred clustered places to examine the size distribution of historical places in the U.S. and place-specific population growth. A large literature in urban economics models and empirically quantifies the formation and growth of cities. This literature focuses on two 'laws': Zipf's Law, which states that there is a linear relationship at the city-level between log(population) and log(rank) of population, and Gibrat's Law, which states that the population growth rate is independent of city size. Gabaix (1999) showed that if a set of cities grow independently of initial city size, following Gibrat's Law, then the steady-state size distribution will follow Zipf's Law. Testing these predictions using high-quality historical data gives urban economists the ability to evaluate theories of long-run city population dynamics.

[16]Figures A5–A8 show full-page versions of these state-level figures for easy readability.

We use our geocoded historical places to evaluate these two laws. In Figures 7 (for 1870 places) and 8 (for 1940 places), the top panel shows the relationship between log(population) and log(rank) for IPUMS-defined cities and the bottom panel shows the same relationship for our geocoded places. We focus on places with populations over 20,000. In the IPUMS-based top panels, there is a deviation from Zipf's Law at the right tail of the city size distribution in both 1870 and 1940—the most populous cities look smaller than what Zipf's Law predicts if we use IPUMS's city classification. In the bottom panel of each figure, we plot the same log(population)-log(rank) graph with our geocoded and clustered places. Using our places, we match the predictions of Zipf's Law almost exactly. Our decision to cluster places combines large cities with their suburbs, and these clustered places match the predictions of Zipf's Law.

In Figures 9 and 10, we extend Zipf's Law to all tracked places in 1870 and 1940 respectively. In the top panels, we show the IPUMS-based log(population)-log(rank) plot and in the bottom panels, we present the log(population)-log(rank) plot for all of our geocoded clusters. In both years (1870 and 1940), we see sharp deviations from Zipf's Law for places with fewer than 500 residents in our geocoded data. Focusing on the smallest places, we see that they are underrepresented in our sample of places relative to the predictions of Zipf's Law. In 1870, we do not see a similar pattern in IPUMS's data because the publicly available crosswalks do not contain the locations of small cities and towns. In 1940, when IPUMS coverage is higher, we do see the same deviation from Zipf's Law for smaller cities and towns.

In Figure 11, we compare the prediction of Gibrat's Law in IPUMS' city data (panel A) and our geocoded clusters (panel B). We focus on place-level population growth from 1870 to 1940 for places with populations less than 50,000 in 1870.[17] IPUMS consistently tracks very few cities over this time period, but for the 144 cities with a population over 10,000 in 1870, we see a close match to the predictions of Gibrat's Law–city growth from 1870 to 1940 seems uncorrelated with the

[17]The results are unchanged if we include the largest cities, but including the largest cities in the panels makes it more difficult to see the non-monotonic population growth rate dynamics for cities with lower initial population levels in 1870.

initial 1870 population. Cities of all sizes quadrupled in size between 1870 and 1940. But in our geocoded places we see a strikingly different conclusion. We show that population growth rates were U-shaped over this 70-year period. The population of smaller places grew almost nine-fold on average while the population of the largest places more than quadrupled. But for mid-sized places with populations around 1,000 people, we see much smaller growth rates around 150%. This is a pattern that also exists at the county level, as shown by Desmet and Rappaport (2017). We are the first to show these historical patterns at the town and city level for all places in the United States.

4 Discussion and application to additional datasets

So far, we have discussed our method and applications exclusively in the context of the historical US decennial censuses. However, much of the code that we release can be used to geocode other sources of historical data. In addition, the steps that we use can serve as a conceptual guide for other researchers. However, like all methodological contributions, our approach will apply very well in some cases and less well in others. In this subsection we discuss these tradeoffs.

Our current code is optimized to geocode historical US cities and townships. It is most easily applied to other documents that contain the same level of geographic detail. Two important examples are patent documents and birth/death certificates. Both typically contain the city of the invention or event, and both — because of the limits of modern OCR software — are often measured with some error. Our code can clean these location strings and fuzzily match them to historically accurate geocoded places. All that is required as an input is a vector of possible strings for each document. Since our code was developed using US census data, it may need to be modified: For example, in the censuses there are predictable strings that need to be cleaned before geocoding (e.g., “WARD”, “DISTRICT”). To the extent that different datasets contain different strings that need cleaning, this code should be adjusted. Otherwise, our procedure has few census-specific steps.

By contrast, because of our setting our code cannot directly geocode sub-city US data (e.g., streets or blocks) or locations outside the US. However, with appropriate changes, the structure of our code could be used in these cases. For example, to geocode streets, one could take information on raw streets in the censuses, clean them using our algorithms, and match them to contemporary street databases (instead of NHGIS/GNIS place points). Similarly, our approach and code can be generalized to other countries, though many methodological choices will need to be made as a function of the underlying strings and location databases available for that country.

Beyond our code, our geocoded census locations can also be used in methodological projects. For example, researchers linking birth certificates to decennial census microdata face the limitation that within a state or county, there can be multiple people with similar names. Using our geocoded sub-county locations to aid in those links can increase match rates and lower false positive rates.

5 Conclusion

Researchers often use place-level data to measure the causal effects of local policies and to describe historical trends. These analyses are often done at the county- or state-level because it is challenging to link individuals to consistently defined local places across census years. In this paper, we describe and release public crosswalks linking the vast majority of 1790-1940 census respondents to longitudes and latitudes. These crosswalks allow analysts to explore sub-county research questions and trends using public census data.

We present two applications of our crosswalks to demonstrate their value. First, we iteratively cluster geocoded places with close neighbors, producing a consistent definition of place. This application addresses the common concern that regularly-updated county borders and shifting municipal boundaries make it difficult to match and compare places over time. Second, we test the predictions of Zipf's Law and Gibrat's Law in a historical context, finding clear deviations from theoretical predictions about the city size and city growth distribution. While these findings have been observed in more aggregated data, we are the first to illustrate these patterns over long time periods with national data on "places".

The most important application of this paper is the method itself. Researchers spend significant and often-duplicated time standardizing common spatial datasets, particularly when working with historical sources. We hope that the process we present in this paper helps researchers link other datasets that include unstructured place names—for example, patent data or birth and death records—to sub-county geocodes.

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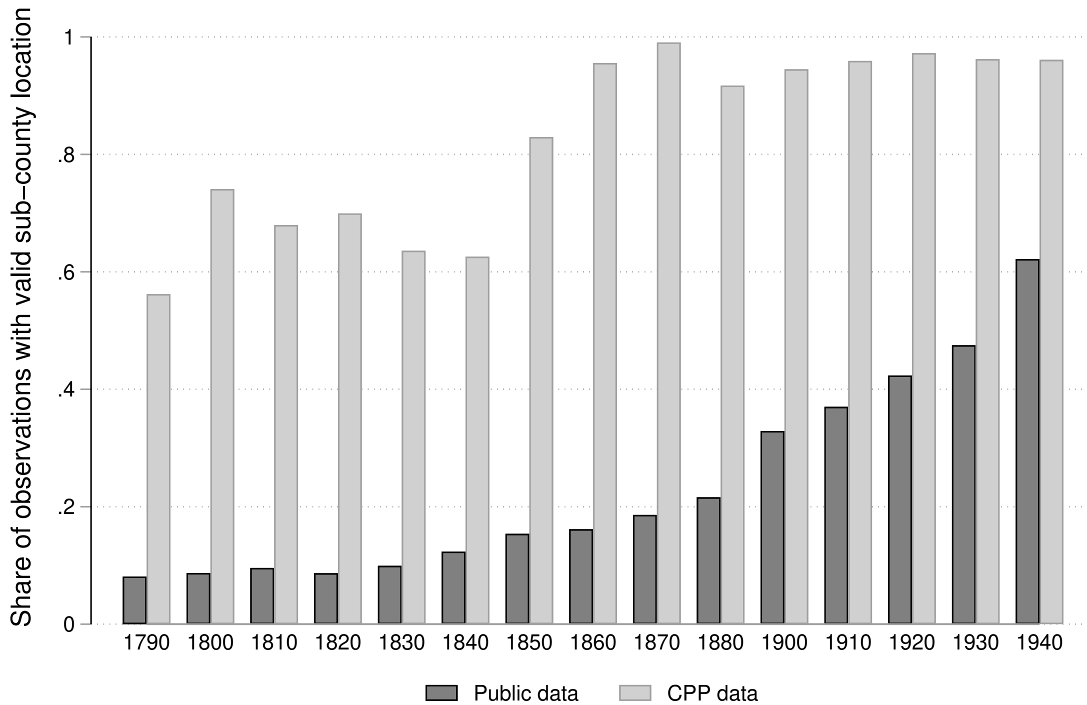
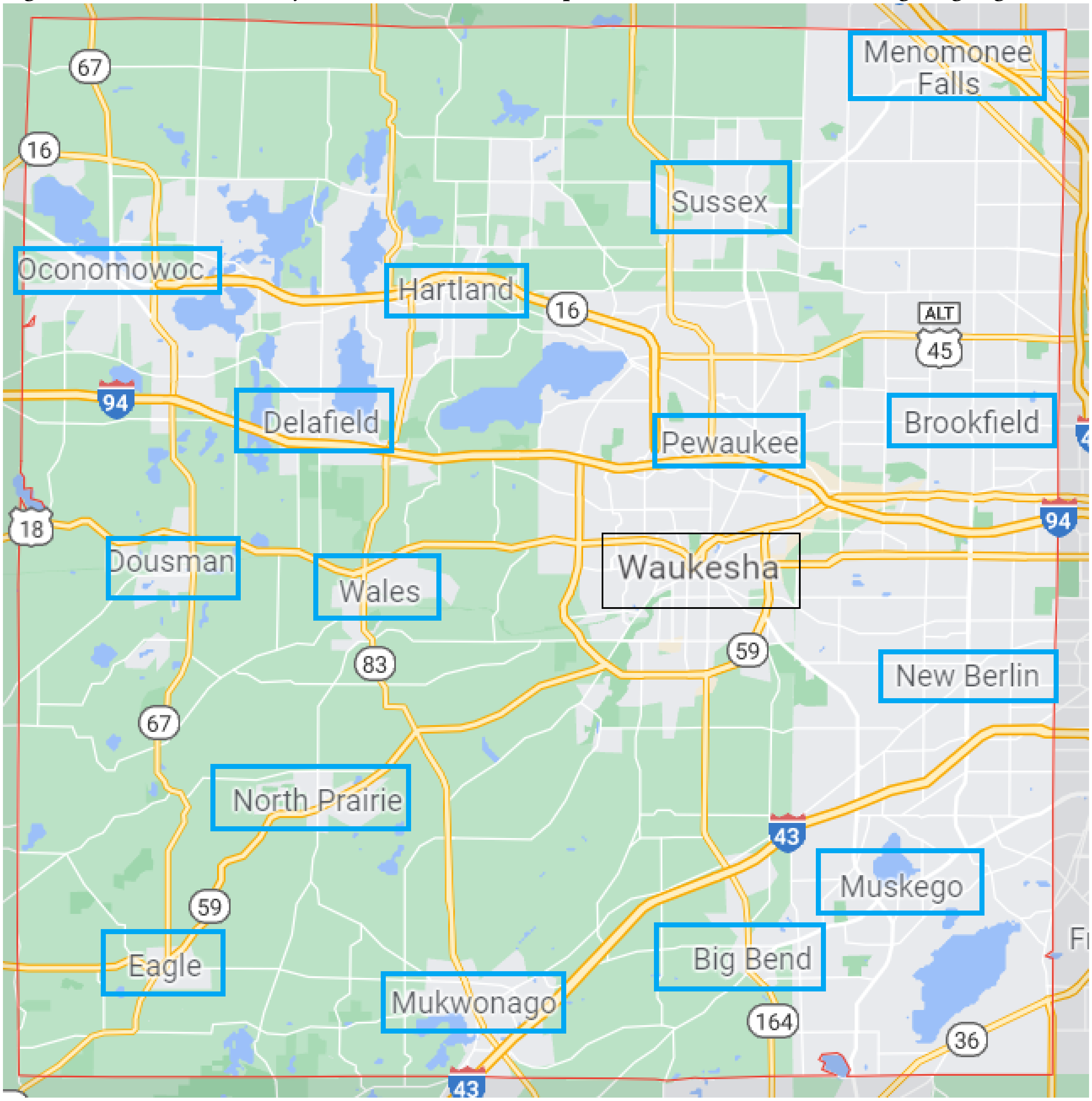
Figure 1: Census observations with valid sub-county locations, by data source and census year



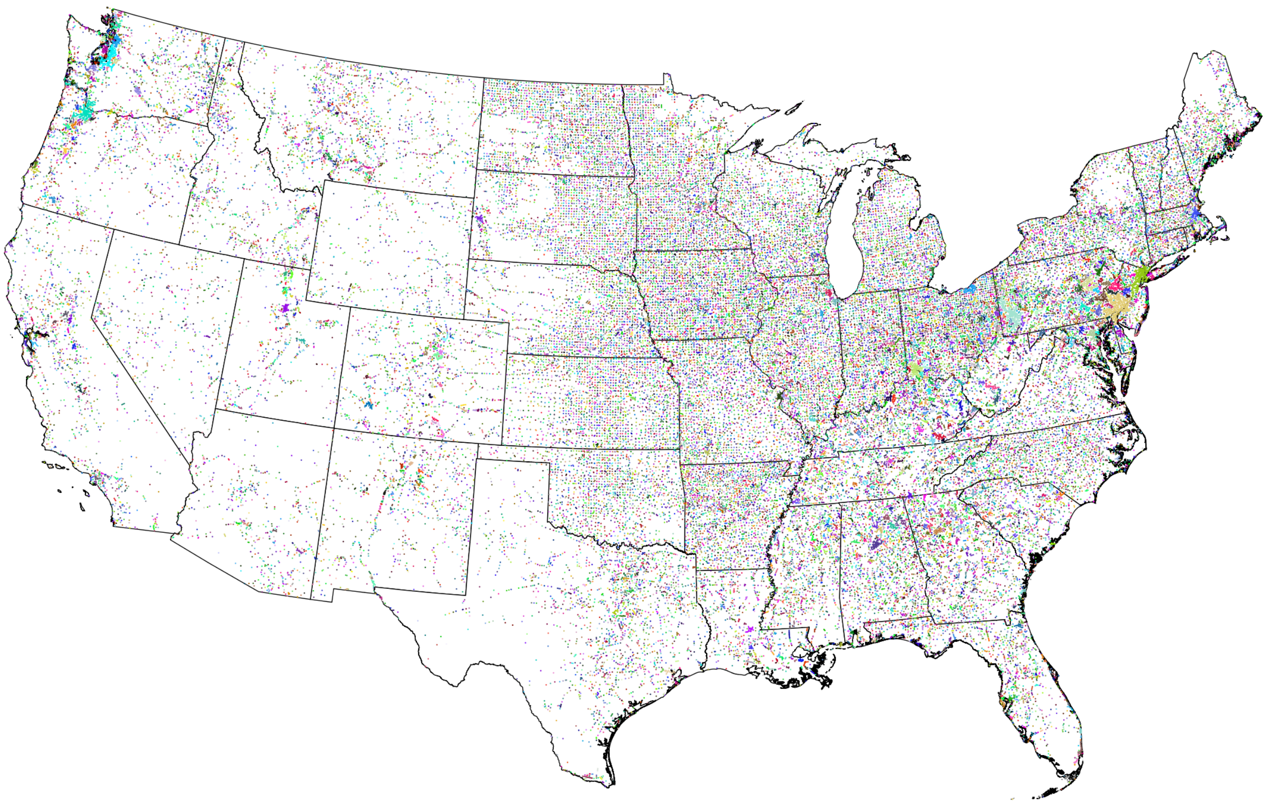
Notes: This figure shows the share of census observations with a valid sub-county location in each census year separately for publicly available IPUMS census data and the newly constructed Census Place Project data. An observation in 1790-1840 is a household. Starting in 1850, each observation is a non-slave member of the household. The 1890 census manuscripts were lost in a fire.

Figure 2: Waukesha County Wisconsin, modern map with 1930 census data coverage highlighted



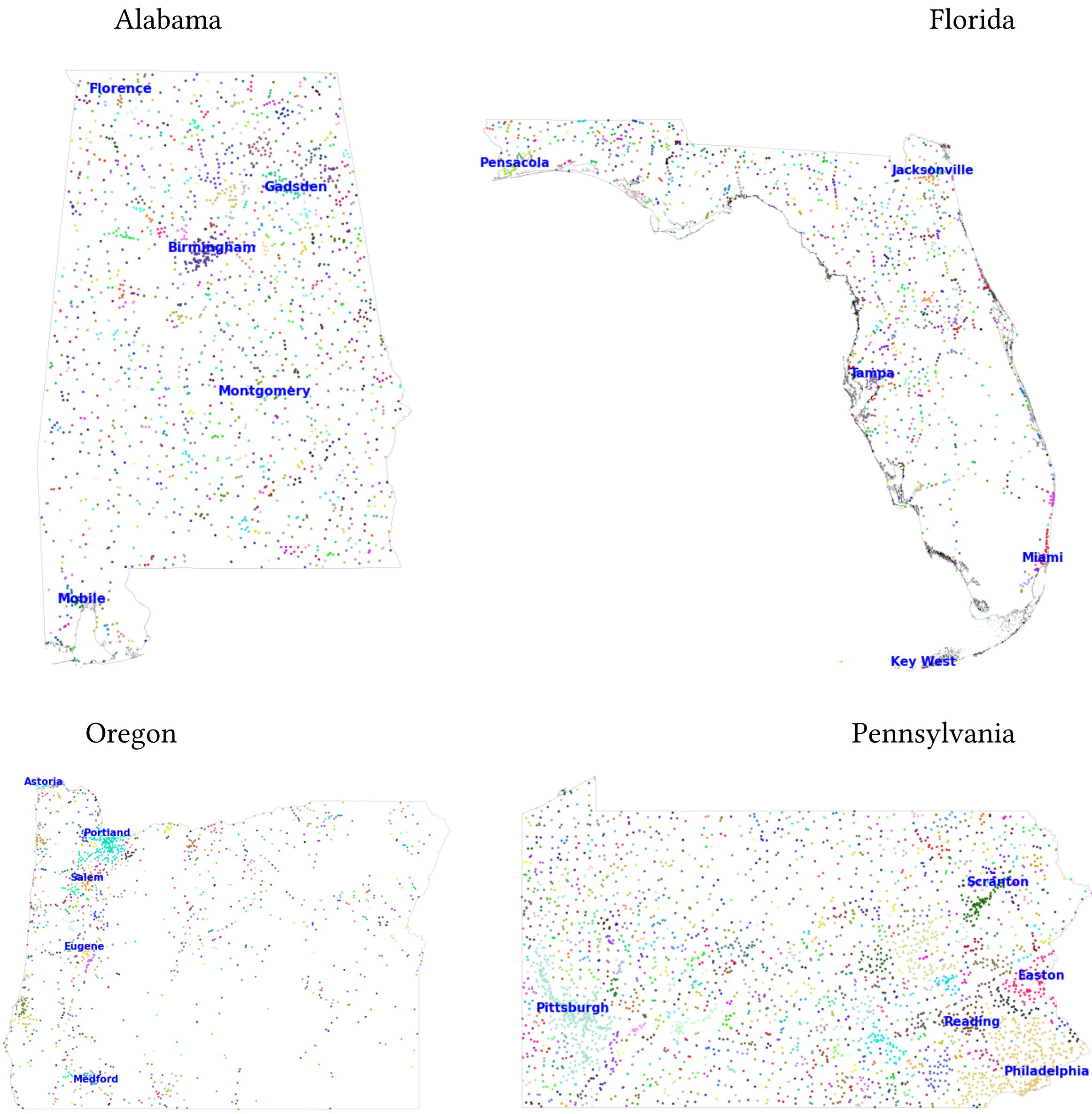
Notes: This figure is a modern-day map of Waukesha County, accessed via Google Maps. Only the city of Waukesha (highlighted in black) is identified in public 1930 census data. Our geocoded data identifies all the cities highlighted in blue, in addition to smaller areas not labeled on the map

Figure 3: All clustered places



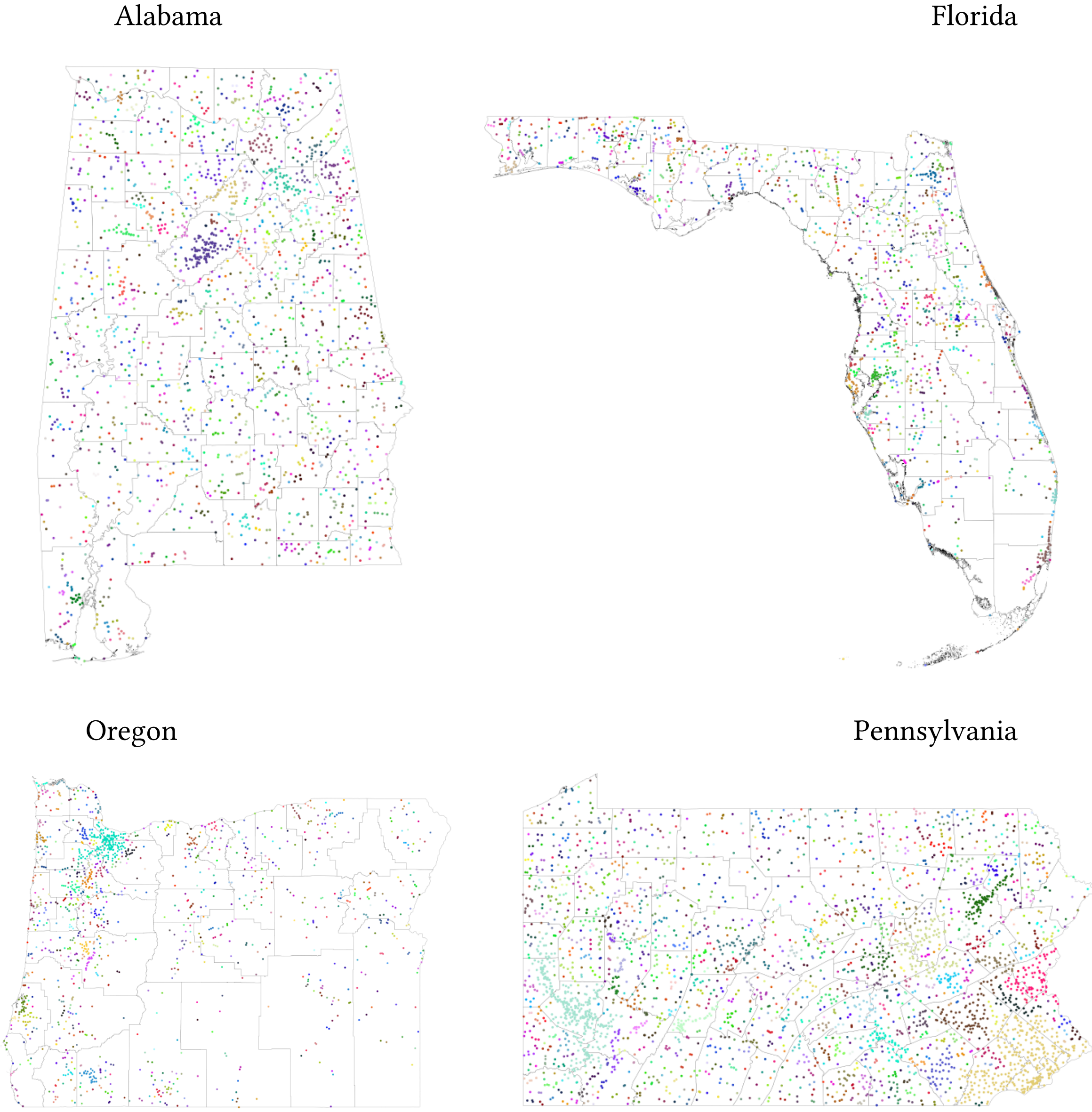
Notes: This figure maps all of our 69,393 unique places across the years 1790–1940 after assigning the places to consistent clusters (with $K_{cluster} = 5$). Places within a cluster are given the same color, highlighting large colors surrounding major metropolitan areas (like New York City).

Figure 4: State-level maps of clustered places



Notes: This figure maps our geocoded places in four states: Alabama, Florida, Oregon, and Pennsylvania. We highlight the five largest clusters in each state (with $K_{cluster} = 5$).

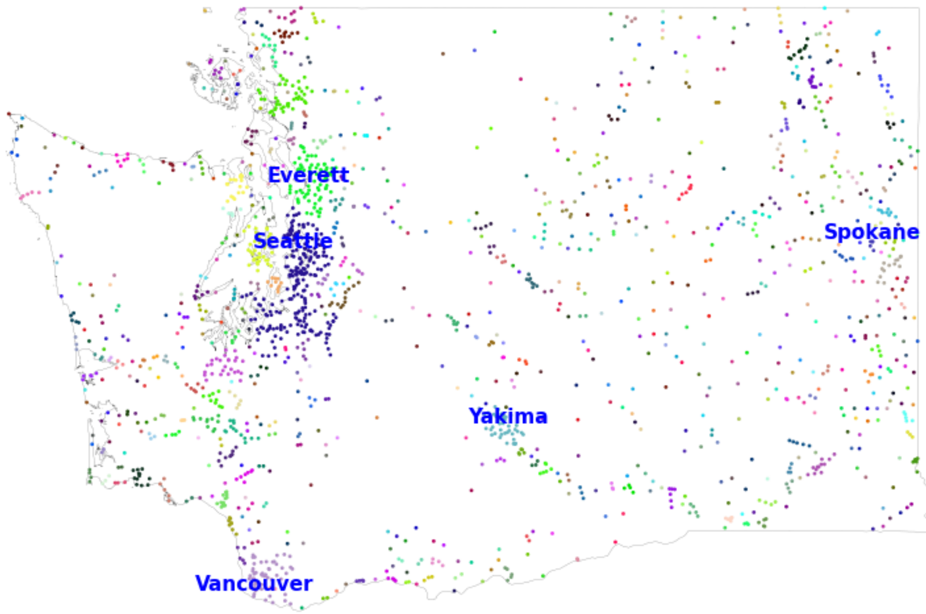
Figure 5: State-level maps of clustered places with county borders



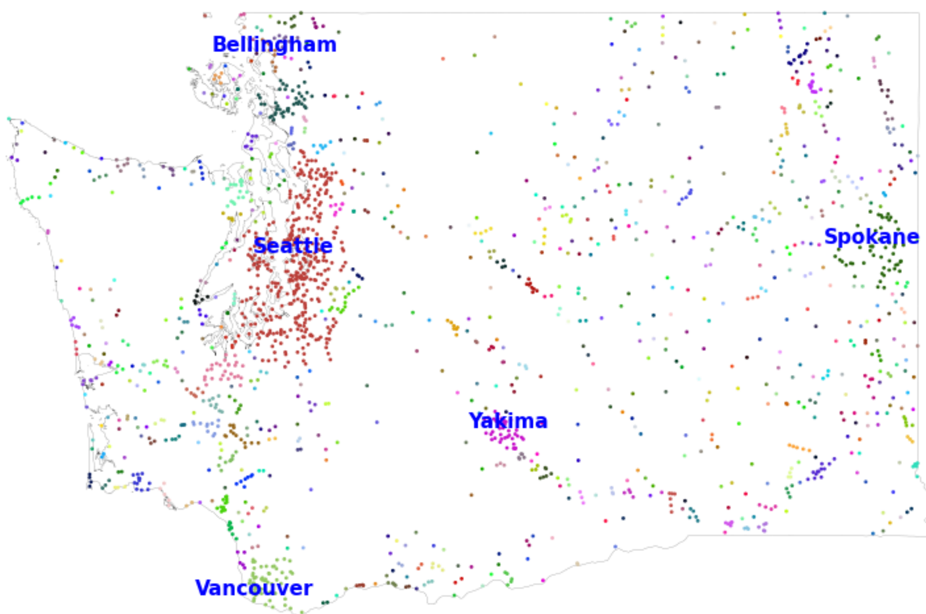
Notes: This figure maps our geocoded places in four states: Alabama, Florida, Oregon, and Pennsylvania. We highlight the county borders in each state to emphasize the granularity of our geocoded places relative to the larger counties.

Figure 6: Clusters in Washington State with different levels of $K_{cluster}$

$K_{cluster} = 5$

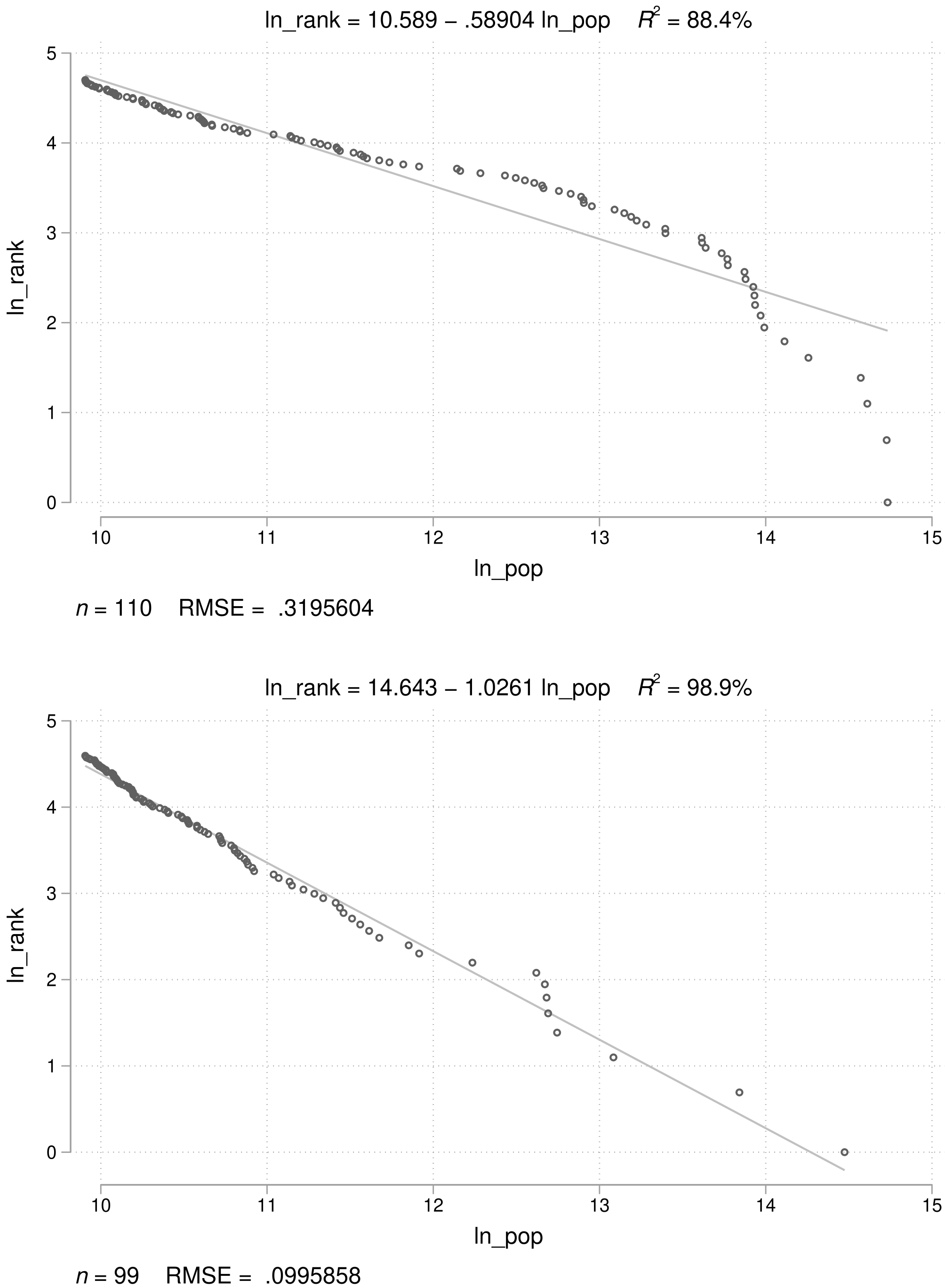


$K_{cluster} = 500$



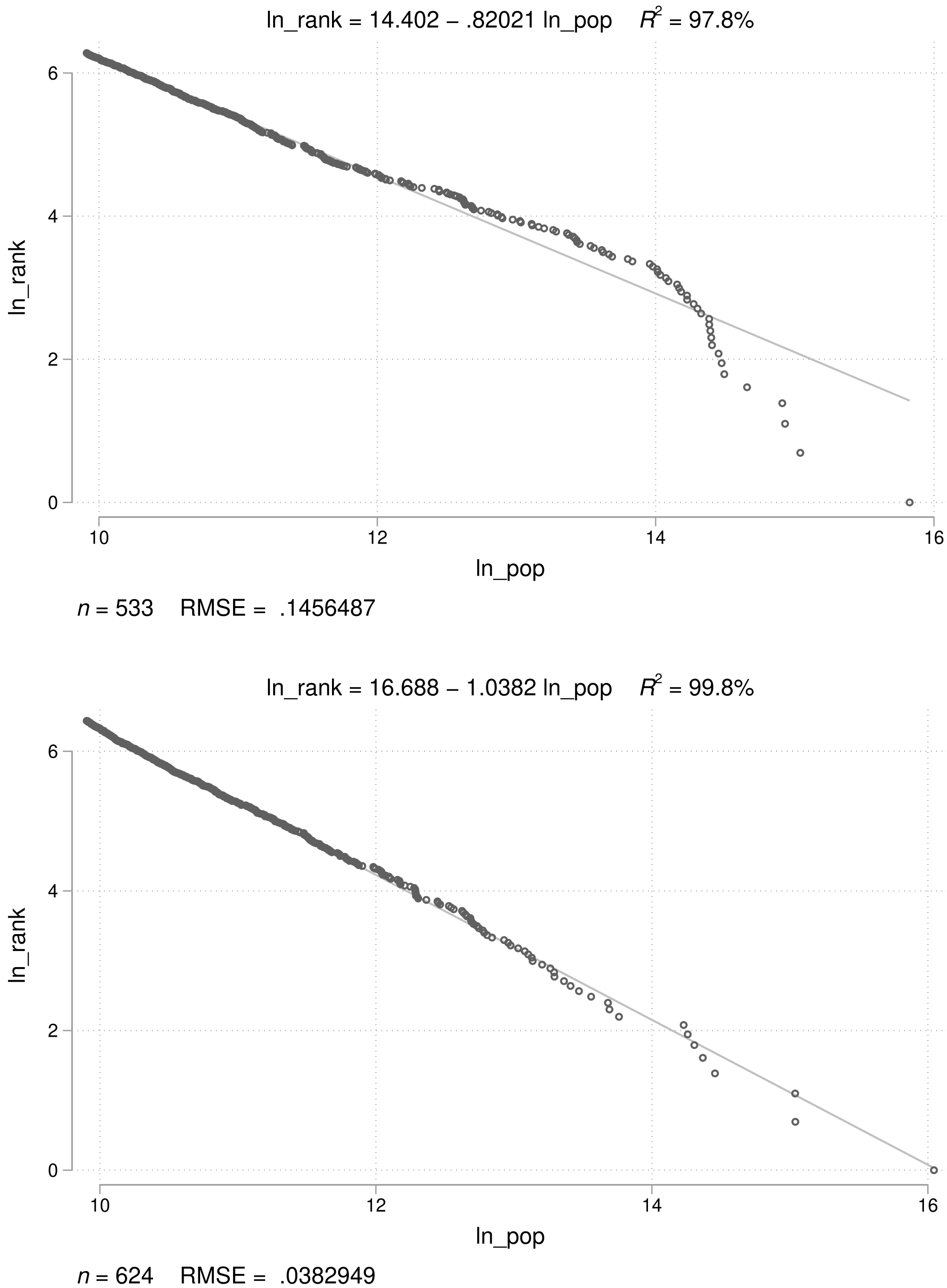
Notes: This figure maps our geocoded places in Washington with more conservative clustering ($K_{cluster} = 5$) and more aggressive clustering ($K_{cluster} = 500$). The largest difference is in the implied size of the Seattle metropolitan area.

Figure 7: Zipf's Law for 1870 places with population 20,000+ (CPP vs. IPUMS)



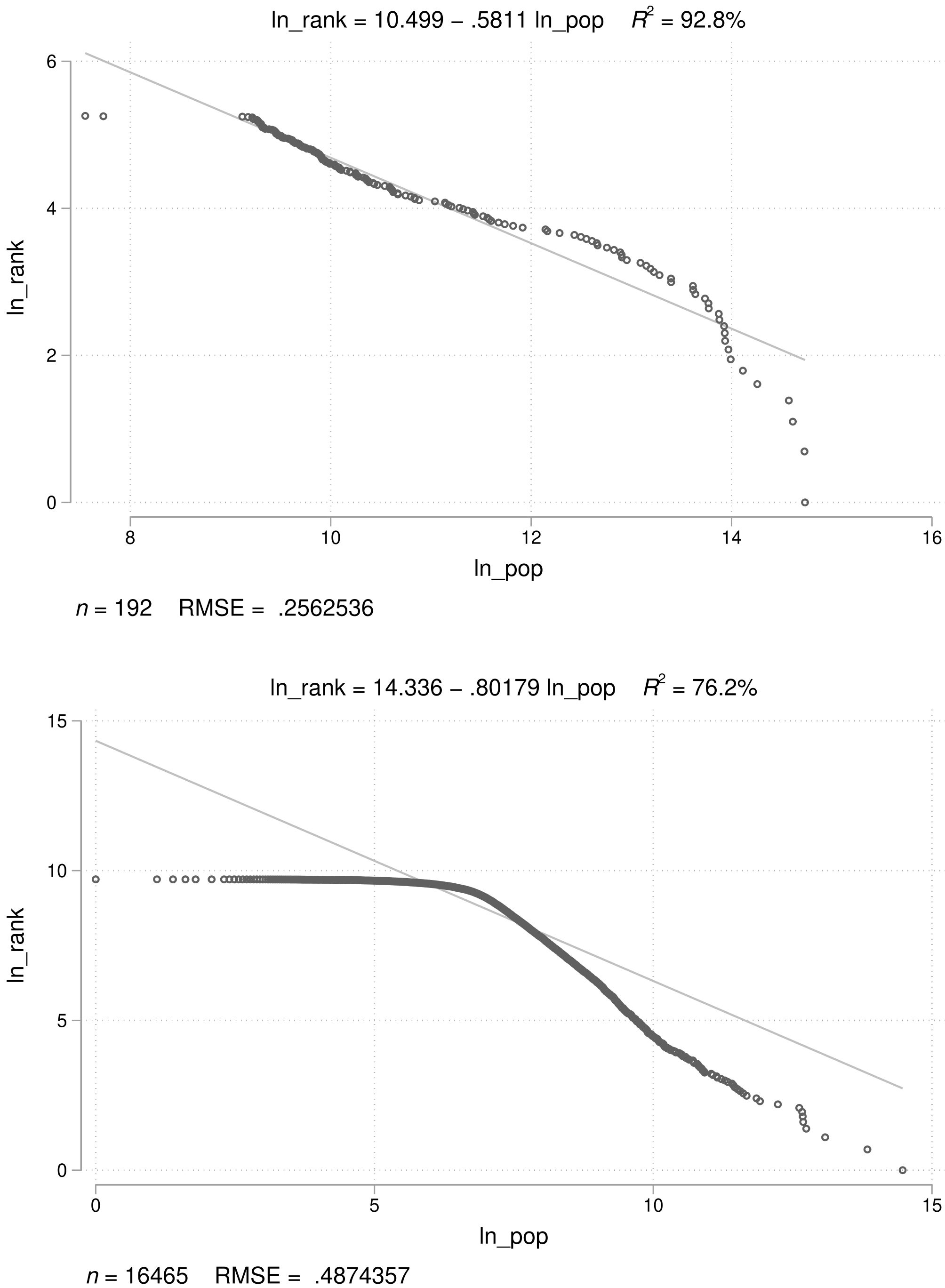
Notes: This figure plots log(population) vs. log(rank) for all cities with population greater than 20,000 in 1870 labeled by IPUMS (top panel) and in our geocoded places (bottom panel).

Figure 8: Zipf's Law for 1940 places with population 20,000+ (IPUMS vs. CPP)



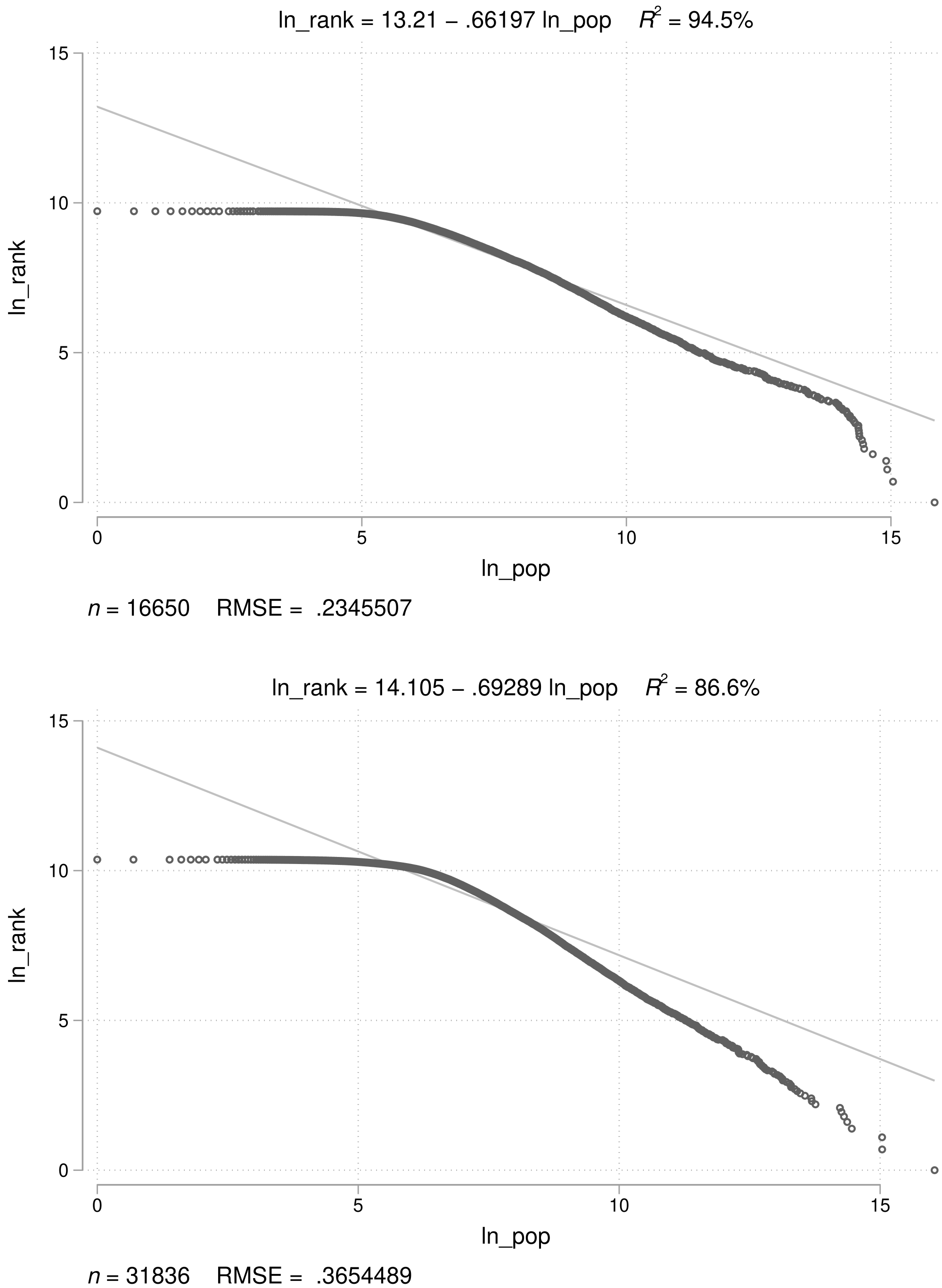
Notes: This figure plots log(population) vs. log(rank) for all cities with population greater than 20,000 in 1940 labeled by IPUMS (top panel) and in our geocoded places (bottom panel).

Figure 9: Zipf's Law for all places in 1870 (IPUMS vs. CPP)



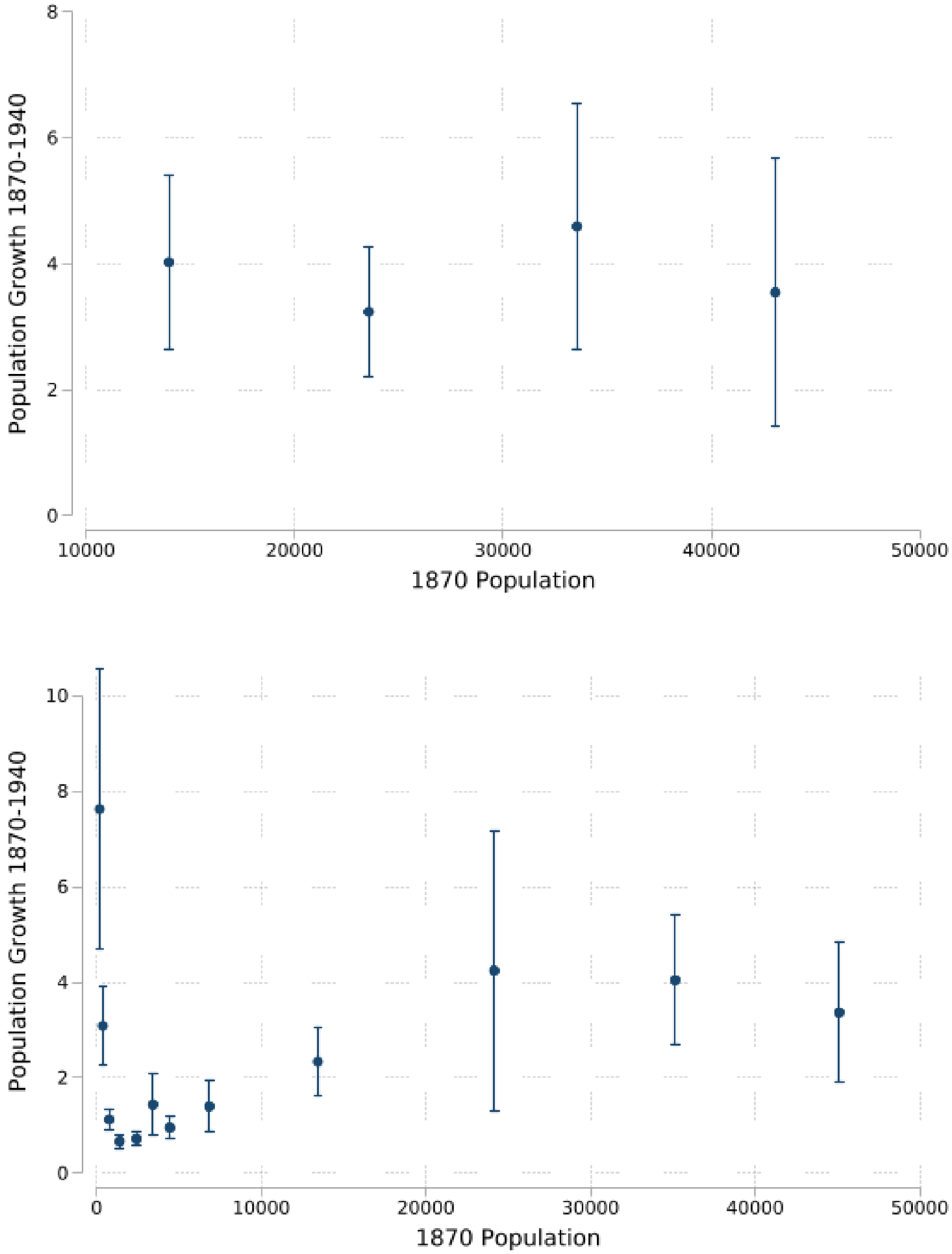
Notes: This figure plots log(population) vs. log(rank) for all cities in 1870 labeled by IPUMS (top panel) and in our geocoded places (bottom panel).

Figure 10: Zipf's Law for all places in 1940 (IPUMS vs. CPP)



Notes: This figure plots log(population) vs. log(rank) for all cities in 1940 labeled by IPUMS (top panel) and in our geocoded places (bottom panel).

Figure 11: Gibrat's Law (IPUMS vs. CPP)



Notes: This figure tests Gibrat's Law by plotting the relationship between population growth rates between 1870 and 1940 (y-axis) and baseline 1870 population levels for places labeled by IPUMS (top panel) and in our geocoded places (bottom panel). We plot binscattered growth rates. We focus on places with population less than 50,000 to emphasize the difference between the two approaches for small cities and towns. The y-axis units is percent growth, so a value of 2 indicates that a place tripled in size from 1870 to 1940.

A Data Appendix

This appendix describes that data and approach that we use to standardize place names in the historical censuses.

- Place name variables in IPUMS data:
  1. 1790–1820: township
  2. 1830: general_township_orig
  3. 1840: locality
  4. 1850: stdcity, us1850c_0043, us1850c_0053, us1850c_0054, us1850_0042
  5. 1860: us1860c_0040, us1860c_0042, us1860c_0036
  6. 1870: us1870c_0040, us1870c_0042, us1870c_0043, us1870c_0044, us1870c_0035, us1870c_0036
  7. 1880: mcdstr, us1880e_0071, us1880e_0069, us1880e_0072, us1880e_0070
  8. 1890: stdcity, us1900m_0045, us1900m_0052
  9. 1900: stdcity, us1900m_0045, us1900m_0052
  10. 1910: stdcity, us1910m_0052, us1910m_0053, us1910m_0063
  11. 1920: stdmcd, stdcity, us1920c_0057, us1920c_0058, us1920c_0068, us1920c_0069
  12. 1930: stdmcd, stdcity
  13. 1940: stdcity, us1940b_0073, us1940b_0074
- State variables in IPUMS data:
  1. 1790–1820: fullstate (name)
  2. 1830: self_residence_place_state (name)
  3. 1840: fullstate (name)
  4. 1850: stateicp (code)
  5. 1860–1870: statefip (code)
  6. 1880: stateicp (code)
  7. 1900–1940: statefip (code)
- County variables in IPUMS data:
  1. 1790–1820: county (name)
  2. 1830: self_residence_place_county (name)
  3. 1840: county (name)
  4. 1850: stcounty (code)

5. 1860–1870: countyicp (code)
6. 1880–1930: stcounty (code)
7. 1940: countyicp (code)

Location cleaning procedure:

- Substitute mt. (and mt followed by a space) with mount, and st. with saint. Note that we cannot simply substitute st with saint because sometimes place names do end in st, but if the string starts with st followed by a space then we substitute it with saint
- Substitute Indian reservation with reservation to match external sources of place names
- Remove anything in parentheses (e.g., (i), (ii), etc.)
- Remove numbers, commas, question marks, periods, parentheses, and slashes (/)
- Remove range(s) if the range is preceded and followed by a space or if it it's at the end of the string and preceded by a space
- Remove substrings that match any of the following (note the space at the end of some strings): 'police jury', 'justice ward', 'court house', 'militia district', 'civil district', 'justice precinct', 'election district', 'undetermined', 'not stated', ' village', 'tract', ' ward', 'assembly district', 'district', 'no', 'precinct', 'subdivision', 'beat', 'plantation', 'census designated place', 'post office', 'township of ', 'town of ', 'borough of ', 'city of '
- Remove ward or township followed by a space if it's at the beginning of the string
- If the place name at this point contains "division" return an empty string (note that at this point we've already taken care of subdivisions etc.)
- Remove "[east, west, south, north] side" or "[east, west, south, north]ern side" from the string
- Substitute multiple spaces with only one
- If at this point the place name string has less than two characters or corresponds to township(s) or ward(s) return an empty string
- Trim white spaces
- Force all letters to lowercase

Extra Cleaning for Round 3:

- Drop hyphens (-)
- Drop cardinal points (south, north, east, west) and their adjectives (southern, northern, eastern, western)

- Drop township and point when preceded by a space
- Remove all the spaces to standardize our merge process

Geotag procedure:

- Load GNIS data
- Load county shape file from NHGIS. We standardize IPUMS county variables to match 3-digit FIPS variables per IPUMS documentation. IPUMS county variables are usually identical to FIPS standards. An exception is Maryland, where IPUMS county identifiers are shifted relative to FIPS codes. We manually adjust these codes to match shapefiles
- For all the decades at and after 1900, we load the point place files downloaded from NHGIS. We standardize the place names to match the format of our raw census place strings.
- We determine the order in which we consider the raw census place name variables by ordering the variables from most unique places to least unique places within each year. The reason for this is that the more unique names there are, the more disaggregated this variable is likely to be. The more standardized the place name is, the fewer unique values of places we see in the raw files (for example, Charlestown and Boston may be combined into one place called Boston in some of the place name variables).
- We have lexicographic preferences over the sequence of census place names. In other words, we have three matching rounds that we apply to the first place name in our ordered list, if do not get a match we move to the second one, and so on.
- For decades at and after 1900, we try to match our census place names to NHGIS and GNIS places. There are three matching rounds:
  - Round 1: find the place name in the NHGIS/GNIS places file that is most similar to the one in the census microdata. We require that the potentially matching NHGIS/GNIS place needs to be in the same state and county as the place name from the IPUMS file (using historical boundaries) and also that the string matching score using the FuzzyWuzzy package in Python is ≥ 95.
  - Round 2: same thing as above with the slight difference that the matching requirement is no longer a FuzzyWuzzy score ≥ 95 but a Levenshtein distance of 1. Since this threshold does not depend on the length of the place name, it is a less stringent requirement for shorter place names (but a stricter requirement for long ones). Note that here if there are multiple cities with a Levenshtein distance of 1, then we skip this step for that place.
  - Round 3: The same as round 1, with the exception that we apply the extra cleaning described above to the raw place names of cardinal references (e.g., strip Township, cardinal points, etc.).

- We begin by attempting to find census places in the NHGIS place point data, and we then proceed to look in the GNIS file, where we consider the following feature classes in order: populated place, locale, civil, census, area, beach, harbor, island, military, mine, park, post office, unknown, basin, bay, falls, rapids, reserve, reservoir, ridge, spring, stream, valley. The classes are ordered in terms of importance. That is, we first try to match the census place names to cities in the GNIS feature class 'populated place', then we match the census place names to locales, and so on.

- For each class of places in GNIS, we first drop the "distant duplicates," which we define as all the places that have the same exact name and are more than 5km apart, because we are unsure which place to match to. Note that if two places have the same name and are within 5km, we keep the first listed GNIS place.

- We look for matches in the NHGIS and GNIS features (in the order described above), first completing round 1 for NHGIS places, GNIS populated places, GNIS locales, GNIS civil features,... until we match GNIS valleys. We then proceed to round 2, searching for NHGIS places, then GNIS populated places,... We then proceed to round 3.

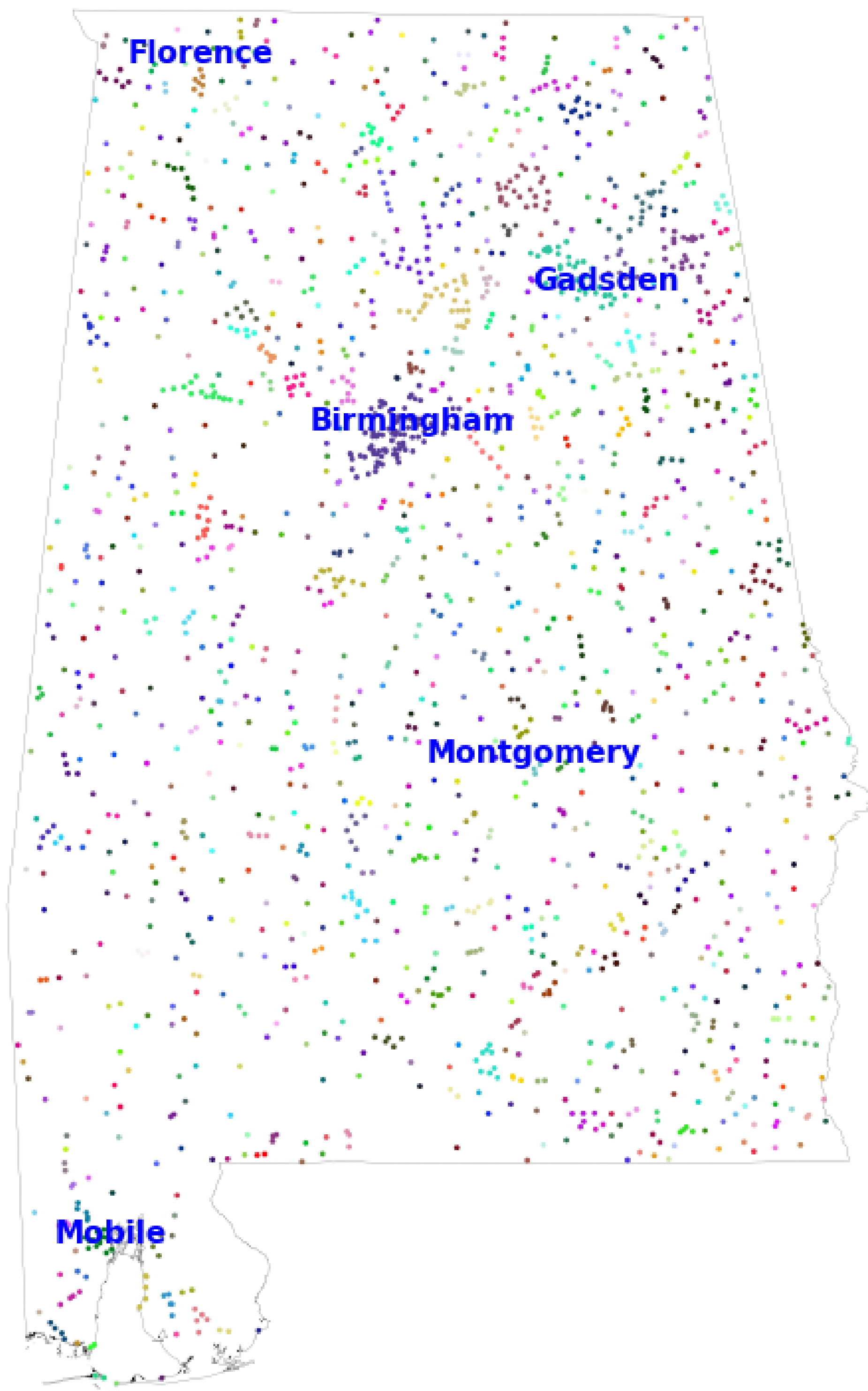
- We have an extra step for the GNIS data where we take all places with duplicates more than 5km apart and we attempt to match our raw census place name to the GNIS duplicate in the correct county. If there are multiple matches within the same county, we keep the match with the lowest latitude.

- For 1850 data and all census years at or after 1880, the census data contains enumeration districts and we use them to impute the coordinates of towns that we are not able to geocode in the previous steps. The procedure works as follows:

  - if an as-of-yet ungeocoded place is in the same state, county, and enumeration district as one (or more) place with known latitude and longitude, we assign the place name the same longitude and latitude as the already geocoded place (if multiple places within the same enumeration district have already been successfully geocoded, we use the mean of the previously geocoded coordinates);
  - if an as-of-yet ungeocoded place is in an enumeration district that is numerically between two (non-necessarily adjacent) enumerations districts that contain already-geocoded places and if the distance between these two enumeration districts is smaller than 50km, then we assign to the ungeocoded place the mean of the means of the already geocoded latitudes and longitudes of places in those enumeration districts. Note that this corresponds to the midpoint between the two mean coordinates of the geocoded enumeration districts. Note that we always use the average. For example, if we have enumeration districts 1, 2, 3, 4 and we have geocoded coordinates for 1 and 4 that are within 50km of each other, then enumeration districts 2 and 3 would receive the same coordinates, equal to the average of the coordinates of geocoded places in enumeration districts 1 and 4.

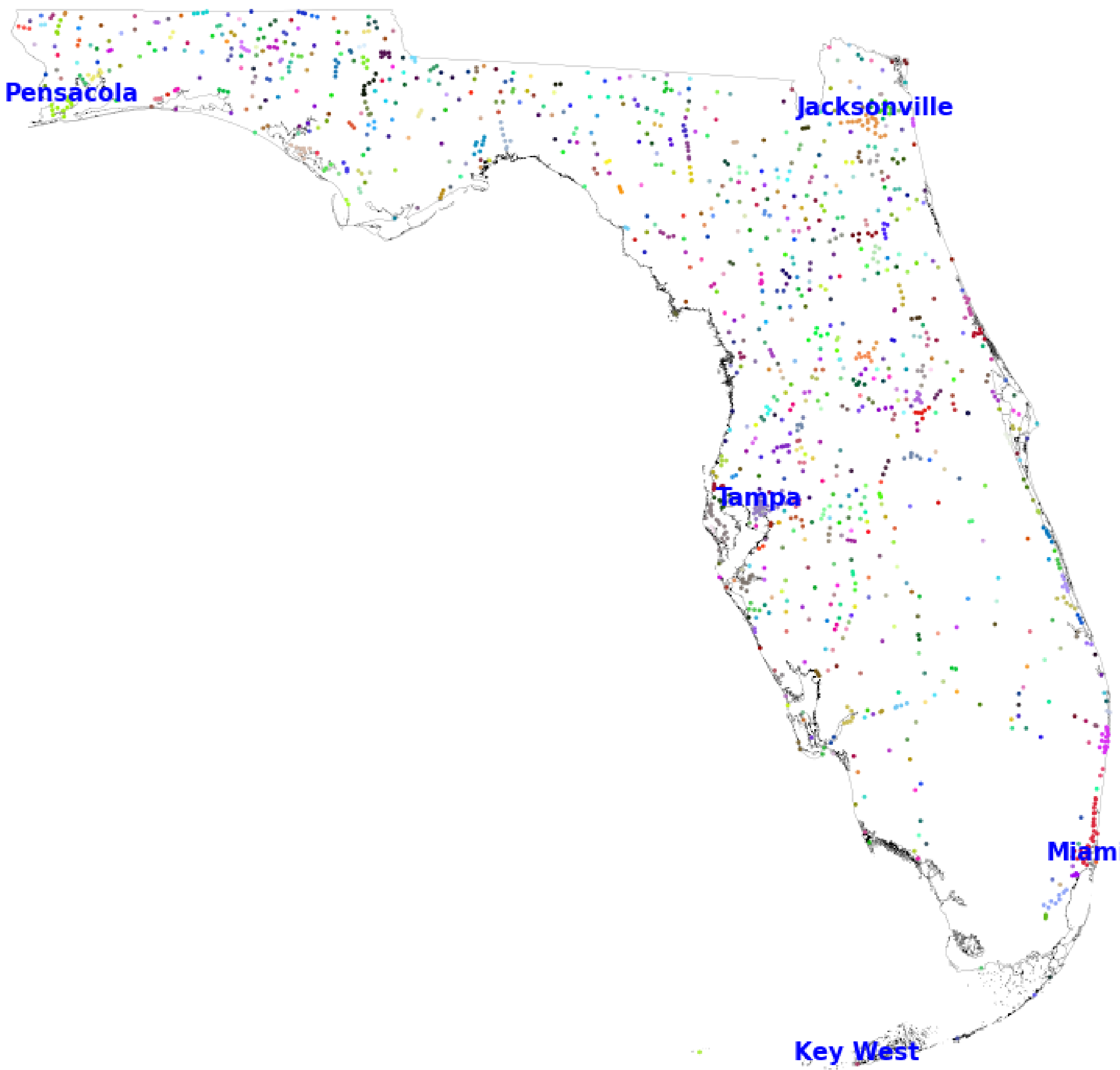
- We then have a second round of matching where we take as-of-yet ungeocoded places and search for them on Google Maps, taking the resulting longitude and latitude after confirming that that Google-based longitude and latitude is in the correct historical county.
- We then have a penultimate round of matching that uses 1910 counties as our reference geography to test whether cities fall within the right county boundaries. The Census data seem to use some county or state names before they were official (e.g., West Virginia in 1860). For this reason, when comparing the coordinates that we obtain through our matching procedure and the location on a contemporaneous map, we sometimes get false negatives (i.e., towns that are outside a county although they should fall within). This step is meant to fix this problem by using a map with state and county boundaries that should be somewhat stable.
- Lastly, we take all geocoded places and look for towns in a specific state that are unique in a given year but geocoded in only some years and not others. This can happen, for example, if the enumeration district imputation step finds a place that was otherwise missing in other years. We take the longitude-latitude for that place in the geocoded year and assign it to the ungeocoded place with the same name in other years.

Figure A1: Alabama: Large map of clusters



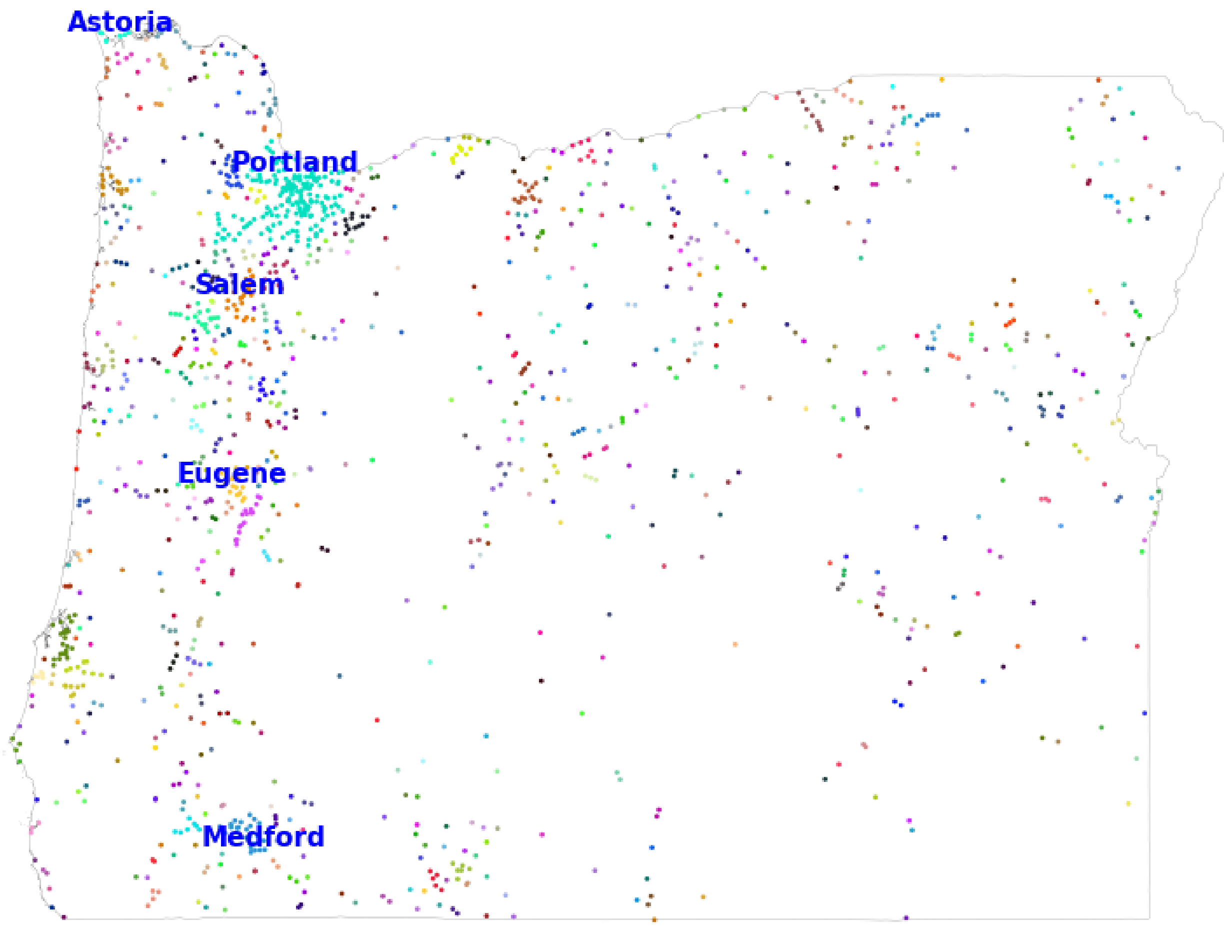
Notes: This figure maps the geocoded places in Alabama, highlighting the five largest clusters (with $K_{cluster} = 5$)

Figure A2: Florida: Large map of clusters



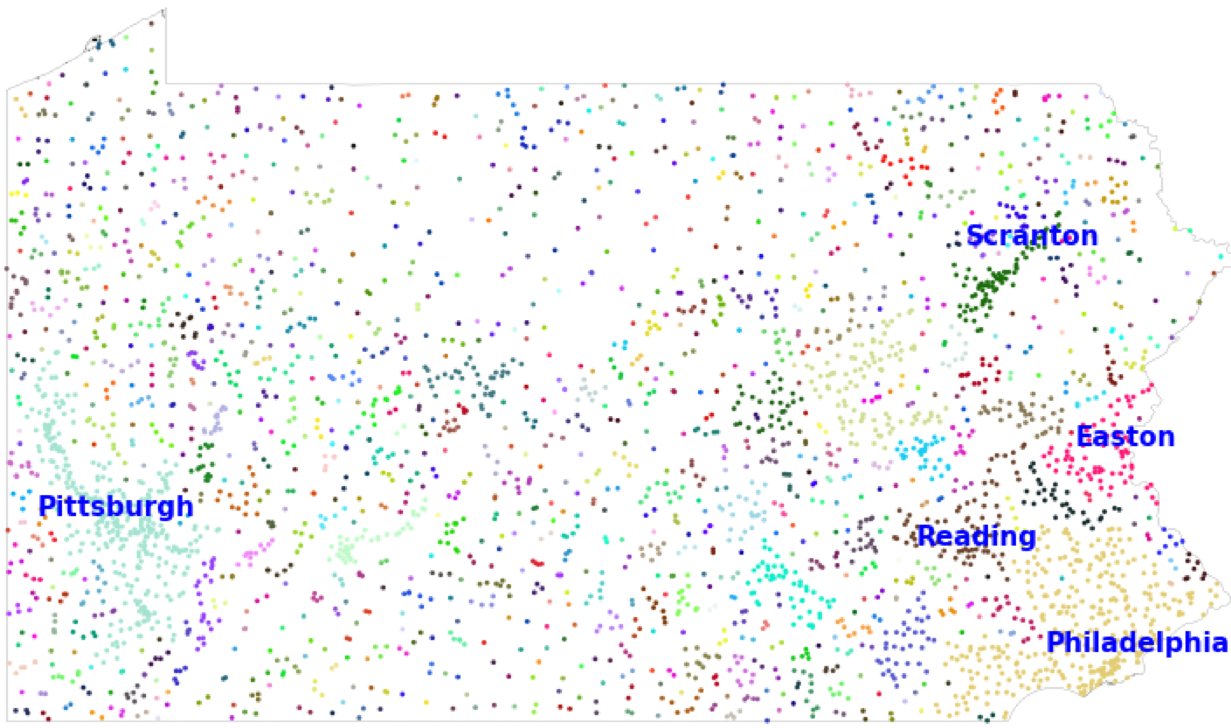
Notes: This figure maps the geocoded places in Florida, highlighting the five largest clusters (with $K_{cluster} = 5$)

Figure A3: Oregon: Large map of clusters



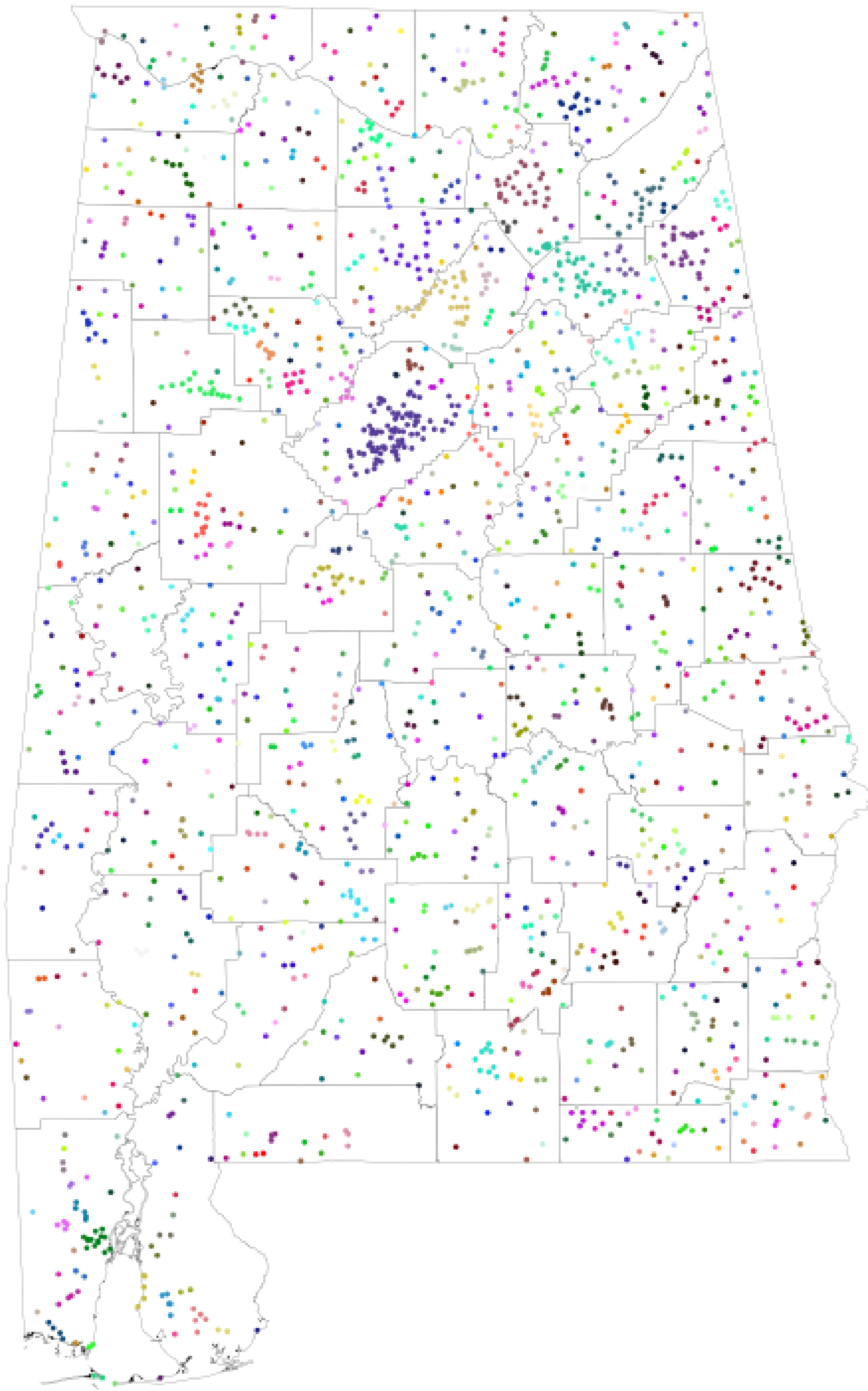
Notes: This figure maps the geocoded places in Oregon, highlighting the five largest clusters (with $K_{cluster} = 5$)

Figure A4: Pennsylvania: Large map of clusters



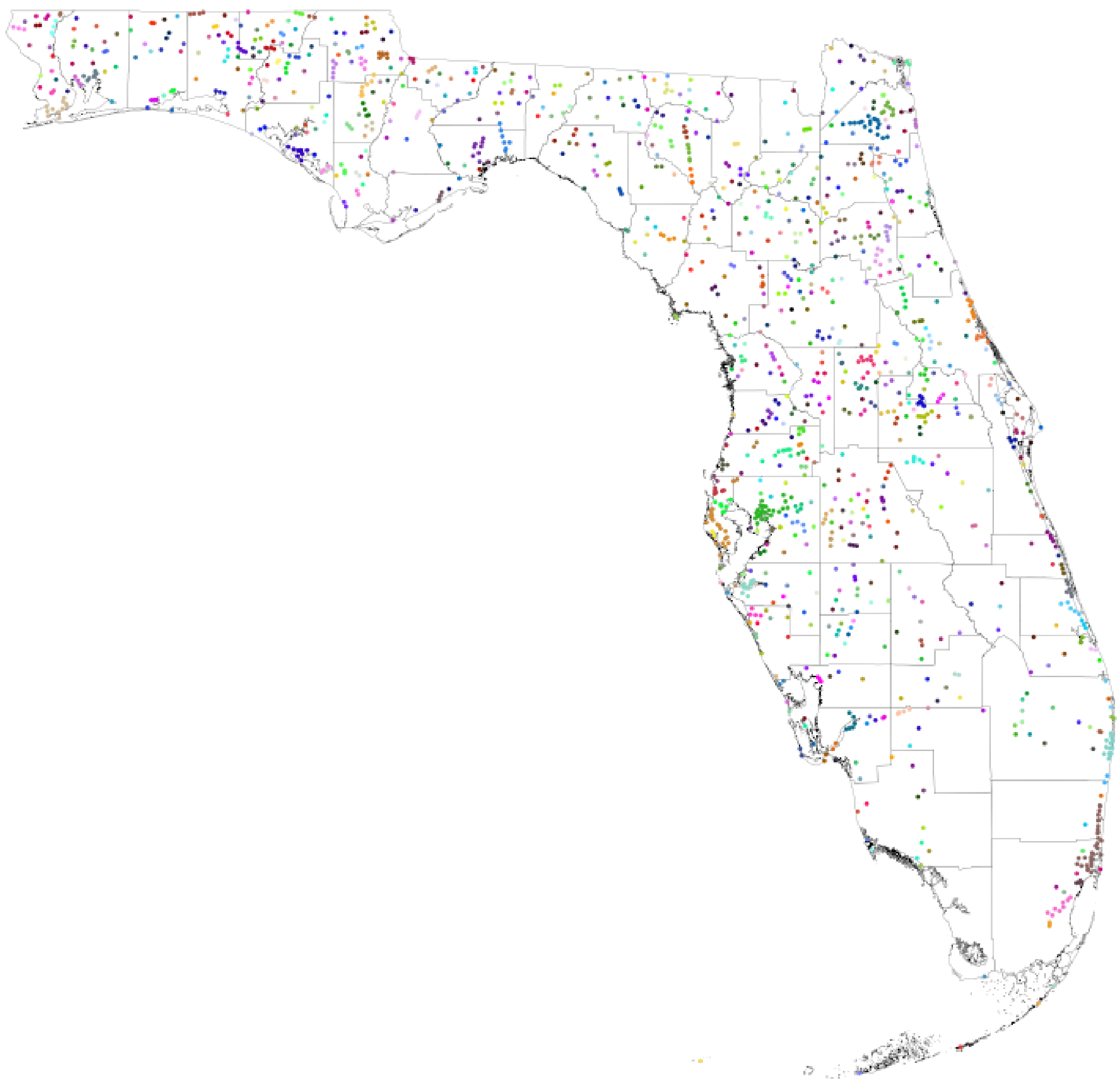
Notes: This figure maps the geocoded places in Pennsylvania, highlighting the five largest clusters (with $K_{cluster} = 5$)

Figure A5: Alabama: Large map of clusters, with county borders



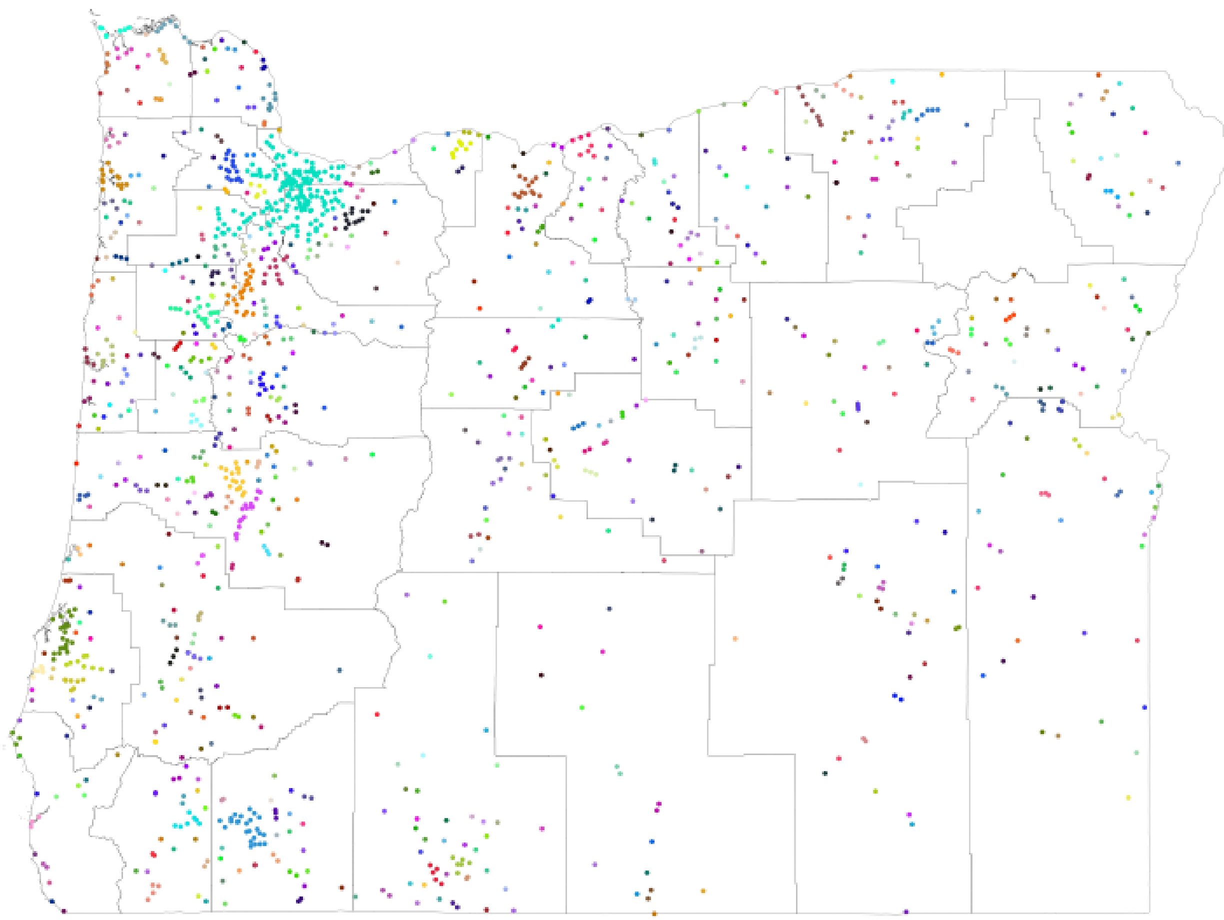
Notes: This figure maps the geocoded places in Alabama, highlighting the county borders in Alabama to emphasize the large number of geocoded places in our data relative to the smaller number of counties. Sets of adjacent places within the same cluster ($K_{cluster} = 5$) are mapped with the same color.

Figure A6: Florida: Large map of clusters, with county borders



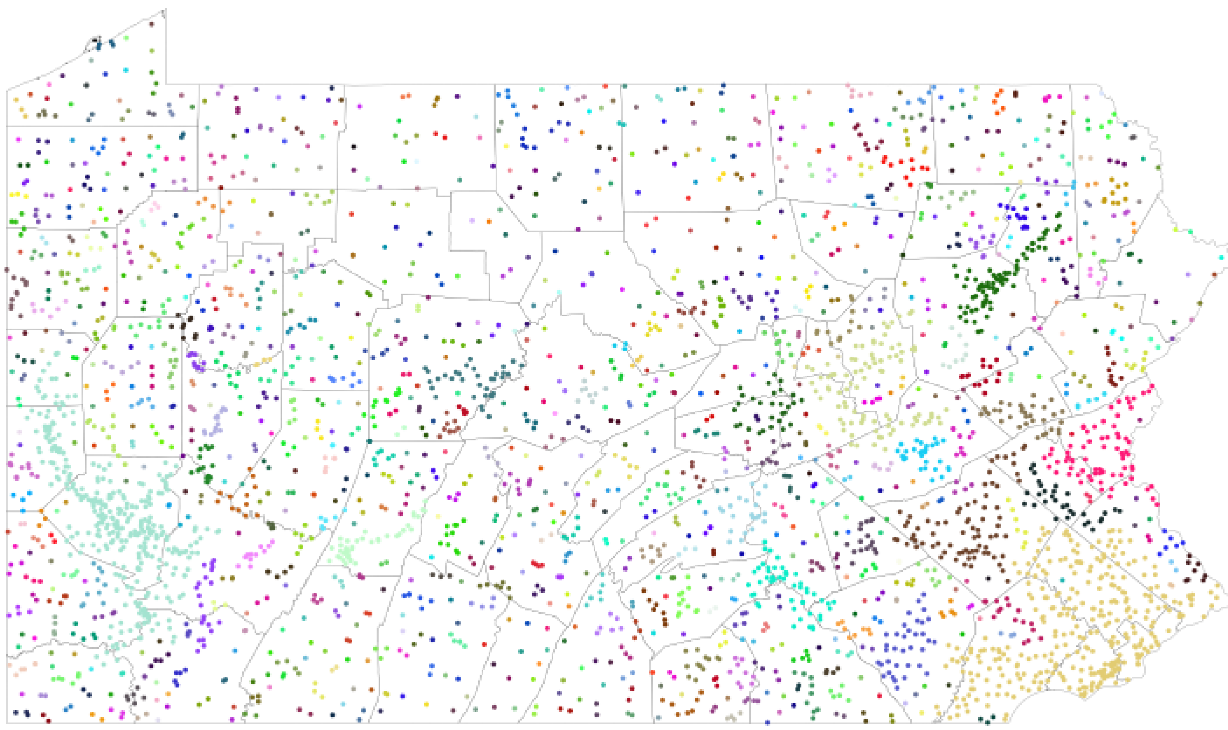
Notes: This figure maps the geocoded places in Florida, highlighting the county borders in Florida to emphasize the large number of geocoded places in our data relative to the smaller number of counties. Sets of adjacent places within the same cluster ($K_{cluster} = 5$) are mapped with the same color.

Figure A7: Oregon: Large map of clusters, with county borders



Notes: This figure maps the geocoded places in Oregon, highlighting the county borders in Oregon to emphasize the large number of geocoded places in our data relative to the smaller number of counties. Sets of adjacent places within the same cluster ($K_{cluster} = 5$) are mapped with the same color.

Figure A8: Pennsylvania: Large map of clusters, with county borders



Notes: This figure maps the geocoded places in Pennsylvania, highlighting the county borders in Pennsylvania to emphasize the large number of geocoded places in our data relative to the smaller number of counties. Sets of adjacent places within the same cluster ($K_{cluster} = 5$) are mapped with the same color.