Downscaling Occupational Employment Data from the State to the Census Tract Level

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Abstract

The lack of detailed occupational employment data at more granular geographic levels presents significant challenges in forecasting and analyzing local and regional employment changes in the era of the new technological revolution. This study aims to develop detailed occupational employment data by downscaling state-level employment information to the Census tract level. We introduce two downscaling algorithms that leverage employment, population, and sociodemographic composition data sourced from the American Community Survey, the Current Population Survey, and the Occupational Employment and Wage Statistics. This approach allows us to create a tract-level employment dataset covering 808 occupations. Such data are crucial for examining the effects of expected technological and demographic shifts on employment at this scale, which is critical for understanding tax base implications and job mobility opportunities. We demonstrate the value of these datasets by examining employment projections for two occupations anticipated to decline due to technological advancements in the near future.

Keywords: Data downscaling, occupational employment, localized labor market, employment trends, labor market analysis

1. Introduction

There is an increasing need for analyzing and forecasting local and regional employment changes in this era of technological revolution driven by the advancements of the internet, artificial intelligence (AI), and robotics (Acemoglu & Restrepo, 2019; Card & DiNardo, 2002; Goos & Manning, 2007; Kluge et al., 2019; Wang et al., 2023) However, we lack fine-scaled geographic information about where these occupations are located. Access to this type of data is important because it is well-established that the types of work people do shape the growth trajectory of regional economies (Florida, 2002; Gabe, 2006; Markusen, 2004; Markusen & Schrock, 2006; Moretti, 2012). Having finer-grained data to identify which regions may be more negatively impacted by the technological advancements and the resulting worker displacement can help policy makers to better plan for the shift. A complicating factor is the localized nature of labor markets: 54% of Americans reside close to where they grew up, and 61% of respondents do not want to relocate (Eriksson & Lindgren, 2009; Moretti, 2012; White, 2015). This suggests that even when more attractive jobs exist elsewhere, potential workers may not be willing or able to pursue them due to the localized labor market.

Unfortunately, in the United States, there is a dearth of detailed occupational data at fine geographic scales. Occupational data at the state and metropolitan level are available from the Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) program. Fine-scaled data are available from the U.S Census Bureau, but they are limited to several broad occupational categories, which blend different types of work together. For example, the category of "Transportation and Material Moving Occupations" include occupation types ranging from "Airline Pilots, Copilots, and Flight Engineers" to "Crane and Tower Operators." These occupations perform a variety of different tasks and functions, and also require different knowledge and skill levels from workers, yet are grouped together into one category. The O*NET database contains detailed information about more than 800 occupations ranging from educational requirements to the necessary skills, tasks performed, and personal values and interests that will most closely align with the occupation. Unfortunately, O*NET does not contain geographic information about these occupations.

There is a wealth of industry-level employment information at a variety of geographic scales from government databases, including the Bureau of Economic Analysis (BEA), the U.S. Census Bureau, and the Bureau of Labor Statistics. However, this information is not necessarily helpful in understanding occupational trends. Studies indicate that the availability of industry-level data for analyzing employment trends may not accurately depict regional economic specialization when compared to occupational data (Barbour & Markusen, 2007). For instance, companies within a specific industry, like information technology, can have different activities across various locations. As a result, industry-level employment figures may not capture the actual occupational employment within an area (Barbour & Markusen, 2007). Therefore, finer-level data are important for identifying not only regional specialization trends, but also information about people's skills and activities (Markusen, 2004). This focus can provide detailed information for tailoring economic and workforce development initiatives to help people find good-paying jobs that best match with their training and interests (Barbour & Markusen, 2007; Markusen, 2004; Markusen & Schrock, 2006).

Downscaling occupational data from larger geographic spatial scales may offer a solution to the present lack of fine-grained occupational data. There is a long tradition in science to downscale various types of data to understand the impacts of global phenomena at finer spatial scales (Hewitson & Crane, 1996; Khan et al., 2006). Downscaling is common in some scientific disciplines, of which, climate modeling is perhaps the most visible example (Hewitson & Crane, 1996; Prudhomme et al., 2002; Wood et al., 2004). Downscaling of population data is also common and has applications for emergency management and public health (Mennis & Hultgren, 2006). Some methods have been developed to downscale higher-level population data to finer granularity. Particularly, "*dasymetric mapping*" uses ancillary information (e.g., sociodemographic, land use, elevation, transportation network, and zoning) with areal interpolation to display data in spatial zones (Carella et al., 2020; Eicher & Brewer, 2001; Sleeter & Gould, 2007). This technique exploits available spatial information to obtain the probable demographic structure of source zones, which informs the redistribution of population counts (Kim & Yao, 2010; Langford, 2003). The "*area-based areal interpolation*" approach preserves the values of the source zones when downscaling the data to a finer level (Flowerdew, 1988; Lam, 1983). Historically, downscaling is less prominent in labor market studies, however, recent research has begun to utilize develop downscaling techniques to identify occupational trends. For example, a study focused on Vietnam used machine learning to produce grid-level occupational data in six categories from country-level labor market data (van Dijk et al., 2022). This study used a machine learning algorithm to predict the shares of six major occupation categories at a 1 km^2 scale, using a variety of factors (e.g., land cover, climate, topography, urbanization, transportation infrastructure, nightlights, and economic activity).

Nevertheless, there is still a need for designing techniques to downscale employment data about detailed occupations. Given recent industry evidence that the majority of people (84%) do not move long distances to find work (Biermeier, 2023), and the connection between the work that people do and the economic vitality of regional economies, there is a need for fine-grained geographic data about occupations. This is particularly true for datasets in the United States where there is a mismatch between existing high-level occupational employment data and the need for analyzing fine-scale employment trends. The production of such data would be helpful for local governments to make informed economic or workforce policies, to prepare for potential employment growth or decline, and to forecast the impact of demographic changes and technological advancements on the local workforce. To construct the data that are critical for meeting these challenges, we present and evaluate strategies for downscaling occupational data from the state to the Census tract level. The source data for downscaling is state-level 2017 occupational employment data. To incorporate sociodemographic characteristics, we integrated the individual-level Current Population Survey (CPS) for 2017 and tract-level American Community Survey (ACS) estimates for 2015-2019. Two different strategies for downscaling state-level occupational data are assessed and compared. By combining the two strategies, a dataset of 808 downscaled occupations is produced, which can be used to analyze a variety of topics affecting labor markets, including but not limited to employment trends and the impacts of workforce development initiatives. Our method can be used to continuously update the downscaled data as OEWS, CPS, and ACS are updated and also applicable for downscaling other similar employment or demographic datasets with different geographic units and contexts. The utility of these data is demonstrated by conducting a geographic analysis at the Census tract level of employment projections for an occupation that is expected to face decline as a consequence of the rapid advancement of automation and AI technologies.

2. Data for Downscaling

This study downscales occupational employment data at the Census tract level for 72,538 tracts in the contiguous 48 states and the District of Columbia. Three datasets are used in the downscaling methodology developed in this paper: (1) state-level occupational employment data from the Occupational Employment and Wage Statistics (OEWS) from the Bureau of Labor Statistics; (2) sociodemographic data from the Current Population Survey (CPS) from the United States Census Bureau; and (3) working population and sociodemographic characteristics from the American Community Survey (ACS) from the U.S. Census Bureau.

2.1. Occupational Employment and Wage Statistics (OEWS)

OEWS estimates provide information on detailed occupations classified in the Standard Occupational Classification (SOC) system. The OEWS estimates the total number of employees across different SOC occupations at the national level, state level, and metropolitan and non-metropolitan areas. The OEWS data include the number of all wage and salary workers in nonfarm industries, both full-time and part-time, but does not include self-employed workers, owners and partners in unincorporated businesses, domestic workers, and unpaid family employees (*OEWS Documentation Archive*, 2021). The primary objective of this study is to downscale these data to the Census tract level. To make it comparable with the CPS data, we use the 2017 OEWS data in the analysis.

2.2. Current Population Survey (CPS)

Data from the CPS is utilized because it contains information about both occupations and demographic characteristics at the individual level. We use it to calculate the sociodemographic composition for each occupation. CPS sampling is based on the geographic location of the sampled households to reflect the distribution of workers for the entire country, individual states, counties, and other defined areas (Ruggles et al., 2019). The Annual Social and Economic Supplement (ASEC) is a subset of CPS data that provides geographic, sociodemographic, and occupational data for samples that represent the working population, computed as three-year weighted averages centered on the target estimation year. Occupations are classified in the Census Occupation Codes (COC) system. To obtain sociodemographic composition by occupation, we group the data based on the demographic matrix listed in **Table 1**. The selection of these sociodemographic variables is based on the availability of the cross-tabulated spreadsheet of age groups by sex by race in the American Community Survey. Nevertheless, our downscaling approach is flexible regarding the selection of variables. If there is a cross-tabulated spreadsheet table that integrates other demographic variables, such as Hispanic ethnicity or educational attainment, or economic status such as income, with the existing variables, we can easily replace our current demographic matrix with the more detailed one. Data are extracted for employed workers only. To match the CPS data with the OEWS data, we excluded self-employed workers from the CPS sample. We included the weights variable in the ASEC dataset (ASECWT) to adjust the sample size when deriving the demographic groups for each occupation. [1]

[1] The ASECWT variable is a person-level weight that accounts for the potential biases and errors of CPS sampling (IPUMS CPS, n.d.).

Table 1: Sociodemographic Groups

Characteristics	Sub-category
Age	15-24
	25-54
	55-64
	65+
Sex	Male
	Female
Race	White
	Black
	Asian
	Others

2.3. American Community Survey (ACS)

We use the ACS data as a source of information about the working population and sociodemographic composition at the tract level. The ACS is administered annually by the U.S. Census Bureau (United States Census Bureau, 2017) and provides 1-, 3-, and 5-year pooled estimates of the number of employed civilian workers and the demographic characteristics of the population. This study uses 5-year ACS estimates because, unlike 1- and 3-year estimates, they are available for smaller geographic levels, including Census tracts (U.S. Census Bureau, 2018). We select the variables of age, sex, and race from the ACS data and group them in a similar manner to the CPS data shown in **Table 1**. These sociodemographic variables are not specified for the working population but for the entire population within an area.

2.4. Selection of the years of the data

We used the CPS, OEWS, and ACS data prior to the COVID-19 pandemic outbreak in early 2020. As each of them contains different years of data, we carefully select the tables to make them comparable and consistent. We use the CPS ASEC table for the year 2017, which represents the average for the three years: 2016, 2017, and 2018. The OEWS data are extracted for the year 2017, and the ACS 5-year estimates are obtained as the average between 2015 and 2019. The ACS 5-year estimates collect data based on a rolling sample over a moving period of 60 months (five years) (US Census Bureau, 2023). Therefore, we used the midpoint of the time window, 2017, as the proxy for the data year to match other 1-year datasets. **Table 2** contains a summary of the key information provided by each of these datasets and the finest geographic scale for which each of these data is available.

Table 2. Comparison of Datasets

Dataset Summary Information	American Community Survey	Current Population Survey	Occupational Employment and Wage Statistics
Aggregate-level total employment	×		×

Detailed occupations in the COC system		×	
Detailed occupations in the SOC system			×
Demographic information	×	×	
Self-reported data	×	×	
Finest Geographic Scale	Census Block	County	State
Year selected	2015-2019	2017	2017

3. Methods

3.1. Connecting datasets across occupational classification systems

It is essential to identify occupations in different datasets before downscaling the employment data. CPS and OEWS classify and specify detailed occupations in two different systems. The CPS uses COC, and the OEWS uses SOC. The CPS uses COC, and the OEWS uses SOC. We used COC and SOC for the year 2010 to maintain consistency between the classification systems. Both SOC and COC systems contain major occupational groups. However, the COC system contains 540 detailed occupations within these major groups (U.S. Census Bureau, 2021b), while the SOC system contains more than 800 detailed occupations (the exact number varies in different years' data) (U.S. Bureau of Labor Statistics, 2021). We use the crosswalk provided by the Census Bureau to link the occupations between the two classification systems (U.S. Census Bureau, 2021b). **Appendix TA1** shows the matched codes for major occupational groups between SOC and COC using this crosswalk. However, since the SOC system has more detailed occupations than the COC system, they have a one-to-many mapping. For example, the COC code '2555', which refers to "other education, training, and library workers," corresponds to the SOC code '25-90XX' in the crosswalk, which refers to 18 different occupations in the SOC system.

3.2. Two downscaling strategies and four base geographic units

Now we demonstrate two methods to downscale OEWS state-level occupational employment data to the tract level. The tract-level ACS data help determine the working population in each tract. We draw on the concept of dasymetric mapping which utilizes ancillary information as supplementary data to improve the accuracy of downscaling (Carella et al., 2020; Eicher & Brewer, 2001; Sleeter & Gould, 2007). Our ancillary information uses three sociodemographic characteristics: age, sex, and race. Additionally, we refer to the concept of area-based areal interpolation to preserve the values of the source zones (Flowerdew, 1988; Lam, 1983).

Ideally, we want to account for sociodemographic characteristics of workers in each occupation derived from the CPS data in the process of downscaling because Census tracts have different demographic compositions. Therefore, we calculated the percentages of demographic groups for each occupation based on the variables age, sex, and race in the 2017 CPS data. However, the CPS data can provide only a portion of occupations identifiable in the OEWS data. Therefore, we need an alternative downscaling strategy without using the CPS data to downscale the full list of occupations in OEWS. In the remainder of this paper, we refer to the method that includes the CPS demographic information as the Full Method and the alternative method without using the CPS as the Base Method. **Table 3** describes the variable notations used for both methods.

Table 3. Variable Notations

Notation	Description
$g \in G$	Demographic group
$o \in O$	Occupation
$r \in R$	Geographic level: state, division, region, or nation
$s \in S_r$	State in state/division/region r
$t \in T_s$	Tract in state s
W_{gor}^{C}	Number of workers in occupation o belonging to demographic group g in state/division/region r (available from the CPS-ASEC data)
X_{gor}^{C}	The proportion of workers in occupation o belonging to demographic group g in state/division/region r
W_{os}^{B}	Total number of workers in occupation o in state s (available from the BLS-OEWS data)
W_{gos}^{BC}	Total number of workers in demographic group g in occupation o in state s
$W_{st}^{A'}$	Total number of workers across all occupations in tract t in state s (available from the ACS data)
$X_{st}^{A'}$	The proportion of total workers in tract t by state s
$W_{ost}^{\mathcal{A}}$	Number of workers in major occupation o in tract t of state s (available from the ACS data)
$X_{ost}^{\mathcal{A}}$	The proportion of workers in major occupation o in tract t of state s
W_{gst}^{A}	Number of people in demographic group g in tract t in state s (available from the ACS data)
X_{gst}^{A}	The proportion of people in tract t by state s for demographic group g
$W_{ost}^{*'}$	Total number of workers in occupation o in tract t of state s (downscaled data using Base Method)
$X_{ost}^{*'}$	The proportion of workers in occupation o in tract t of state s (downscaled data using Base Method)
W_{gost}^{*}	Total number of workers in occupation o in demographic group g in tract t of state s (downscaled data using Full Method)
X_{gost}^{*}	The proportion of workers in occupation o for demographic group g in tract t of state s (downscaled data using Full Method)

The CPS provides data at multiple geographic scales (e.g., state, Census division, and Census region). For most occupations identifiable in the CPS, we can get a sufficient sample size to calculate the percentages of demographic groups based on age, sex, and race at the state level. Therefore, we use the state as the base geographic unit to calculate the demographic composition for most occupations. If the sample size for a particular occupation within a state is too small, we expand our analysis to a higher geographic level, such as the Census division. If even at the division level the sample remains inadequate, we further broaden the scope to the Census regional level. Ultimately, if a sufficient sample size cannot be obtained across these finer geographic levels, we resort to using the nation as the base geographic unit. The relationship between geographic levels can be found in **Appendix TA 2**.

3.3. Base Method: Occupational downscaling without using demographic information

The Base Method is a simple downscaling approach that uses labor force participation (i.e., the number of employed workers) at the Census tract and state levels from the ACS data shown in **Figure 1**. First, we use the number of total workers across all occupations ($W_{st}^{A'}$) in tract t to calculate the proportion of total workers ($X_{st}^{A'}$) within its corresponding state s as illustrated in Eq. (1).

$$X_{st}^{A'} = \frac{W_{st}^{A'}}{\sum_{t \in T_s} W_{st}^{A'}}, \qquad \forall s, t \tag{1}$$

Second, for each state s, we use the total number of workers (W_{os}^{B}) for each occupation and the proportion of total workers in tract t within that state to estimate the downscaled number of workers ($W_{ost}^{*'}$) in occupation o in the corresponding tract using Eqs. (2) and (4). Finally, we compute the proportion of workers in occupation o in tract t using Eq. (3). Note that since $\sum_{t \in T_s} W_{ost}^{*'} = W_{os}^{B}$, $X_{ost}^{*'}$ is equal to $X_{st}^{A'}$.

$$W_{ost}^{*'} = W_{os}^{B} \times X_{st}^{A'}, \qquad \forall o, s, t \tag{2}$$

$$X_{ost}^{*'} = \frac{W_{ost}^{*'}}{\sum_{t \in T_s} W_{ost}^{*'}}, \qquad \forall o, s, t \tag{3}$$

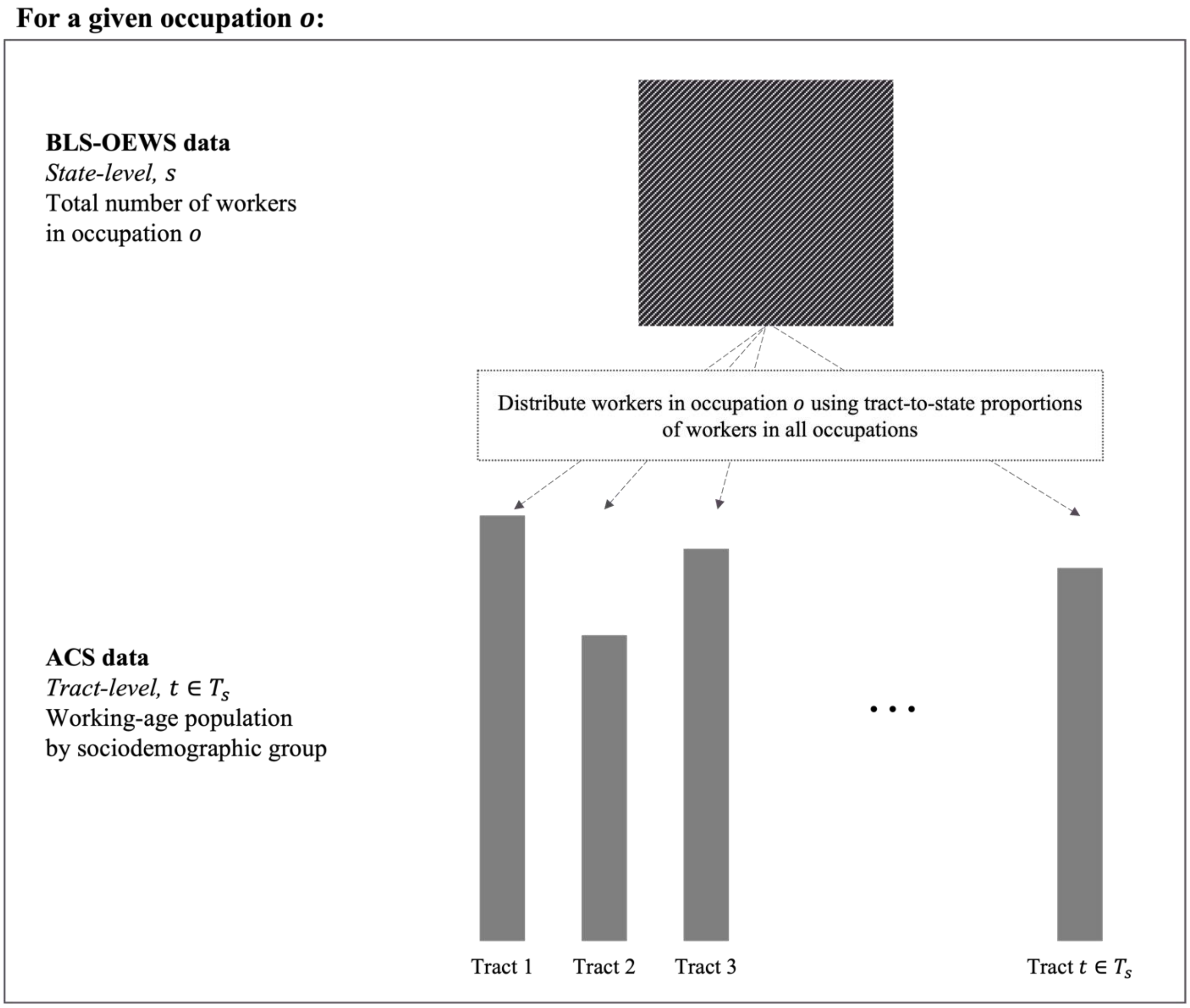


Figure 1. Flow chart illustrating downscaling by Base Method

3.4. Full Method: Occupational downscaling using demographic information

The Full Method can be categorized into five steps. Figure 2 illustrates the steps in this method. First, we identify the demographic factors (i.e., age, sex, race) that are available in all three datasets (i.e., CPS, OWES, and ACS). We enumerate the combinations of these factors to create 32 demographic groups (4 age groups × 2 sex groups × 4 race groups; see **Table 1**).

Second, for each occupation o and demographic group g, we use the number of workers (W_{gor}^{C}) for a given state, division, region, or nation r in the CPS data to compute the proportion of workers (X_{gor}^{C}) using Eq**. (4)**.

$$X_{gor}^{C} = \frac{W_{gor}^{C}}{\sum_{g \in G} W_{gor}^{C}}, \qquad \forall g, o, r \tag{4}$$

Third, we use the OEWS data to get the total number of workers (W_{os}^{B}) in each occupation for every state. Using the proportions of workers in demographic groups from the CPS data, we distribute the total number of workers from the OEWS data in different demographic groups (W_{gos}^{BC}) as shown in Eq. (5). It should be noted the OEWS and CPS data may represent different geographic levels, that is, state-level for the OEWS data and state-, division-, regional, or national-level for the CPS data. Therefore, when r represents a division or a region in the CPS data, this method assumes that the computed proportions of workers are the same across all states within that division or region.

$$W_{gos}^{BC} = W_{os}^{B} \times X_{gor}^{C}, \qquad \forall g, o, r, s \in S_r \tag{5}$$

Fourth, for each demographic group g and state s, we use the tract-level number of people (W_{gst}^{A}) for all tracts in that state from the ACS data to compute the tract-to-state proportion of people (X_{gst}^{A}) belonging to group g using Eq. (6). Here we assume that the demographic distribution of workers is similar to that of the general population within the tract.

$$X_{gst}^{A} = \frac{W_{gst}^{A}}{\sum_{t \in T_s} W_{gst}^{A}}, \qquad \forall g, s, t \tag{6}$$

Finally, we use the tract-to-state proportions of people in different demographic groups computed using the ACS data and the number of workers in corresponding groups and states to estimate the downscaled number of workers (W_{gost}^{*}) and the tract-to-state proportion of workers (X_{gost}^{*}) in occupation o belonging to demographic group g in tract t of state s as shown in Eq. (7) and Eq. (8). Note that since $\sum_{t \in T_s} W_{gost}^{*} = W_{gos}^{BC}$, X_{gost}^{*} is equal to X_{gst}^{A}. Finally, we combine the workers across all demographic groups to get the total number of workers in occupation o in tract t of state s using Eq. (9).

$$W_{gost}^{*} = X_{gst}^{A} \times W_{gos}^{BC}, \qquad \forall g, o, s, t \tag{7}$$

$$X_{gost}^{*} = \frac{W_{gost}^{*}}{\sum_{t \in T_s} W_{gost}^{*}}, \qquad \forall g, o, s, t \tag{8}$$

$$W_{ost}^{*} = \sum_{g \in G} W_{gost}^{*}, \qquad \forall o, s, t \tag{9}$$

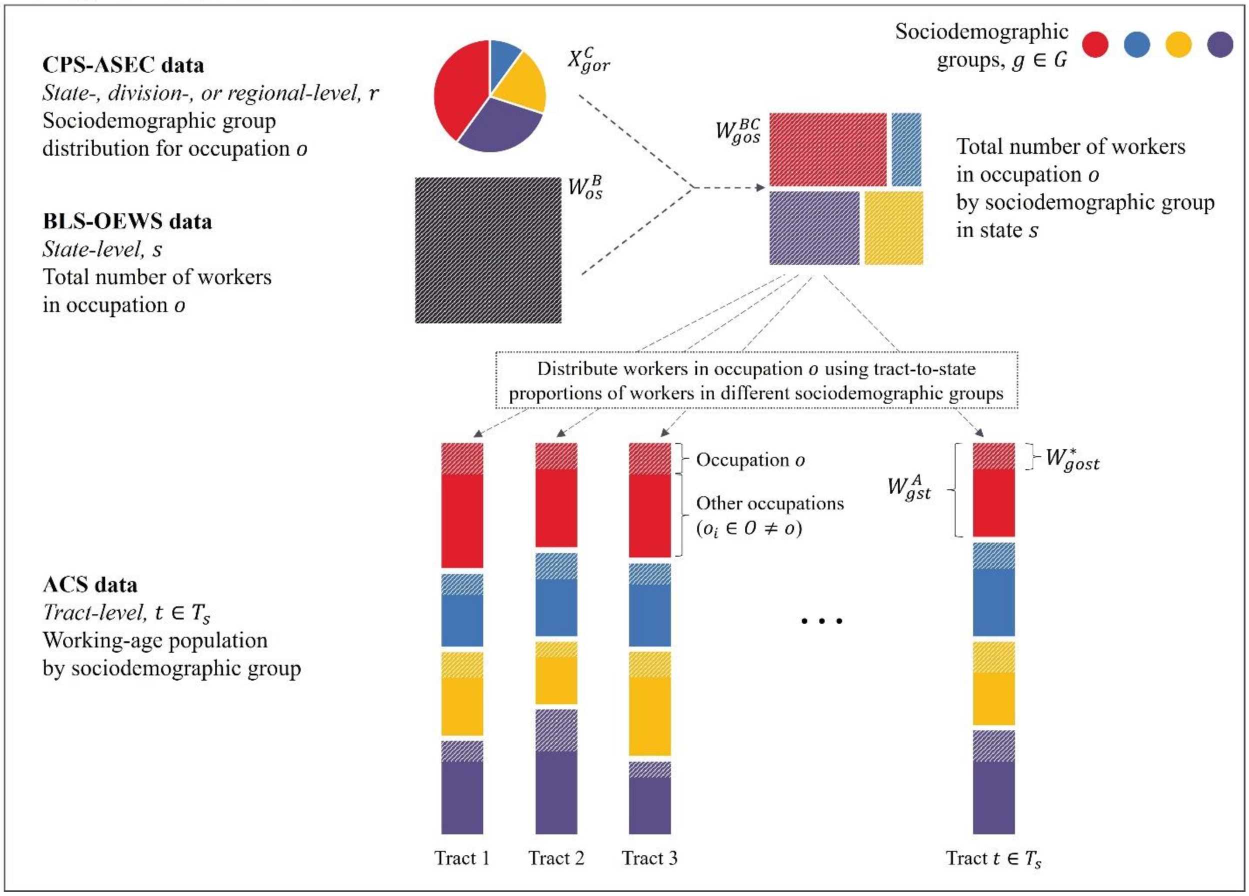


Figure 2. Flow chart illustrating downscaling by Full Method

3.5. Assessment of downscaling methods

By combining the two methods, we can create a data set that contains tract-level employment for 808 occupations. To assess the accuracy of the method, we need to compare the downscaled data to actual employment data. In the ACS, tract-level employment data are available for 22 categories of occupations, consistent with the major occupational groups in the SOC system in OEWS data (as shown in **Appendix TA1)**. Therefore, we compare the downscaled data and the real data for 22 major occupational groups at the tract level.

To compare results, we compare the tract-to-state proportions instead of the absolute numbers of workers. This is because the number employment of an occupation in a state is known, and the tract-to-state ratio can better reflect the accuracy of the estimation regarding the spatial distribution. Using the ACS data, the proportions of workers ($X^{\mathcal{A}}_{ost}$) in major occupation o in tract t are computed from the number of workers ($W^{\mathcal{A}}_{ost}$) in that occupation in the corresponding state s using Eq. (10).

$$X_{ost}^{\mathcal{A}} = \frac{W_{ost}^{\mathcal{A}}}{\sum_{t \in T_s} W_{ost}^{\mathcal{A}}}, \qquad \forall o, s, t \tag{10}$$

Then, we compute the root mean square error (RMSE) to evaluate the overall performance of the proposed methods for every major occupation o across all Census tracts in the U.S. (T_N) using Eq. (11).

$$RMSE_o = \sqrt{\frac{\sum_{t=1}^{T_N} \left(\sum_{g \in G} X_{gost}^{*} - X_{ost}^{\mathcal{A}}\right)^2}{T_N}}, \qquad \forall o \tag{11}$$

4. Results

4.1. Tract-level occupation-specific employment data

Using the two downscaling approaches and the four base geographic units in the CPS data, we produced a dataset that provides employment data for 808 occupations at the Census tract level. Each occupation's data are stored in a separate CSV file. Each CSV file contains 72,538 rows, presenting employment estimates for an occupation for 72,538 Census tracts. About 93% (n=752) of the 808 occupations can be matched with the Census occupation codes in the CPS data through the SOC-COC crosswalk. Therefore, estimates derived from the Full Method are available for these 752 occupations. The rest of the occupations are only available for estimates using the Base Method (n=56).

Note that the Full Method uses the sociodemographic in the CPS data to downscale employment data from the state level to the tract level, but the CPS sample size is limited and may not provide a sufficient subsample for an occupation in a state or even higher geographic levels. Therefore, we provide estimated values based on four different geographic levels of the CPS sample: state, division, region, and nation. The accuracy of outputs based on different geographic levels will be discussed in the later section. **Figure 3** illustrates the logic and workflow to generate estimation outputs using different geographic scales and CPS samples. **Appendix TA3** displays the structure of the dataset. **Appendix TA4** summarizes the availability of outputs based on different methods.

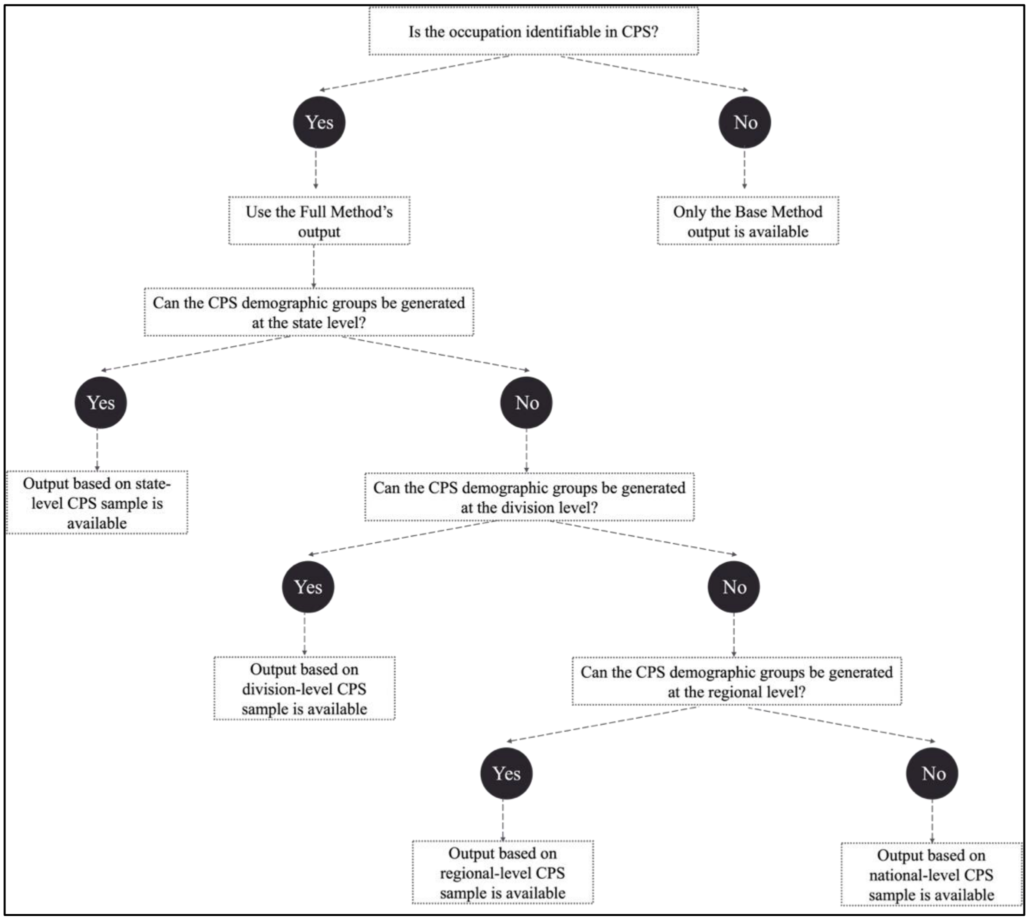


Figure 3. Availability of the downscaled outputs for CPS samples with different geographic scales for an occupation

4.2. Performance of downscaling

It was not possible to evaluate the performance of individual occupations (e.g., heavy and tractor-trailer truck drivers) because this information is not available in the ACS. Nevertheless, the ACS provides employment estimates at the Census tract level for 22 major occupational groups in the SOC system. These occupational groups are represented by the first two digits of the SOC codes. Therefore, we were able to evaluate the performance of each of the downscaling methods using the RMSEs for the 22 major occupation groups available in the ACS. Note that a major occupation group includes many detailed occupations. For example, the Group 11-0000 "Management Occupations" includes the Occupation 11-3031 "Financial Managers." Thus, the assessment results for the major occupations do not reflect the quality of detailed occupations. Rather, the results we present here help us to understand factors that influence the downscaling results.

Table 4 lists the 22 occupation groups and the method that produces the minimum RMSE for each occupation group. For 45% of the occupation groups, using a state-level sociodemographic sample in CPS will lead to an optimal RMSE if it gets a sufficient representation of sociodemographic groups at the state level. The Base Method performs better for 40% of occupation categories which have relatively smaller employment sizes.

Table 4. Occupation Groups and the Method with the Minimum RMSE

Occupation Code	Occupation Title	Minimum RMSE
11-0000	Management Occupations	Base Method
13-0000	Business and Financial Operations Occupations	Base Method
15-0000	Computer and Mathematical Occupations	Full Method (national CPS sample)
17-0000	Architecture and Engineering Occupations	Base Method
19-0000	Life, Physical, and Social Science Occupations	Full Method (national CPS sample)
21-0000	Community and Social Service Occupations	Base Method
23-0000	Legal Occupations	Full Method (regional CPS sample)
25-0000	Education, Training, and Library Occupations	Base Method
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	Base Method
29-0000	Healthcare Practitioners and Technical Occupations	Base Method
31-0000	Healthcare Support Occupations	Full Method (state CPS sample)
33-0000	Protective Service Occupations	Full Method (state CPS sample)
35-0000	Food Preparation and Serving Related Occupations	Full Method (state CPS sample)
37-0000	Building and Grounds Cleaning and Maintenance Occupations	Full Method (state CPS sample)
39-0000	Personal Care and Service Occupations	Full Method (state CPS sample)
41-0000	Sales and Related Occupations	Base Method
43-0000	Office and Administrative Support Occupations	Base Method
45-0000	Farming, Fishing, and Forestry Occupations	Full Method (state CPS sample)
47-0000	Construction and Extraction Occupations	Full Method (state CPS sample)
49-0000	Installation, Maintenance, and Repair Occupations	Full Method (state CPS sample)
51-0000	Production Occupations	Full Method (state CPS sample)
53-0000	Transportation and Material Moving Occupations	Full Method (state CPS sample)

One of the most important factors is the sample size of an occupation identified in the CPS data, as it determines the availability of sociodemographic groups for that occupation that can be matched with the ACS data. A small sample size can lead to the loss of several demographic groups for certain occupations. In other words, some sociodemographic groups may not be represented at all (i.e., zero workers sampled in the group). This can significantly magnify the error in the downscaled estimates. This issue is also related to another factor that influences the performance of estimates – the geographic level at which the occupational sociodemographic information in the CPS data is collected. Using a higher geographic level (e.g., a national sample) may overlook spatial heterogeneity across states, divisions, and regions. However, opting for a higher geographic level generally provides a larger sample size, ensuring more non-zero representations of sociodemographic groups in the sample. Therefore, we compare the relationship between RMSE, the geographic level for the occupational sociodemographic information, and the number of non-zero sociodemographic groups available in CPS and at the corresponding geographic level.

Figure 4 presents the RMSEs for different geographic levels used in the Full Method, along with the average numbers of non-zero sociodemographic groups across all tracts for all 22 major occupations. It clearly shows that the number of non-zero demographic groups increases with the geographic level of the CPS sample. The results also indicate a clear decreasing trend in RMSE as the representation of sociodemographic groups increases for a given geographic level.

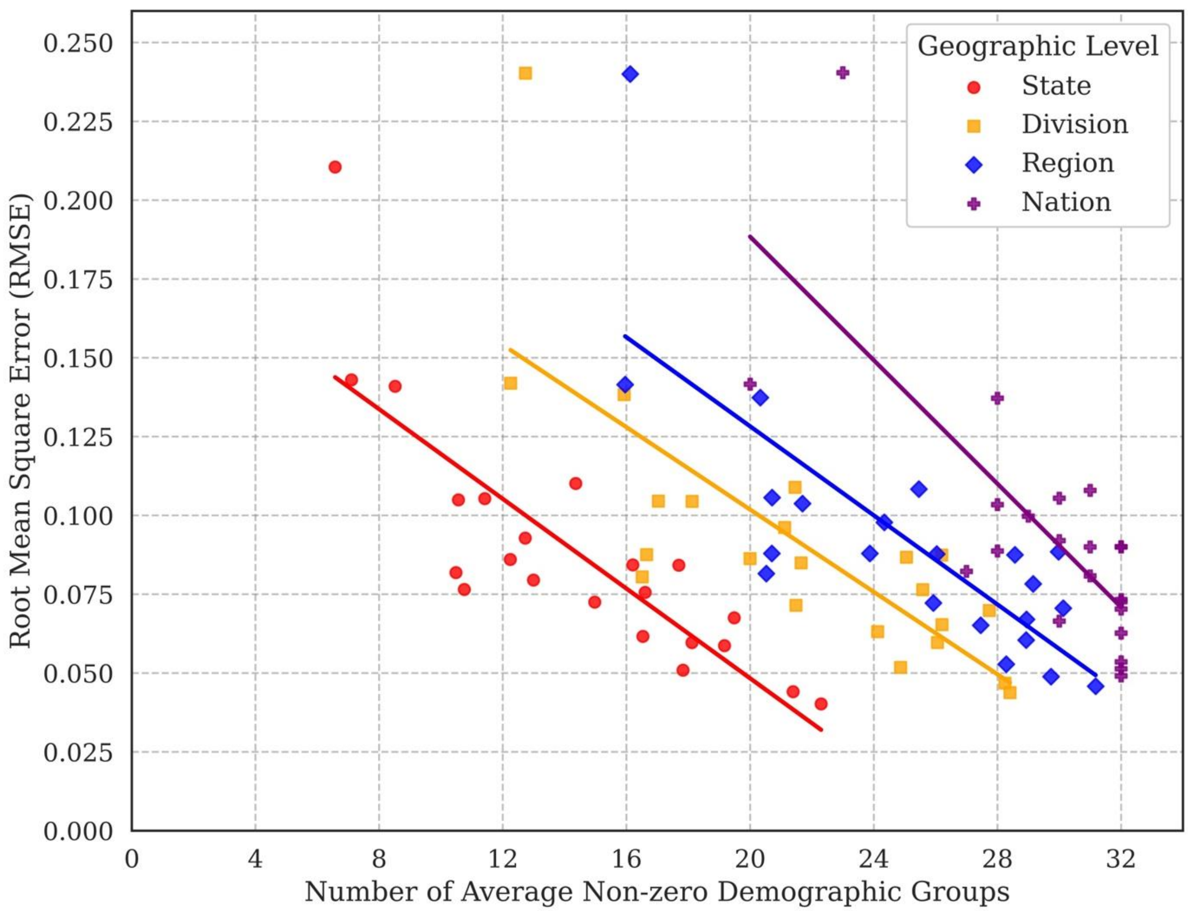


Figure 4. Relationship between RMSE and average number of demographic groups across tracts for all major occupation groups

Detailed occupations usually have much smaller samples in the CPS compared to the 22 major occupation groups. Most detailed occupations feature fewer sociodemographic groups with non-zero counts. **Figure 5** illustrates the average number of sociodemographic groups with non-zero counts across all tracts for detailed occupations within the SOC system. This figure shows that the average number of sociodemographic groups with non-zero counts decreases when analyzing detailed occupations as opposed to major occupational groups (refer to **Figure 4**), particularly at more granular geographic levels (e.g., state). Given the reduced number of non-zero groups for several occupations, it is anticipated that the Full Method, when applied at a higher geographic level, will yield better results for these occupations.

The assessment underscores the trade-offs between spatial resolution and data availability. The Full Method takes into account the sociodemographic characteristics of both a specific occupation and a Census tract in its employment estimates. However, this method is generally less flexibility and in some cases is infeasible for analysis (due to data sparsity). Particularly, using the Base Method allows for the downscaled employment of all 808 occupations in the SOC system, with the downscaled data available for most Census tracts which reported working-age populations in ACS. In contrast, employing the Full Method limits the number of downscaled occupations to 752, and the geographic coverage of downscaled estimates depends on the availability and selection of the geographic scale of the CPS demographic sample (estimates based on a specific geographic scale in CPS are available only if the CPS sample at that scale is available in that area). Nevertheless, even with restricted geographic coverage, the Full Method's estimates could still be valuable. We will demonstrate an example in the discussion section. Moreover, if the number of non-zero demographic groups in the CPS data is minimal, the Full Method may not outperform the Base Method in terms of estimation accuracy. This will be discussed later as well.

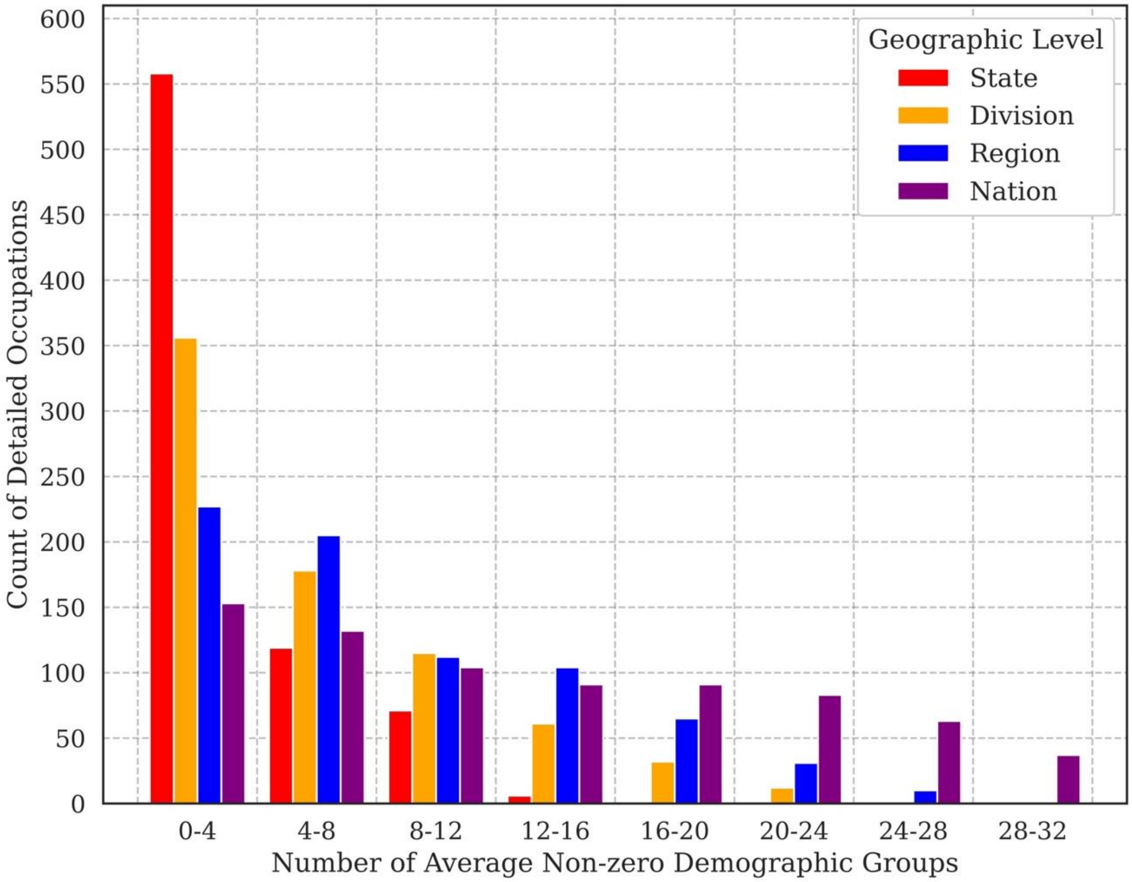


Figure 5. Frequency distribution of the number of characteristics in downscaled detailed occupation using Full Method

4.3. Application of the data in occupational projections

One of the main motivations behind downscaling occupational employment data is to make fine-scaled geographic analyses of factors and events impacting labor markets possible. One of the ongoing factors impacting labor markets is technological change. In particular, the newest wave of advances in generative AI, such as ChatGPT, Google Bard, and Midjourney, are threatening jobs with non-routine, innovative tasks (Wach et al., 2023). These are jobs that typically require higher educational qualifications, extensive job training, and pay higher wages. This is a shift from prior waves of technological change, which threatened primarily routine, lower-wage jobs (Goos, 2018).

To demonstrate the application of the downscaled data produced by this paper in analyzing labor losses due to technological change, we examine the projected job changes for the occupations of executive secretaries and executive administrative assistants (43-6011) and claims adjusters, examiners, and investigators (13-1031). The former occupation is projected to experience one of the largest job declines, at 21.1%, over the next decade (U.S. Bureau of Labor Statistics, n.d.). This decline is attributed to labor substitution caused by technological advancements that "allow workers to perform tasks with fewer secretaries" (U.S. Bureau of Labor Statistics, n.d.). Meanwhile, the latter occupation is projected to see a 3.1% job decline because 'computer software will automate much of this work' (U.S. Bureau of Labor Statistics, n.d.). These projections come from the Employment Projections (EP) database of the BLS, which outlines employment trends and the drivers behind these trends for each occupation within the SOC system (U.S. Bureau of Labor Statistics, n.d.). The current median annual wages for 43-6011 and 13-1031 are $65,980 and $72,230, respectively, significantly higher than the median wage for all occupations, which is $46,310. The total employment for these two occupations stands at 511,100 and 329,000, respectively. Detailed information about these occupations and their employment trend projections can be found in **Table 5**. We choose these two occupations to demonstrate an application of the downscaled data in understanding where job losses will occur at a fine-grained geographic level is lacking. By using our downscaled data, we can present the projected job losses for these two occupations at the tract level.

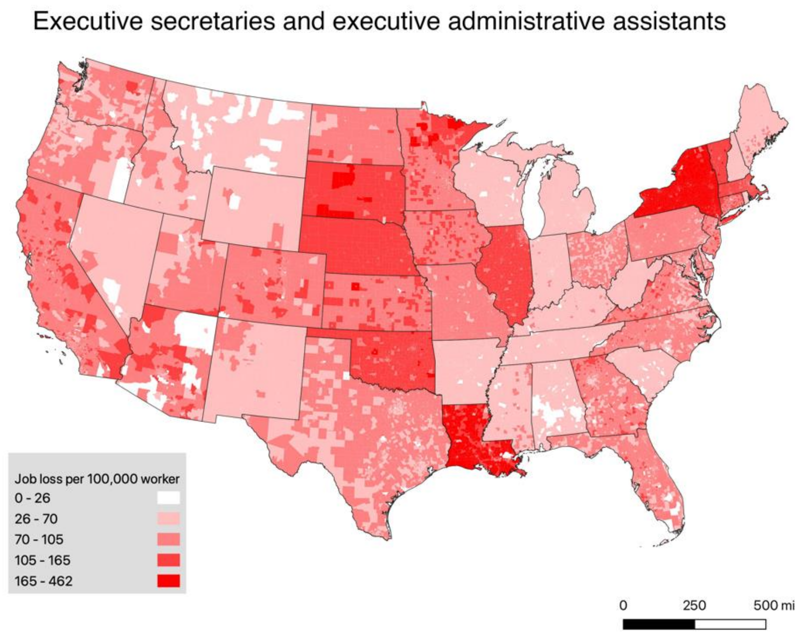
Table 5. **Occupational Information**

Occupation name	SOC	Current employment (in thousands)	% change in employment by 2032	The current median annual wage	Drivers of occupational projection
Executive secretaries and executive administrative assistants	43-6011	511.1	-21.1%	$65,980	Occupational substitution-share decreases as improved technology allows workers to perform with fewer secretaries.
Claims adjusters, examiners, and investigators	13-1031	329.0	-3.1%	$72,230	Productivity change-share decreases as computer software will automate much of this work, reducing the needed number of adjusters.

Figure 6 displays the projected employment losses in each Census tract by 2032 for occupations 43-6011 and 13-1031. We estimated the current tract-level employment for these two occupations using the Full Method. Then, we calculated the job reduction per 100,000 workers in each Census tract, assuming that all tracts will experience the same percentage losses of 43-6011 and 13-1031 jobs as projected by the EP database, which is 21.1% and 3.1%, respectively.

The two maps in the figure clearly highlight states that will experience significant job losses in both occupations. For executive secretaries and executive administrative assistants, certain states particularly stand out, including New York, Massachusetts, Vermont, Illinois, Louisiana, Oklahoma, Nebraska, and South Dakota. Parts of California, Arizona, and Minnesota will also experience substantial job losses in this occupation. While some of these states are not surprising (e.g., New York, Massachusetts, California, and Illinois), the impact on others is unexpected (e.g., Louisiana, Oklahoma, North Dakota, and Nebraska). This outcome may be caused by suburbanization and the proliferation and relocation of back offices (e.g., human resources, accounting and finance, information technology) outside major metropolitan areas (Rowlands & Loh, 2021). Nevertheless, these results indicated the utility of finer-scaled data. Other states, such as Alabama and Montana, will lose very few, if any, jobs in this occupation. For claims adjusters, examiners, and investigators, significant job losses will be concentrated in some West and Midwest states, such as Arizona, Nebraska, Kansas, Missouri, and Tennessee, while Wyoming will experience very few job losses.

Another critical aspect of the downscaled data is its ability to capture employment variability within a state and pinpoint where the greatest job losses will occur. Our analysis highlights significant employment declines for two specific occupations across various metropolitan areas. For executive secretaries and executive administrative assistants, substantial job losses are anticipated in cities and communities within Southern California, the Bay Area, Phoenix, Arizona, and Northern Minnesota. Similarly, for claims adjusters, examiners, and investigators, notable declines are expected in metropolitan areas of Northern Alabama, Northern Florida, and Northern Minnesota. These findings illustrate the widespread impact of technological change, affecting regions beyond traditional technology hubs or economic centers. **Figure 7** further illustrates the job loss among claim adjusters in the New York-New Jersey-Pennsylvania region, which is home to several megacities and important metropolitan areas, such as New York City and Philadelphia. The figure highlights significant job losses in the peripheral suburbs of these large metropolitan areas.



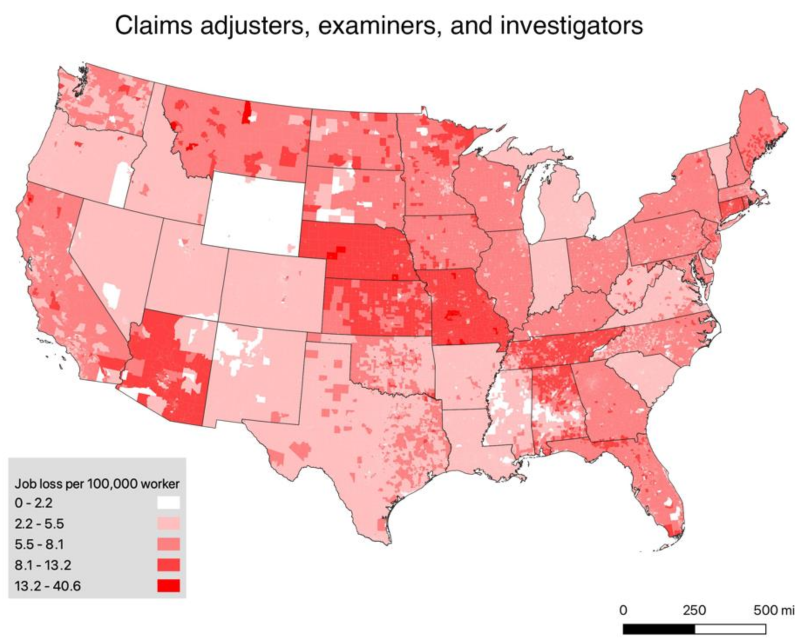


Figure 6. Job loss for executive secretaries and executive administrative assistants (43-6011) and claims adjusters, examiners, and investigators (13-1031) by Census tract

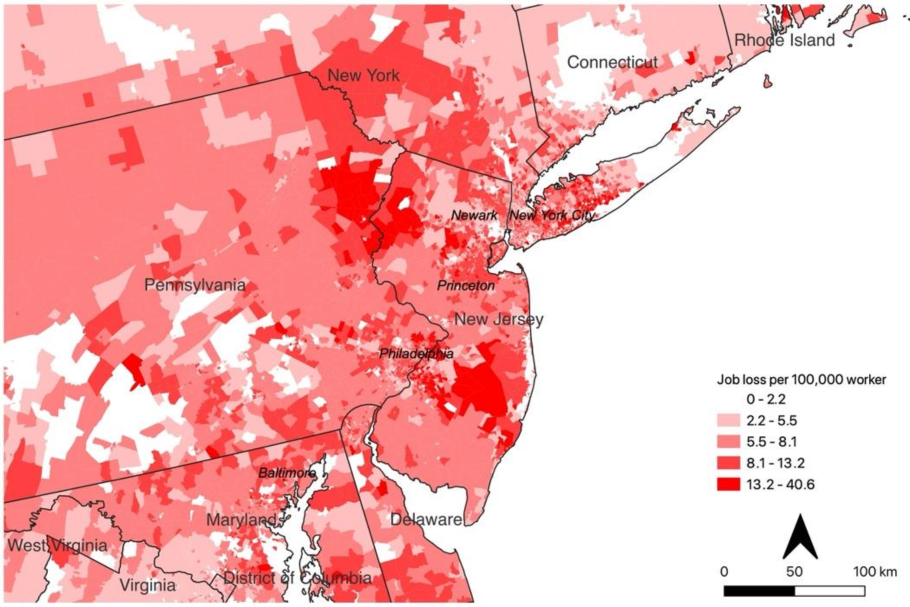


Figure 7. Job loss for claims adjusters, examiners, and investigators (13-1031) in the New York-New Jersey-Pennsylvania region

5. Discussion

The dynamic nature of the workforce, driven by rapid technological advances, merits detailed geographic assessments to understand how these changes impact people's employment prospects and the growth trajectory of regional economies. Unfortunately, the lack of comprehensive data in the United States hampers the ability of researchers and policymakers to conduct spatial analyses of occupational trends and changes over time. Particularly, there is no employment data for detailed occupations at any fine-grained geographic levels, such as county, Zip Code, Census tract, or public use microdata area (PUMA). This study introduces two approaches to downscale occupational data from coarser state-level data to the more granular level of Census tracts. We further showcase an application of these approaches by analyzing projected job losses for two high-paid occupations that are projected to be significantly disrupted by technological change.

The analysis of the two downscaling approaches revealed two factors impacting the RMSEs of the estimates: 1) The total employment of an occupation and 2) the sample size of an occupation in the CPS data. As the employment size of an occupation increases, the error in the downscaled estimates decreases. This is because a larger employment size is more likely to be represented proportionally across Census tracts with more demographic groups, which reduces the estimation errors. For occupations with a large number of employees, both the Base Method and the Full Method perform equally well. More specifically, when the overall national employment size is greater than 70,000, the estimates of occupation are likely to be available for both methods and all geographic-level samples.

Also, when the workforce size is larger (e.g., > 100,000), the CPS data is more likely to have an adequate sample size for all states and more representative sociodemographic groups across states, which results in better performance of the Full Method. If a smaller number of people work in an occupation, the sample size of the occupation would be limited in the CPS, resulting in missing demographic groups, which leads to larger estimation errors. In this case, the Base Method would work better.

Relatedly, the second factor impacting the accuracy of the two downscaling techniques is the sample size of an occupation in the CPS data. When the sample size in the CPS data is relatively large, the Full Method usually performs better. Estimates based on finer-level CPS samples are more theoretically reliable (state > division > region > nation). Nevertheless, if the sample size of the CPS data is small, the Base Method is preferable.

Researchers can use the data produced by this study for a broad range of occupational analyses that request Census tract-level employment data. Although finer-level CPS data may not be universally available for some occupations, the dataset is still useful for certain areas. For example, when studying the employment of forest and conservation workers (45-4011), only 13,142 (15.8%) of Census tracts have estimates based on state-level CPS samples (**Figure 8(a)**). However, these Census tracts are in states that have large numbers of forest and conservation workers, according to the OEWS database (**Figure 8(b)**). Therefore, researchers who are interested in studying this occupation can get sufficient and reliable data in the highly concentrated areas.

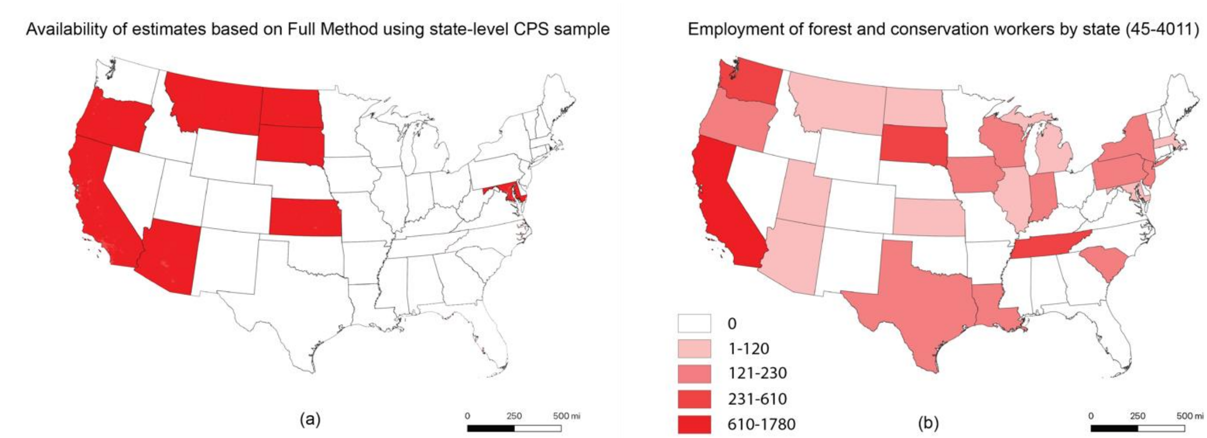


Figure 8. Example of data coverage and reliability: Forest and Conservation Workers (45-4011)

The comparative analysis of the two methods also revealed some constraints of the downscaling approaches that are important to consider. The first constraint associated with the method is the amount of ancillary data needed to use the Full Method. This technique requires detailed information about occupational characteristics from the CPS-ASEC data, employment data from the BLS-OEWS program, and demographic characteristics from ACS data. Thus, this method is more computationally intensive than the Base Method. The second constraint is that the proposed methods do not incorporate geographical prerequisites for certain occupations. This may lead to less accurate estimates for occupations that require specific resources available in specific regions (e.g., Farming, Fishing, and Forestry Occupations). The third constraint is that since tract-level demographic Census data can be available from the ACS in only five years, the reconstruction of both methods could lead to delayed replication of newer data. The fourth constraint of the downscaling approach can be the unavailability of any Census occupational dataset in the ACS that could inform about all the SOC occupations. This creates an issue in assessing the accuracy of individual downscaled occupations. For example, there is no data available to evaluate the accuracy of the "Computer Programmer" occupation (15-1251). Therefore, major occupational groups (e.g., 15-000 Computer and Mathematical Occupations) were used. This further underscores the need for downscaled data for individual occupations.

Both methods are based on the proportion of the working population in a tract relative to the state. Also, in the Full Method, we used the same demographic characteristics and sub-categories (see **Table 1**) to define demographic groups (i.e., G) to downscale all occupations. For example, all three datasets could be combined based on "age," "sex," and "race" only. This indicates a major assumption of the method: if the working population size and the sociodemographic composition for age, sex, and race are identical in two tracts, the downscaling outputs would be the same. However, this approach may ignore the spatial heterogeneity of occupations across a state (urban, suburban, and rural areas) and other factors that may affect the distribution of jobs. For some occupations, other demographic characteristics like 'education' or 'income' might have worked better. Future studies can explore ways to define demographic groups using different demographic characteristics and sub-categories for individual occupations (i.e., G_o, which denotes the set of demographic groups for occupation o), potentially based on the population-level demographic distribution of each occupation, which may help increase the number of non-zero demographic groups and reduce the estimation error.

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6. Conclusion

This study addresses the challenges associated with the lack of detailed occupational data at fine geographic scales by downscaling state-level data and generating a dataset of 808 downscaled occupations with estimated employment by Census tract. The downscaling algorithms combine existing information on employment, population, and sociodemographic composition. The validity and reliability of the data were tested, and the usability was demonstrated. Despite the limitations associated with the assumptions of the technique presented and the availability of ancillary information, our study offered an opportunity to conduct research focusing on regional and local occupation-related analysis by producing occupational employment data at the Census tract level in the US for the first time. These data can be used in a variety of contexts to understand employment dynamics by occupation over space and time. Given the pace of technological change and its projected impacts on the workforce, fine-scaled analyses of occupational dynamics will be important to develop strategies for responding to these changes to sustain and/or enhance the economic vitality of regional economies.

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