Characterizing the Burden and Distribution of Occupational Exposures by Sociodemographic Groups in the United States: A Novel Application of Job-Exposure Matrix (JEM) Data

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Abstract

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Introduction: Occupational exposure surveillance has historically been of limited focus in the United States (US). However, understanding the burden of occupational exposures is critical for the primary prevention of work-related injuries and illnesses. The primary objective of this analysis was two-fold: to estimate the number and prevalence of workers exposed to over 200 occupational hazards in the US, and to explore patterns of exposure across sociodemographic groups. The secondary objective was to identify occupations with the highest exposure burdens for each of the occupational hazards explored in this analysis.

Methods: For this analysis, occupational exposure data from the Canadian job-exposure matrix (CANJEM) was combined with worker demographic and wage data from the US Census Bureau and US Bureau of Labor Statistics (BLS) Current Population Survey (CPS) and US BLS Occupational Employment and Wage Statistics (OEWS) survey to characterize the burden and distribution of hazardous exposures by sociodemographic groups in the US. Further, an Exposure Burden Index (EBI) was developed to identify occupations with high burdens of exposure, based on the average of the rank orders for probability of exposure (i.e., likelihood of exposure), frequency-weight intensity of exposure (i.e., magnitude of exposure), and the number of estimated exposed workers (i.e., extent of exposure) for each agent in the analysis. Occupations were additionally characterized by wage and other measures of inequity.

Results: Of the occupational hazards examined in this analysis, the most prevalent exposures experienced by workers in the US were cleaning agents (11.8% of workforce exposed), engine emissions (10.9%), organic solvents (10.4%), biocides (8.4%), and PAHs from any source (7.8%). Exposures were found to be unevenly distributed by sociodemographic groups. The majority of exposures in this analysis disproportionately burdened workers who were of color, except those identifying as Asian; male; lower educated; and foreign-born.

Conclusions: The findings from this descriptive analysis suggest that the least privileged sociodemographic groups tend to bear the greatest burden of occupational exposures in the US. To our knowledge, this is the first study to combine a population-based job-exposure matrix (JEM) with employment and demographic data to estimate the burden of occupational exposures and characterize exposure disparities among sociodemographic groups in the US. The wealth of data generated in this analysis can help identify the extent of occupational exposures, specific populations disproportionately burdened by exposures and at risk of excess occupational illnesses, and occupations with high exposure burdens that may not otherwise have been identified through current health outcome-based occupational health surveillance systems. This information can be used to target occupational health research, policy, and intervention efforts aimed at reducing occupational illnesses in the US. The incorporation of sociodemographic information can additionally help inform equitable approaches to reduce occupational exposure and health disparities.

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I dedicate this work to my son. It is my hope that he will grow up in a more equitable and healthy society that values their workers and protects them from occupational injury and illness.

Introduction

Occupational health surveillance is the ongoing systematic collection, analysis, interpretation, and dissemination of data related to occupational hazards and health outcomes for the purpose of preventing work-related injuries and illnesses.[1–4] Occupational health surveillance informs priorities for research, policy development, and intervention efforts to improve worker health and safety.[2] However, current occupational health surveillance systems in the United States (US), such as the Bureau of Labor Statistics (BLS) Survey of Occupational Injuries and Illnesses (SOII) and state workers' compensation systems, are limited as they primarily focus on the collection of health outcome data.[2,5] Such systems have been shown to undercount and therefore underestimate the true burden of occupational injuries and illnesses.[6–10] Additionally, these systems fail to capture many latent and chronic occupational illnesses.[8,10–12] Additionally, initiatives of the National Institute for Occupational Safety and Health (NIOSH) Worker Health Surveillance Program are generally limited to specific health outcomes, exposures, and occupations/industries.[13]

A major factor that may contribute to the undercount of injuries and illnesses in current occupational health surveillance systems is the underrecognition of work as a contributor or cause of health issues. Work-related illnesses may be underrecognized due to reasons that include lag time between initial exposure and the onset of illness; lack of employee awareness of hazards, which is reflective of an employer's hazard communication program; lack of occupational health training, awareness, and expertise in the medical community; and difficulty ascertaining work as a contributor or cause of a disease with multiple causal factors or for which a clear dose-response relationship has not been established.[2,6,8] Other notable factors that may contribute to the undercount include fear of reprisal including job loss; perceived negative impact to an employee's reputation; inability to afford lost work time; difficulty in navigating workers' compensation systems and bias in accepted claims; incentive programs that reward employees and supervisors for low reports of injuries and illnesses; deliberate underreporting to avoid inspections, increases in workers' compensation premiums, and maintain competitiveness of contract bids; and non-compliance with proper reporting requirements.[6,14] Many of these factors disproportionately affect certain working populations, such as low-wage and immigrant workers, and may result in differential undercounting of injuries and illnesses among these groups.[6,15] In a study by Sabbath et al.,[15] researchers compared occupational injuries reported in administrative versus self-reported data and concluded that undercounting of injuries in administrative data may be greater among Black workers compared to White workers. Undercounting presents a false reality of the true burden of occupational injuries and illnesses and may obscure the magnitude of health disparities,[10,15] the consequences of which can hinder the development of effective interventions.

Current occupational health surveillance systems could be improved by increasing occupational exposure surveillance,[2,12,16] which has historically had little focus in the US.[2,5] In a 2018 report by the National Academies of Science, Engineering, and Medicine (NASEM),[2] *A Smarter National Surveillance System for Occupational Safety and Health in the 21st Century*, the development of a comprehensive approach for exposure surveillance was identified as a top priority as there is no such system currently in place in the US. Exposure surveillance is a subset of occupational health surveillance and is defined as the collection, analysis, interpretation, and dissemination of data relating to hazardous exposures in the workplace.[1,2,5,16] Exposure surveillance can be used to determine the burden of occupational exposures, defined in this analysis as the number of workers exposed, the magnitude of exposure, or both.[17] Such data could be used to identify high risk working populations, trends in exposures, and emerging hazards of concern, which could inform workplace controls and other public health initiatives.[1,16,18] A key advantage of exposure surveillance is that it is a form of primary prevention, with the capability to inform risk and identify opportunities for intervention before work-related injuries and illnesses occur.[1,2,16,19] This is particularly important for the prevention of latent and chronic diseases.[2,16,18] Additionally, in comparison to occupational illnesses, exposures are generally easier to recognize, occur at greater frequency, and serve as better indicators of effective control measures as they are the targets of control themselves.[18] In conjunction with current occupational health surveillance systems, exposure surveillance can help inform more effective preventive measures and provide greater understanding of the overall status of occupational health in the US.

In addition to characterizing the burden and distribution of exposures across occupation and industry groups, it is also important to consider how they may vary and influence health outcomes across different working populations – a need also highlighted in the 2018 NASEM report.[2] While recent public health research has highlighted health disparities related to race, ethnicity, gender, and socioeconomic status, the role of work has largely been excluded.[20] However, work is increasingly recognized as an important social determinant of health and health disparities, as it is a source of exposure to hazards, psychosocial stressors, income, benefits, health insurance, and access to healthcare.[20–22] The type of work that one does is influenced by social and economic factors, which is reflected in the heavily segregated workforce in the US.[2,20,21,23] As a result, work-related exposures, in addition to other harms and benefits of work, are unevenly distributed across sociodemographic groups and may contribute to health disparities in certain working populations.[2,20,23–26]

There are many documented examples of certain sociodemographic groups experiencing occupational health disparities due to their overrepresentation in high-risk occupations, with overrepresentation driven primarily by a systematic denial of access to equitable occupational opportunities.[20,26–30] The sociodemographic groups expected to be most impacted are described by the inverse hazard law, which postulates that the "accumulation of health hazards tends to vary inversely with the power and resources of the populations affected."[31] One of the most infamous cases illustrating the inverse hazard law occurred during the Hawk's Nest Tunnel Disaster.[32] In addition to making up the majority of the workforce, Black workers were subject to racist treatment and inequitably assigned to jobs with high exposures to crystalline silica, resulting in a substantially higher mortality rate from acute silicosis than White workers.[32] An analysis of 2010 nonfatal work-related injury and illness data by Baron et al.[33] showed that workers of color (except those identifying as Asian or multiracial), males, foreign-born workers, and low-wage workers were overrepresented in high-risk occupations, which was defined by the Council of State and Territorial Epidemiologists (CTSE) as an occupation with a "days away from work" (DAFW) nonfatal injury and illness rate of at least twice the 2008 national rate of 113.3 cases per 10,000 full-time equivalent employees. Although males overall were overrepresented in high risk occupations, women are disproportionately employed in service occupations, such as health aides, which have some of the highest injury rates.[29,33] A separate analysis by Marsh et al.[33] of fatal work-related injuries occurring from 2005 to 2009 showed that Hispanic/Latino and foreign-born workers had the highest work-related fatal injury rates.[33] Using Michigan employment demographic data and occupational health surveillance data, Stanbury and Rosenman[34] found evidence of overrepresentation of Black and Hispanic/Latino employees in lower wage and more hazardous occupations, which they defined as occupations with the highest national incidence rates of occupational injuries and illnesses. Their findings were consistent with the trends found by Baron et al. in the US data.[33] They also found that Black workers were at greater risk of silicosis, work-related asthma, and work-related burns than White workers; and Hispanic/Latino workers had higher rates of work-related acute fatal injuries and pesticide injuries than non-Hispanic workers.[34] To reduce such health disparities, it is vital to understand the burden and distribution of occupational exposures by sociodemographic groups to identify specific working populations disproportionately burdened by work-related exposures and at excess risk of injuries and illnesses. With this information, intervention efforts aimed at reducing occupational injuries and illnesses can be targeted more effectively.

However, characterizing the burden and distribution of occupational exposures is challenging at the population level as the collection of exposure data for a wide variety of hazards and occupations is difficult to obtain and can be very costly. The National Occupational Exposure Survey, a large-scale workplace-based direct observational survey conducted by NIOSH in the early 1980s, was the last nationwide effort to characterize exposures for a wide variety of hazards and occupations across workplaces in the US.[35] This survey required an extensive amount of time and resources, and the data is now considered outdated and of limited use.[2,36] Due to resource constraints, there are no plans to conduct such a large-scale survey in the future.[2,36] In 2010 and 2015, NIOSH funded Occupational Health Supplements to the National Health Interview Survey to collect data on occupational exposures and health outcomes.[37] However, the surveys relied on the respondents' self-assessment of exposure, and the exposures measured were relatively non-specific (e.g., skin hazard; vapors, gas, dust, fumes; outdoor work),[38,39] limiting the utility of the data for informing targeted intervention measures. Two recent studies characterized exposure burden using a job-exposure matrix (JEM),[40,41] a data source that links exposure information to a list of occupations or industries.[42] Although not without limitations, a JEM can be a relatively inexpensive and efficient source of exposure assessment information once it has been developed.[42,43] Beckman et al.[41] developed a data visualization tool by combining American Community Survey employment and demographic data with an internally developed qualitative JEM to estimate the number and prevalence of California working women exposed to a large set exposures linked to breast cancer. Their tool was limited in scope, however, in that it was qualitative in nature and focused only on females, a single geographic region, and specific set of agents. Additionally, while the tool characterized the distribution of exposures by race/ethnicity and age among California working women, it did not explicitly focus on the characterization of exposure disparities. Using similar methods, Doubleday et al.[40] combined state employment data with the Canadian job-exposure matrix (CANJEM)[44] to estimate the number and prevalence of workers in Federal Region X (i.e., Washington, Idaho, Oregon, and Alaska) exposed to a limited set of occupational hazards. However, the study was limited to one geographical region in the US, focused on a small number of occupational exposures, and did not investigate how exposures vary across sociodemographic groups.

In this study, we combined US employment and workforce demographic data with exposure data from CANJEM to characterize the burden and distribution of exposure to a large number of occupational hazards across sociodemographic groups in the US. More specifically, we estimated the number and prevalence of US workers exposed to 248 chemical and physical hazards. We also estimated the absolute and relative number of workers in each sociodemographic group over or underrepresented in exposure to each hazard to determine whether and to what extent certain exposures disproportionately burden specific groups of workers. Lastly, we developed an exposure burden index (EBI) to aid in the prioritization of occupations for intervention efforts by identifying occupations with the highest exposure burdens, which we defined as occupations with high likelihood, magnitude, and extent of exposure, for each occupational hazard. To our knowledge, this is the first study to combine a JEM with worker demographic data to estimate the burden of occupational exposures and characterize exposure disparities among sociodemographic groups in the US. The wealth of data generated through this project will help understand the burden of exposures across and within US working populations, and can help inform equitable intervention strategies aimed at reducing occupational injuries and illnesses in the US.

Methods

Data sources

In this analysis, three sources of data were utilized to link occupational exposure data with employee demographic and wage data in the United States. The statistical software package, R version 4.0.4., was used to complete all data merging and analyses.

Current Population Survey

We obtained employment and demographic data from the US Census Bureau and US Bureau of Labor Statistics (BLS) Current Population Survey (CPS), a monthly survey of households used to generate employment statistics on the civilian, non-institutionalized labor force in the US.[45] Using the Employed Labor Force (ELF) query system developed by the NIOSH Division of Safety Research, we extracted data on the number of employed persons by occupation, stratified by race and ethnicity, sex, education status, and nativity and citizenship status by 2010 Census occupation codes.[46]

We used employment and demographic data from 2019 to reflect pre-COVID-19 pandemic employment conditions.[47,48]

We obtained 2019 employment count estimates by occupation for the following sociodemographic groups from the CPS:

- Race/ethnicity: American Indian and Alaska Native (AIAN); Asian; Black or African American; Multiracial; Native Hawaiian and Other Pacific Islander (NHPI); White, non-Hispanic; Hispanic or Latino
- Sex: Male; Female

- Education: Less than high school diploma or equivalent (<High school); High school diploma or equivalent (High school); Some college or associate degree (Some college/associate); Bachelor's or other advanced degree (≥ Bachelor's)
- Nativity and citizenship status: Native-born; Foreign-born, citizen; Foreign-born, noncitizen

Some of these sociodemographic groups are aggregates of more detailed groups presented in CPS (e.g., "Native-born" is an aggregate of "Native, Born in US", "Native, Born in PR or US Outlying Area", and "Native, Born Abroad of US Parent(s)"). We also created an additional aggregated race/ethnicity group to represent Black, Indigenous, and People of Color (BIPOC). This group describes persons that identify as any race/ethnicity other than non-Hispanic White. In this analysis, persons of any race are of any ethnicity, except for persons who identify as non-Hispanic White, and persons of Hispanic/Latino ethnicity are of any race and are also counted in their preferred race category.

Occupational Employment and Wage Statistics Survey

We obtained 2019 median hourly wages for occupations in the US from the BLS Occupational Employment and Wage Statistics (OEWS) survey, a semi-annual mail survey of non-farm establishments that produces employment and wage statistics for over 800 occupations in the US.[49] Self-employed persons, military occupations, most occupations in the agricultural sector, and private household employers are excluded from the survey.[49]

The 2019 OEWS data organized occupations using a hybrid structure combining 2010 and 2018 Standard Occupation Classification (SOC) codes. In order to merge the CPS data with the OEWS data, we developed a key to translate between 2010 Census codes and the codes used by OEWS (i.e., 2019 OEWS codes). We developed the key using the OEWS 2019 Hybrid

Structure guide,[50] the 2010 Census to 2010 SOC Crosswalk,[51] the 2010 SOC to 2018 SOC Crosswalk,[52] the 2010 SOC Structure,[53] and the 2018 SOC Structure.[54] All occupations in the CPS data were matched with the equivalent or closest equivalent 2019 OEWS code(s). Some of the 2010 Census codes corresponded to more than one 2019 OEWS code. If wage information was available for only a single OEWS code, the single estimate was used to provide an estimate for the corresponding Census code. If wage information was available for some or all the OEWS codes, the weighted average of the median hourly wage of the available codes were used to provide an estimate for the corresponding Census code. If the median hourly wage was unavailable for an occupation, but the median annual wage was available, the median annual wage was divided by 2080 hours to obtain the median hourly wage. This assumes a 40-hour work week for 52 weeks of the year.

Canadian Job Exposure Matrix

We obtained exposure data from the CANJEM[44] occupational exposure information system, which provides estimates of the probability, intensity, frequency, and reliability of exposure to 258 occupational hazards in a given occupation or industry.[55] To develop CANJEM, researchers at the University of Montreal compiled exposure data from four case-control studies of cancer conducted between 1979 and 2004 in Montreal, Canada.[55] It is a semi-quantitative JEM based on over 40-person years of expert assessment of occupational exposures from over 30,000 jobs described by nearly 9,000 subjects in lengthy in-depth interviews.[55,56] A team of expert chemists, industrial hygienists, and engineers coded each job using standard occupation and industry classification systems and assessed each job for potential exposure to approximately 300 occupational agents.[55] For each job thought to be exposed, the experts assigned an intensity of exposure (low, medium, high), a frequency of exposure (hours/week), and a degree of confidence in the exposure (possible, probable, definite).[55] Of the 258 occupational agents in CANJEM, 3 are physical agents (e.g., ionizing radiation) and the remaining 255 are specific chemicals (e.g., formaldehyde), mixtures (e.g., gasoline), classes of chemicals (e.g., aliphatic aldehydes), or chemical groups based on use (e.g., cleaning agents).[44,55]

CANJEM represents a set of JEMs, each defined by a set of selection parameters, including the desired industry or occupation classification and resolution, time period, sample size, and agents of interest.[56] In this analysis, we used multiple versions of CANJEM based on the following selection parameters: occupations based on 2010 SOC codes at the minor, broad, and detailed occupation level; jobs held between 1985 and 2005; and occupations with a sample size of ≥ 10 jobs from ≥ 10 interviewed subjects. We restricted the data to jobs held between 1985 and 2005 to reflect exposure information closest to our time period of interest. We additionally restricted the data to SOC codes with ≥ 10 jobs from ≥ 10 interviewed subjects to exclude those codes with low numbers of jobs or subjects. These restrictions are consistent with a similar study by Doubleday et al.[40] Of the 258 available agents in CANJEM, 248 were included in the analysis. We combined some agents into one group (e.g., amphibole asbestos and chrysotile asbestos were combined into one group for asbestos), and we excluded others if they were determined to be irrelevant to the present day (e.g., cutting fluids pre-1955) or could be represented as an aggregated agent (e.g., PAHs from any source was included in the analysis instead of PAHs from specific sources).

We used the following exposure metrics from CANJEM: probability of exposure, exposure assignment reliability, and frequency-weighted intensity of exposure (FWI). Probability of exposure is a measure of the proportion of jobs that were considered exposed to an agent for a given occupation.[42] Experts considered a job to be exposed to an agent if it was determined to be present above background levels found in the general population.[56] Exposure assignment reliability is a measure of the experts' confidence in their assessment of each exposed job, each given a rating of possible, probable, or definite.[44] In this analysis, jobs assigned with any of the three ratings were considered exposed. FWI is a measure of intensity of exposure (i.e., low = 1, medium = 5, high = 25) averaged over a 40-hour workweek (FWI = exposure intensity*frequency of exposure in hours worked per week/40 hours).[44] In this analysis, jobs were considered exposed if the FWI was $\geq$ 0.05, which corresponds to a low level of exposure for two hours per week, and highly exposed if the FWI was ≥ 5, which corresponds to a medium level of exposure for 40 hours per week or a high level of exposure for eight or more hours per week.[44]

The 2010 Census to 2010 SOC crosswalk[57] provided by the US BLS was used to merge the CANJEM data with the CPS data. Some 2010 Census codes corresponded to more than one 2010 SOC code; however, exposure information in CANJEM was either not available for any of the corresponding SOC codes or only available for a single SOC code, in which case the exposure information from the single SOC code was applied to the corresponding Census code.

Analytic Approach

CANJEM coverage of US occupations and workers

We totaled the number of 2010 Census occupation codes that matched between CANJEM (after using a crosswalk) and the CPS data to determine the number of occupations that CANJEM provided exposure information for. We then calculated coverage of the US workforce by summing the total number of workers in each of the matched occupations.

Estimates of exposure burden

We calculated the number of workers estimated to be exposed to each agent by multiplying the agent-occupation specific probability of exposure by the number of workers in each occupation, and summing the estimated number of exposed workers across all occupations for each agent, as shown in Equation (1):

$$n_{exposed} = \sum(\frac{p_o}{100} x\, n_o) \quad (1)$$

where $n_{exposed}$ = number of workers exposed, p_o = agent-occupation specific probability of exposure, and n_o = number workers in occupation.

We calculated the prevalence of workers estimated to be exposed to each agent by dividing the number of workers exposed by the total number of workers in the US, as shown in Equation (2):

$$p_{exposed} = \frac{n_{exposed}}{n_t} x\ 100 \quad (2)$$

where $p_{exposed}$ = percent of workers exposed, $n_{exposed}$ = number of workers exposed, and n_t = number of workers in total workforce.

We calculated the number and proportion of workers estimated to be highly exposed to each agent similarly, except probability of high exposure was used instead of probability of exposure. We calculated the probability of high exposure by dividing the number of jobs with an FWI ≥ 5 by the total number of jobs assessed in each occupation. We calculated these estimates for all workers and for each sociodemographic group.

Estimates of exposure disproportionality

Estimates of exposure disproportionality reflect the extent to which sociodemographic groups are over or underrepresented in exposure. We calculated estimates of exposure disproportionality by finding the absolute and relative differences between the number of workers estimated to be exposed and the number of workers expected to be exposed in a counterfactual scenario in which workers of each sociodemographic group are evenly distributed across all occupations in the US based on their overall proportion of the total workforce.

First, we calculated the number of workers expected to be exposed by multiplying the occupation-specific probability of exposure by the total number of workers in the occupation by the proportion of the sociodemographic group in the total workforce, and summing the number of workers expected to be exposed across all occupations for each agent, as shown in Equation (5):

$$n_{expected} = \sum\left(\frac{p_o}{100} x\, n_o x\, p_{s,t}\right) \tag{5}$$

where $n_{expected}$ = number workers expected to be exposed, p_o = agent-occupation specific probability of exposure, n_o = number of workers in occupation, and $p_{s,t}$ = proportion of sociodemographic group in total workforce.

We then calculated the absolute and relative differences between the number of workers estimated to be exposed and the number of workers expected to be exposed as shown in Equation (3) and (4):

$$n_{excess} = n_{exposed} - n_{expected} \tag{3}$$

where n_{excess} = number of excess workers exposed (or under the expected), $n_{exposed}$ = number of workers exposed, and $n_{expected}$ = number of workers expected to be exposed; and

$$p_r = \frac{n_{exposed} - n_{expected}}{n_{expected}} x\ 100 \tag{4}$$

where p_r = percent of workers over or underrepresented, $n_{exposed}$ = number of workers exposed, and $n_{expected}$ = number of workers expected to be exposed.

Exposure Burden Index

We developed an exposure burden index (EBI) to identify occupations with high burdens of exposure for each agent. In the context of the EBI, occupations with high burdens of exposure reflect those with a high number of exposed workers (i.e., extent of exposure), a high probability of exposure (i.e., likelihood of exposure), and a high FWI of exposure (i.e., magnitude of exposure) for the agent of interest. Our approach was informed by previous research that used workers' compensation data to identify and prioritize industries with high risk of workplace injury.[58,59] The EBI ranks occupations based on the average of the rank orders of the probability of exposure, FWI, and the number of exposed workers for each agent. The EBI is dependent on equal weighting of the three exposure measures, so occupations with a higher EBI generally reflect those that have medium to high ranks across all three exposure measures, rather than occupations that rank low for at least one of the measures. The EBI was calculated using the following steps:

1) Calculate the *probability rank* by ranking occupations by the probability of exposure.
2) Calculate the *FWI rank* by ranking occupations by the average FWI.
3) Calculate the *worker estimate rank* by ranking occupations by the number of exposed workers.
4) Calculate the *average exposure rank* by averaging the *probability rank*, *FWI rank*, and *worker estimate rank*.
5) Calculate the *EBI rank* by ranking occupations by *average exposure rank*.

To allow decision makers to incorporate measures of equity in prioritizing occupations for intervention efforts, occupations were also characterized by wage and whether they were overrepresented by workers that are BIPOC, are female, have less than a high school level education, or are foreign-born without citizenship status. In this analysis, we define low-wage as an occupation with a median hourly wage of less than $15 per hour, which is the minimum salary of a full-time worker needed to achieve a modest but adequate standard of living for a single adult without children in all areas across the US.[60] In addition, we define overrepresentation as any number of workers in a sociodemographic group greater than would be expected based on their overall share of the total workforce.

Sensitivity analysis

An analysis of the CANJEM data by Sauvé et al. found that experts assigned 62% of exposed jobs with a "definite" exposure assignment reliability rating, compared to 27% of jobs with a "probable" rating and 11% of jobs with a "possible" rating.[56] We conducted a sensitivity analysis to determine how the estimates of exposure burden were affected by using a more stringent criteria of exposure in our calculations. In the more stringent analysis, we based our exposure estimate calculations solely on jobs assigned with a definite exposure assignment reliability rating; jobs with a possible or probable exposure rating were considered unexposed. The results were compared with estimates calculated in the primary analysis, which considered jobs assigned with a possible, probable, or definite assignment reliability exposure rating as exposed. We further compared the relative ranking of each agent in terms of the number of exposed workers. Agents in which no workers were estimated to be exposed in the primary analysis were excluded. We also examined whether using the more stringent criteria of exposure affected the number of agents that were found to disproportionately burden each of the sociodemographic groups. Specifically, we compared the total number of agents that were found to disproportionately burden each of the sociodemographic groups in the primary analysis to the more stringent analysis.

Results

In 2019, the US workforce comprised approximately 157.5 million workers based on CPS estimates. Average employment estimates by sociodemographic group are presented in Table 1. CANJEM provided exposure information for 126 of 483 (26.1%) 2010 US Census codes with employment data in the CPS, covering approximately 103.3 million of 157.5 million (65.6%) workers in the US.

Table 1. Average employment estimates in the US, 2019.

Category	Sociodemographic group	Employee Count[c]	Percent of Workforce
	American Indian and Alaska Native	1,617,000	1.0%
	Asian	10,179,000	6.5%
	Black or African American	19,381,000	12.3%
	Multiracial	3,283,000	2.1%
	Native Hawaiian or Other Pacific Islander	638,000	0.4%
	White	122,441,000	77.7%
	White, non-Hispanic	97,729,000	62.0%
	White, Hispanic	24,712,000	15.7%
	Hispanic or Latino, any race	27,805,000	17.6%
	Not Hispanic or Latino, any race	129,733,000	82.4%
Race/Ethnicity[a]	Black, Indigenous, and People of Color	59,809,000	38.0%
	Female	74,078,000	47.0%
Sex	Male	83,460,000	53.0%
	Less than high school diploma	12,535,000	8.0%
	High school diploma or equivalent	40,928,000	26.0%
	Some college or associate degree	43,520,000	27.6%
Education Status	Bachelor's or other advanced degree	60,556,000	38.4%
	Native-born	130,059,000	82.6%
Nativity and Citizenship Status	Foreign-born, citizen	13,798,000	8.8%
	Foreign-born, noncitizen	13,681,000	8.7%
Total		**157,538,000**	**100%**

[a]Persons of Hispanic or Latino ethnicity are of any race and are also counted in their preferred race category.
[b]Black, Indigenous, and People of Color include persons who identify as any race or ethnicity other than non-Hispanic White.
[c]Employee counts are rounded to the nearest thousand.

Table 2 shows the number and prevalence of US workers exposed to the 10 most common CANJEM agents based on number of exposed workers in 2019. The results are provided for all workers and by sociodemographic groups. Among all US workers, the most prevalent exposures were cleaning agents (18.6 million US workers exposed; 11.8%), engine emissions (17.2 million; 10.9%), organic solvents (16.4 million; 10.4%), biocides (13.2 million; 8.4%), and PAHs from any source (12.3 million; 7.8%).

Table 2. Number, in thousands, and percent of US workers by sociodemographic group exposed to the 10 most common CANJEM agents, 2019.

	Number of workers exposed[b,c] (% of group exposed)									
Sociodemo-graphic group	**Cleaning agents**	**Engine emissions**	**Organic solvents**	**Biocides**	**PAHs from any source**	**Aliphatic aldehydes**	**Diesel engine emissions**	**Alkanes (C5-C17)**	**Aliphatic alcohols**	**Formalde-hyde**
All	18599 (11.8)	17230 (10.9)	16408 (10.4)	13204 (8.4)	12315 (7.8)	11459 (7.3)	10623 (6.7)	9434 (6.0)	9362 (5.9)	9174 (5.8)
Race/ Ethnicity[a]										
AIAN	253 (15.6)	196 (12.1)	216 (13.4)	173 (10.7)	160 (9.9)	144 (8.9)	133 (8.2)	129 (8.0)	114 (7.0)	116 (7.2)
Asian	1066 (10.5)	733 (7.2)	721 (7.1)	829 (8.1)	514 (5.1)	687 (6.7)	391 (3.8)	341 (3.4)	555 (5.5)	555 (5.5)
Black	3042 (15.7)	2445 (12.6)	1980 (10.2)	2226 (11.5)	1572 (8.1)	1487 (7.7)	1604 (8.3)	1128 (5.8)	1478 (7.6)	1208 (6.2)
Multiracial	468 (14.3)	338 (10.3)	367 (11.2)	295 (9.0)	276 (8.4)	310 (9.4)	230 (7.0)	201 (6.1)	204 (6.2)	249 (7.6)
NHPI	78 (12.1)	64 (10.1)	72 (11.3)	55 (8.7)	55 (8.6)	55 (8.6)	46 (7.2)	42 (6.6)	36 (5.7)	45 (7.0)
White, non-Hispanic	9713 (9.9)	10142 (10.4)	9300 (9.5)	6866 (7.0)	6968 (7.1)	6293 (6.4)	5767 (5.9)	5155 (5.3)	5335 (5.5)	4933 (5.0)
Hispanic or Latino	4533 (16.3)	3678 (13.2)	4188 (15.1)	3129 (11.3)	3073 (11.1)	2817 (10.1)	2700 (9.7)	2692 (9.7)	1871 (6.7)	2341 (8.4)
BIPOC	8886 (14.9)	7088 (11.9)	7108 (11.9)	6338 (10.6)	5347 (8.9)	5166 (8.6)	4856 (8.1)	4280 (7.2)	4027 (6.7)	4242 (7.1)
Sex										
Female	11618 (15.7)	4802 (6.5)	6277 (8.5)	8590 (11.6)	3070 (4.1)	5478 (7.4)	1967 (2.7)	1810 (2.4)	6136 (8.3)	4259 (5.7)
Male	6981 (8.4)	12428 (14.9)	10131 (12.1)	4614 (5.5)	9246 (11.1)	5980 (7.2)	8656 (10.4)	7624 (9.1)	3226 (3.9)	4915 (5.9)
Education Status										
<High school	2853 (22.8)	1909 (15.2)	2321 (18.5)	1894 (15.1)	1768 (14.1)	1699 (13.6)	1620 (12.9)	1598 (12.8)	973 (7.8)	1448 (11.6)
High school	6335 (15.5)	6091 (14.9)	6155 (15.0)	4030 (9.8)	5155 (12.6)	4270 (10.4)	4638 (11.3)	4022 (9.8)	2631 (6.4)	3509 (8.6)
Some college/ associate	5476 (12.6)	4845 (11.1)	4514 (10.4)	3606 (8.3)	3595 (8.3)	3500 (8.0)	2912 (6.7)	2484 (5.7)	2647 (6.1)	2745 (6.3)
≥Bachelor's	3936 (6.5)	4385 (7.2)	3418 (5.6)	3674 (6.1)	1797 (3.0)	1989 (3.3)	1455 (2.4)	1330 (2.2)	3111 (5.1)	1473 (2.4)
Nativity and Citizenship Status										
Native-born	14110 (10.8)	13905 (10.7)	12629 (9.7)	9788 (7.5)	9690 (7.5)	8951 (6.9)	8236 (6.3)	7060 (5.4)	7390 (5.7)	7078 (5.4)
Foreign-born, citizen	2002 (14.5)	1594 (11.5)	1543 (11.2)	1576 (11.4)	1105 (8.0)	1071 (7.8)	1021 (7.4)	908 (6.6)	995 (7.2)	873 (6.3)
Foreign-born, noncitizen	2487 (18.2)	1731 (12.7)	2236 (16.3)	1840 (13.5)	1520 (11.1)	1437 (10.5)	1367 (10.0)	1467 (10.7)	977 (7.1)	1223 (8.9)

[a]Persons of any race are of any ethnicity, except for the White race/ethnicity group, which only includes estimates for persons who identify as non-Hispanic. Persons of Hispanic or Latino ethnicity are of any race are also counted in their preferred race category.

[b]Cells shaded in red indicate any overrepresentation of the sociodemographic group in exposure to the respective agent.

[c]Number of workers are expressed in thousands.

Table 3 shows the percent of US workers in each sociodemographic group over or underrepresented in exposure to the 10 most common agents. Together, Table 2 and 3 demonstrate how the representation of exposed workers among the most common agents was unequal across sociodemographic groups. Asian and non-Hispanic White workers were underrepresented for all of the most common agents, whereas all other race/ethnicity groups were overrepresented for the majority of the most common agents. Hispanic/Latino workers were the most overrepresented for eight of the 10 most common agents. For example, the proportion of Hispanic/Latino workers exposed to cleaning agents was 16.3% compared to 15.6% for American Indian/Alaska Native, 10.5% for Asian, 15.7% for Black, 14.3% for multiracial, 12.1% for Native Hawaiian/Pacific Islander, and 9.9% for non-Hispanic White workers. The prevalence among all workers was 11.8% – Hispanic/Latino workers were thus overrepresented by 38.1%, which is equivalent to an excess of 1.25 million exposed workers. Representation of BIPOC workers and those in the disaggregated non-White race/ethnicity groups were not always similar. For example, Black workers were underrepresented in exposure to organic solvents despite an overall overrepresentation among BIPOC workers. Examining sex, female workers were overrepresented for four of the agents, and males were overrepresented for six of the agents. Examining education status, workers with an education level equivalent to a high school diploma or less were overrepresented for all 10 of the agents; however, those with less than a high school diploma were overrepresented to a greater extent for each agent. Additionally, workers with some college or associate degree were overrepresented for six agents, whereas those with a bachelor's or other advanced degree were underrepresented for all agents. Examining nativity and citizenship status, native-born workers were underrepresented for all the most common agents. In contrast, foreign-born workers were overrepresented for all the most common agents, and those who did not have US citizenship were the most overrepresented for each of the agents.

Table 3. Percent of US workers in each sociodemographic group over or underrepresented in exposure to the 10 most common CANJEM agents, 2019.

Sociodemographic group	Cleaning agents	Engine emissions	Organic solvents	Biocides	PAHs from any source	Aliphatic aldehydes	Diesel engine emissions	Alkanes (C5-C17)	Aliphatic alcohols	Formaldehyde
	Percent over or underrepresented in exposure (%)									
Race/Ethnicity[a]										
AIAN	32.5	10.9	28.3	27.8	26.8	22.1	22.3	33	18.1	23
Asian	-11.3	-34.1	-32	-2.8	-35.4	-7.3	-43	-44	-8.2	-6.4
Black	33	15.3	-1.9	37.1	3.8	5.5	22.7	-2.8	28.4	7
Multiracial	20.8	-6	7.2	7.3	7.7	29.6	4	2.3	4.5	30.2
NHPI	2.9	-7.8	8.5	3.3	10.3	17.7	6.6	10.2	-4.9	21
White, non-Hispanic	-15.8	-5.1	-8.6	-16.2	-8.8	-11.5	-12.5	-11.9	-8.1	-13.3
Hispanic or Latino	38.1	20.9	44.6	34.3	41.4	39.3	44	61.6	13.2	44.5
BIPOC	25.8	8.4	14.1	26.4	14.4	18.7	20.4	19.5	13.3	21.8
Sex										
Female	32.8	-40.7	-18.6	38.3	-47	1.7	-60.6	-59.2	39.4	-1.3
Male	-29.2	36.2	16.5	-34	41.7	-1.5	53.8	52.5	-35	1.1
Education Status										
<High school	92.8	39.2	77.8	80.3	80.5	86.4	91.6	112.9	30.6	98.3
High school	31.1	36.1	44.4	17.5	61.1	43.4	68	64.1	8.2	47.2
Some college/associate	6.6	1.8	-0.4	-1.1	5.7	10.6	-0.8	-4.7	2.4	8.3
≥Bachelor's	-45	-33.8	-45.8	-27.6	-62	-54.8	-64.4	-63.3	-13.6	-58.2
Nativity and Citizenship Status										
Native-born	-8.1	-2.2	-6.8	-10.2	-4.7	-5.4	-6.1	-9.4	-4.4	-6.5
Foreign-born, citizen	22.9	5.6	7.4	36.3	2.5	6.7	9.7	9.8	21.3	8.6
Foreign-born, noncitizen	54	15.7	56.9	60.5	42.2	44.4	48.1	79	20.1	53.5

[a]Persons of any race are of any ethnicity, except for the White race/ethnicity group, which only includes estimates for persons who identify as non-Hispanic. Persons of Hispanic or Latino ethnicity are of any race are also counted in their preferred race category.
[b]Cells shaded in red indicate overrepresentation of the sociodemographic group in exposure to the respective agent, with each darker shade of red indicating greater percentage of overrepresentation in 25% increments.

Figure 1 shows the total number of disproportionate exposures experienced by each sociodemographic group. Workers of color, except those identifying as Asian, were disproportionately exposed to 92 (37%) to 215 (87%) agents, compared to 46 (19%) for non-Hispanic White and 27 (11%) for Asian workers. Among racial/ethnic groups, Hispanic/Latino workers were disproportionately exposed to the most agents. Males were disproportionately exposed to 197 (79%) agents, compared to 41 (17%) for females. Workers with less than a high school diploma were disproportionately exposed to 212 (85%) agents, and workers with a high school diploma but no more were disproportionately exposed to 224 (90%) agents, compared to 125 (50%) for workers with some college or associate degree and 12 (5%) for workers with a bachelor's or other advanced degree. Considering nativity status, native born workers were disproportionately exposed to the fewest hazards (31, 13%), with foreign-born citizens disproportionately exposed to 163 (66%) agents and foreign-born noncitizens disproportionately exposed to 207 (83%) agents.

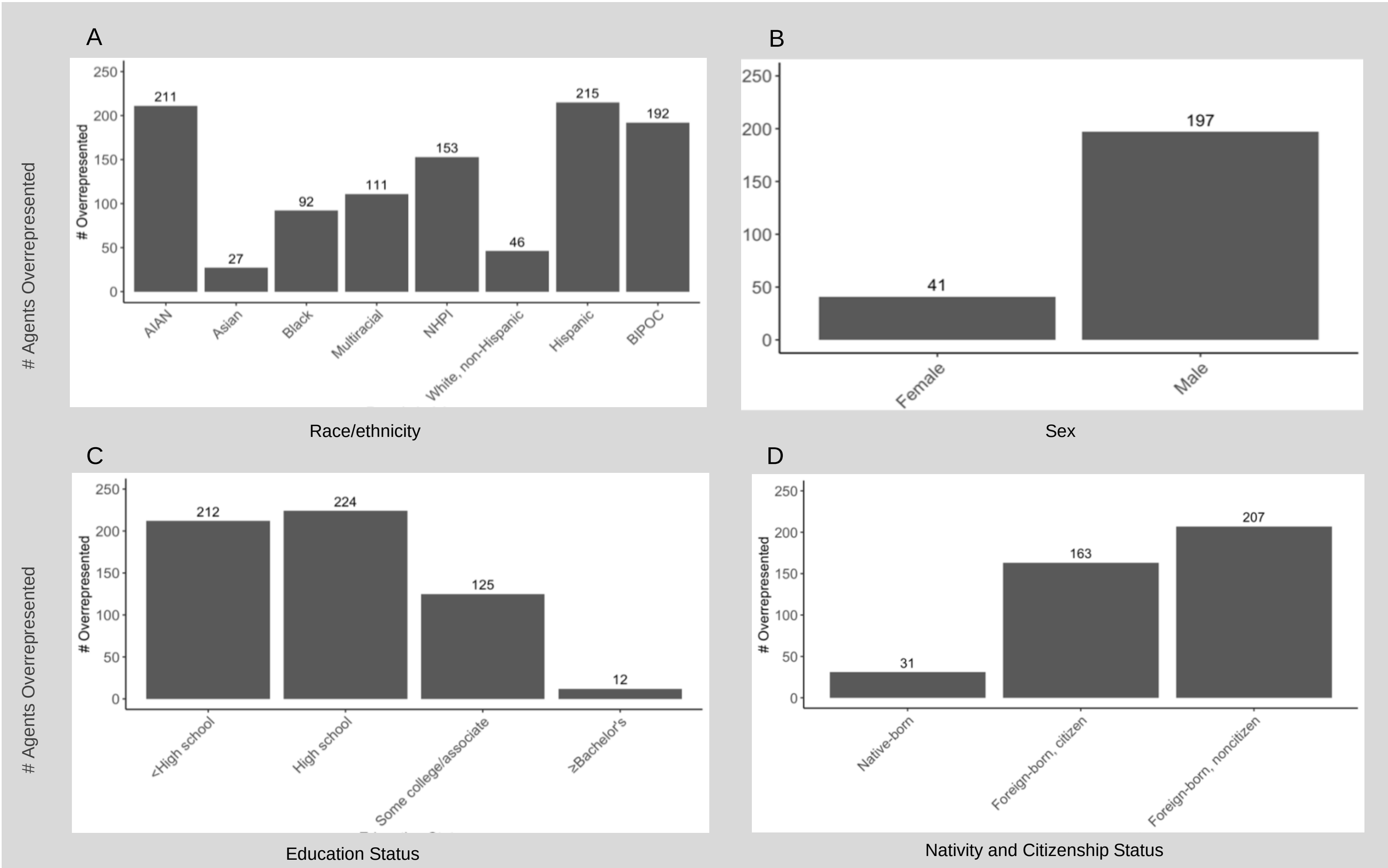

Figure 1. Comparison of the number of disproportionate exposures experienced by sociodemographic groups described by (A) race/ethnicity, (B) sex, (C) education status, and (D) nativity and citizenship status, 2019. Persons of any race are of any ethnicity, except for the White race/ethnicity group, which only includes estimates for persons who identify as non-Hispanic. Persons of Hispanic or Latino ethnicity are of any race are also counted in their preferred race category.

The five agents (out of the full set of 248) with the most excess workers exposed for each sociodemographic group are shown in Table 4. The percent that each sociodemographic group is disproportionately exposed is also provided for each of the agents. The most common agents that ranked highest in the number of excess workers exposed among sociodemographic groups were cleaning agents (10 of 17 groups), organic solvents (7 of 17 groups), biocides (6 of 17 groups), and engine emissions (6 of 17 groups), and alkanes (C5-C17; 5 of 17 groups). Examining BIPOC workers as an example, we identified that agents resulting in the greatest number of excess workers exposed were cleaning agents (1,825,000 excess workers), biocides (1,325,000 excess workers), cooking fumes (883,000 excess workers), organic solvents (879,000 excess workers), and diesel engine emissions (823,000 excess workers). These values correspond to an overrepresentation of BIPOC workers by 25.8% for cleaning agents, 26.4% for biocides, 30.9% for cooking fumes, 14.1% for organic solvents, and 20.4% for diesel engine emissions.

Table 4. Top 5 agents with the most number, in thousands, of excess workers exposed in each sociodemographic group, 2019. The percent that each sociodemographic group is overrepresented in exposure is also provided for each agent.

	Number of excess workers exposed[a] (% of group overrepresented)				
Sociodemographic group	**Agent 1**	**Agent 2**	**Agent 3**	**Agent 4**	**Agent 5**
Race/ethnicity[b]					
AIAN	Cleaning agents 62 (32.5)	Organic solvents 48 (28.3)	Biocides 38 (27.8)	PAHs from any source 34 (26.8)	Alkanes (C5-C17) 32 (33)
Asian	Cosmetic talc 43 (24.7)	Anesthetic gases 34 (43)	Hydrogen peroxide 23 (40.1)	Wool fibers 14 (22.2)	Diethyl ether 11 (64.1)
Black	Cleaning agents 754 (33)	Biocides 602 (37.1)	Isopropanol 346 (39.7)	Aliphatic alcohols 327 (28.4)	Engine emissions 325 (15.3)
Multiracial	Cleaning agents 81 (20.8)	Cooking fumes 71 (45.5)	Aliphatic aldehydes 71 (29.6)	Formaldehyde 58 (30.2)	Ashes 38 (58.2)
NHPI	Aliphatic aldehydes 8 (17.7)	Cooking fumes 8 (26.6)	Formaldehyde 8 (21)	Cellulose 7 (34.2)	Organic solvents 6 (8.5)
White, non-Hispanic	Ozone 295 (7.9)	Calcium carbonate 294 (6)	Methanol 96 (12.7)	Inks 53 (5.7)	Nickel 29 (3.4)
Hispanic or Latino	Organic solvents 1293 (44.6)	Cleaning agents 1250 (38.1)	Wood dust 1114 (88.7)	Alkanes (C5-C17) 1026 (61.6)	Ultraviolet radiation 991 (96.7)
BIPOC	Cleaning agents 1825 (25.8)	Biocides 1325 (26.4)	Cooking fumes 883 (30.9)	Organic solvents 879 (14.1)	Diesel engine emissions 823 (20.4)
Sex					
Female	Cleaning agents 2873 (32.8)	Biocides 2381 (38.3)	Aliphatic alcohols 1734 (39.4)	Isopropanol 1604 (48.2)	Cosmetic talc 944 (74.6)
Male	Engine emissions 3300 (36.2)	Diesel engine emissions 3028 (53.8)	PAHs from any source 2721 (41.7)	Alkanes (C5-C17) 2626 (52.5)	Wood dust 2356 (62.4)
Education Status					
<High school	Cleaning agents 1373 (92.8)	Organic solvents 1015 (77.8)	Wood dust 862 (152.1)	Ultraviolet radiation 850 (183.9)	Alkanes (C5-C17) 848 (112.9)
High school	PAHs from any source 1956 (61.1)	Organic solvents 1893 (44.4)	Diesel engine emissions 1878 (68)	Engine emissions 1615 (36.1)	Alkanes (C5-C17) 1571 (64.1)
Some college/ associate	Cleaning agents 338 (6.6)	Aliphatic aldehydes 335 (10.6)	Cooking fumes 213 (10.2)	Formaldehyde 210 (8.3)	Ozone 195 (11.7)
≥ Bachelor's	Calcium carbonate 1926 (63.1)	Methanol 352 (75.4)	Anesthetic gases 318 (68.6)	Inks 235 (40.2)	Cosmetic talc 102 (9.8)
Nativity and Citizenship Status					
Native-born	Ozone 268 (5.4)	Methanol 75 (7.4)	Inks 52 (4.1)	Calcium carbonate 18 (0.3)	Cutting fluids post-1955 12 (1.1)
Foreign-born, citizen	Biocides 420 (36.3)	Cleaning agents 373 (22.9)	Isopropanol 185 (29.9)	Aliphatic alcohols 175 (21.3)	Cosmetic talc 122 (51.6)
Foreign-born, noncitizen	Cleaning agents 872 (54)	Organic solvents 811 (56.9)	Wood dust 781 (126.2)	Biocides 694 (60.5)	Ultraviolet radiation 686 (136.1)

[a]Number of workers are expressed in thousands.

[b]Persons of any race are of any ethnicity, except for the White race/ethnicity group, which only includes estimates for persons who identify as non-Hispanic. Persons of Hispanic or Latino ethnicity are of any race are also counted in their preferred race category.

Table 5 shows the five occupations with the highest EBI for the five most common exposures based on number of all workers exposed – cleaning agents, engine emissions, organic solvents, biocides, and PAHs from any source. Using cleaning agents as an example, we identified Janitors and Building Cleaners (Census code 4220) to have the highest EBI, followed by Maids and Housekeeping Cleaners (Census code 4230); Nursing, Psychiatric, and Home Health Aides (Census code 3600); Hairdressers, Hairstylists, and Cosmetologists (Census code 4510); and First-line Supervisors of Housekeeping and Janitorial Workers (Census code 4200). Except for First-line Supervisors of Housekeeping and Janitorial Workers, all other listed occupations have a median hourly wage of less than $15 per hour. BIPOC workers were overrepresented in all the listed occupations. Females were overrepresented in Maids and Housekeeping; Nursing, Psychiatric, and Home Health Aides; and Hairdressers, Hairstylists, and Cosmetologists. Lastly, workers who have less than a high school education or are foreign-born without citizenship were overrepresented in all the listed occupations except Hairdressers, Hairstylists, and Cosmetologists.

Table 5. Top 5 occupations with the highest Exposure Burden Index (EBI) rank for cleaning agents, engine emissions, organic solvents, biocides, and PAHs from any source in the US, 2019. The overall EBI rank is based on the average ranking for probability of exposure, FWI, and the estimated number of exposed workers for each occupation.

							Sociodemographic groups overrepresented			
Occupation (2010 Census code)	**# Exposed[a] (% of total exposed)**	**Proba-bility rank**	**FWI[b] rank**	**Worker estimate rank**	**Overall EBI[c] rank**	**Median hourly wage ($)**	**BIPOC**	**Female**	**<High school**	**Foreign-born, non-citizen**
Cleaning agents	18599 (100)									
4220 - Janitors and building cleaners[f]	1948 (10.5)	4	5	2	1	13.21[d]	Yes	No	Yes	Yes
4230 - Maids and housekeeping cleaners[f]	1340 (7.2)	2	7	5	2	11.95[d]	Yes	Yes	Yes	Yes
3600 - Nursing, psychiatric, and home health aides[f]	1773 (9.5)	5	19	3	3	12.84[d]	Yes	Yes	Yes	Yes
4510 - Hairdressers, hairstylists, and cosmetologists	802 (4.3)	1	18	8	3	12.54[d]	Yes	Yes	No	No
4200 - First-line supervisors of housekeeping and janitorial workers	176 (0.9)	15	3	22	5	19.61	Yes	No	Yes	Yes
Engine emissions	17230 (100)									
4250 - Grounds maintenance workers[f]	850 (4.9)	13	1	4	1	14.85[d]	Yes	No	Yes	Yes
9140 - Taxi drivers and chauffeurs[f]	762 (4.4)	5	7	6	1	15.07	Yes	No	Yes	Yes
9130 - Driver/sales workers and truck drivers[f]	3297 (19.1)	6	15	1	3	19.38	Yes	No	Yes	No
7200 - Automotive service technicians and mechanics[f]	534 (3.1)	14	5	8	4	20.24	Yes	No	Yes	Yes
9620 - Laborers and freight, stock, and material movers, hand[f]	762 (4.4)	19	6	5	5	14.19[d]	Yes	No	Yes	Yes
Organic solvents	16408 (100)									
6420 - Painters, construction and maintenance	563 (3.4)	3	10	8	1	19.37	Yes	No	Yes	Yes
7200 - Automotive service technicians and mechanics[f]	614 (3.7)	7	14	6	2	20.24	Yes	No	Yes	Yes
8965 - Production workers, all other	476 (2.9)	19	2	10	3	17.23	Yes	No	Yes	Yes
6240 - Carpet, floor, and tile installers and finishers[f]	158 (1.0)	2	7	31	4	20.22	Yes	No	Yes	Yes
8255 - Printing press operators	110 (0.7)	5	3	41	5	17.74	No[e]	No	Yes	No
Biocides	13204 (100)									
3600 - Nursing, psychiatric, and home health aides[f]	1695 (12.8)	3	22	2	1	12.84[d]	Yes	Yes	Yes	Yes
4230 - Maids and housekeeping cleaners[f]	1135 (8.6)	5	18	4	1	11.95[d]	Yes	Yes	Yes	Yes

Occupation (2010 Census code)	# Exposed[a] (% of total exposed)	Proba-bility rank	FWI[b] rank	Worker estimate rank	Overall EBI[c] rank	Median hourly wage ($)	Sociodemographic groups overrepresented			
							BIPOC	Female	<High school	Foreign-born, non-citizen
4220 - Janitors and building cleaners[f]	1495 (11.3)	7	20	3	3	13.21[d]	Yes	No	Yes	Yes
4250 - Grounds maintenance workers[f]	354 (2.7)	16	5	10	4	14.85[d]	Yes	No	Yes	Yes
4510 - Hairdressers, hairstylists, and cosmetologists	759 (5.8)	1	25	5	4	12.54[d]	Yes	Yes	No	No
PAHs from any source	12315 (100)									
8030 - Machinists	374 (3.0)	1	7	10	1	21.36	No[e]	No	No	No
8140 - Welding, soldering, and brazing workers	402 (3.3)	8	4	7	2	20.24	No[e]	No	Yes	Yes
7200 - Automotive service technicians and mechanics[f]	747 (6.1)	4	14	3	3	20.24	Yes	No	Yes	Yes
8965 - Production workers, all other	286 (2.3)	23	2	13	4	17.23	Yes	No	Yes	Yes
8255 - Printing press operators	116 (0.9)	3	3	33	5	17.74	No[e]	No	Yes	No

[a]Number of workers are expressed in thousands
[b]FWI = frequency-weighted intensity of exposure
[c]EBI = exposure burden index
[d]Indicates median hourly wage lower than $15/hour, which is the minimum salary of a full-time worker needed to achieve a modest but adequate standard of living for a single adult without children in all areas across the US.[60]
[e]Indicates occupation is overrepresented by at least one non-White race/ethnicity group.
[f]Indicates occupation is at high risk of occupational morbidity according to analysis by the Council of State and Territorial Epidemiologists.[61]

Sensitivity analysis

The results of the sensitivity analysis for the 10 most common exposures are presented in Table 6. Among the 10 most common exposures, using the more stringent reliability rating resulted in a reduction of national burden estimates from 13.1% to 69.5%, with seven of 10 exposures resulting in a reduction of estimates of 34% or less. The rank of the three most common exposures did not change, and eight of the 10 most common exposures remained within two ranks.

In the entire data set, using the more stringent reliability rating resulted in a reduction of national burden estimates from 0% (i.e., no change; 4 agents) to 100% (10 agents). The median percent reduction in the exposure estimates was 47.9% (IQR: 32.5%, 70.9%). The rank of exposures changed a minimum of zero positions to a maximum of 90 positions. The median change in ranks was 13 positions (IQR: 5, 24).

Table 6. Comparison of sensitivity analysis to primary analysis results for the 10 most common CANJEM exposures in the US, 2019.

Occupational Agent	Number of exposed workers in primary analysis[a]	Number of exposed workers in sensitivity analysis[a]	Percent change (%)	Primary analysis rank[b]	Sensitivity analysis rank[b]	Rank change
Cleaning agents	18599	16161	-13.1	1	1	0
Engine emissions	17230	13335	-22.6	2	2	0
Organic solvents	16408	12542	-23.6	3	3	0
Biocides	13204	9163	-30.6	4	5	1
PAHs from any source	12315	9673	-21.5	5	4	-1
Aliphatic aldehydes	11459	4548	-60.3	6	17	11
Diesel engine emissions	10623	6302	-40.7	7	8	1
Alkanes (C5-C17)	9434	6264	-33.6	8	9	1
Aliphatic alcohols	9362	6313	-32.6	9	7	-2
Formaldehyde	9174	2800	-69.5	10	30	20

[a]Number of workers are expressed in thousands.

[b]The primary and stringent analysis rank indicate the rank of the agent by estimated number of exposed workers among all agents in the analysis.

Table 7 summarizes number of disproportionate exposures by sociodemographic group in the primary and sensitivity analysis. In the sensitivity analysis, the number of disproportionate exposures decreased for all sociodemographic groups except for Asian, non-Hispanic White, female, and native-born workers. The absolute change ranged from 0 to 29 agents, and the median change was 13 agents (IQR: 10, 20).

Table 7. Summary of sensitivity analysis results comparing the number of disproportionate exposures for all agents in the primary versus more stringent analysis.

Sociodemographic group	**Number of disproportionate exposures in primary analysis**	**Number of disproportionate exposures in sensitivity analysis**	**Change in number of disproportionate exposures**
Race/ethnicity[a]			
AIAN	211	191	-20
Asian	27	27	0
Black	92	79	-13
Multiracial	111	99	-12
NHPI	153	127	-26
White, non-Hispanic	46	56	10
Hispanic or Latino	215	196	-19
BIPOC	192	172	-20
Sex			
Female	41	45	4
Male	197	183	-14
Education Status			
<High school	212	193	-19
High school	224	213	-11
Some college/ associate	125	126	-1
≥Bachelor's	12	14	-2
Nativity and Citizenship Status			
Native-born	31	42	11
Foreign-born, citizen	163	134	-29
Foreign-born, noncitizen	207	187	-20

[a]Persons of any race are of any ethnicity, except for the White race/ethnicity group, which only includes estimates for persons who identify as non-Hispanic. Persons of Hispanic or Latino ethnicity are of any race are also counted in their preferred race category.

The results presented here represent only a small subset of data available from these analyses. Results for all 200+ agents are available in the supplementary materials. Worker estimates for occupational agents with high levels of exposure are also provided in the supplementary materials.

Discussion

Main findings

The purpose of these analyses was to quantify how many US workers are exposed to a large set of occupational hazards, and to characterize patterns of exposure by sociodemographic groups. Of the occupational hazards examined in this study, the most common exposures experienced by US workers were cleaning agents (18.6 million US workers exposed; 11.8%), engine emissions (17.2 million;10.9%), organic solvents (16.4 million; 10.4%), biocides (13.2 million; 8.4%), and PAHs from any source (12.3 million; 7.8%). These results are similar to those found by Doubleday et al.,[40] who found that the most common exposures experienced by workers when applying CANJEM to Federal Region X were cleaning agents (11.3%), organic solvents (9.0%), engine emissions (8.4%), aliphatic aldehydes (7.8%), and PAHs from any source (6.7%). Differences in the prevalence and rankings of the most common exposures is attributed to differences in the occupational make up of Federal Region X compared to the US overall.

Overall, our study's findings are consistent with Krieger's inverse hazard law in that the least privileged populations tended to bear the greatest burden of occupational exposures.[31] Exposures were found to be unevenly distributed by sociodemographic groups, driven by the segregation of workers into occupations with varying hazards and probabilities of exposure. The majority of the most prevalent exposures disproportionately burdened workers who did not identify as non-Hispanic White or Asian; workers who were male; workers with some college experience or an associate degree or less; and workers who were foreign-born. Among racial/ethnic groups, Hispanic/Latino workers bore the greatest burden of exposure to the majority of the most prevalent occupational agents. Women bore a greater burden than men to cleaning agents, biocides, aliphatic aldehydes, and aliphatic alcohols, which are generally associated with service and healthcare occupations. Men bore a greater burden to engine emissions, organic solvents, PAHs from any source, diesel engine emissions, alkanes (C5-C17), and formaldehyde, which are generally associated with production, transportation, and other industrial occupations. Among education groups, a general trend was seen in which the lower the education status of the workers, the greater the exposure burden. A similar pattern was seen when examining nativity and citizenship status; all foreign-born workers were disproportionately burdened by exposure for all the most common agents, but those without citizenship bore a greater burden than those with citizenship. We found a similar pattern of exposure when examining the total number of agents that disproportionately burdened each sociodemographic group in the entire dataset, with a few additional observations. Workers who identified as Asian were disproportionately burdened by 27 agents, which was the least number of agents among all racial/ethnic groups, and female workers were disproportionately burdened by 41 agents, compared to 197 agents for male workers. While one possible explanation for these findings is that Asian and female workers tend to work in less hazardous occupations, it is possible that workplace exposures, injuries, and illnesses experienced by these groups may simply be underrecognized due to lack of representation in past and current occupational epidemiological studies.[62–64] In addition, despite men being overrepresented in exposure for majority of agents in this analysis, they are also agents that are more likely to be recognized as occupational hazards and regulated by OSHA. The creation of OSHA, and subsequently what types of exposures were regulated, was largely due to the lobbying of labor unions, which typically represented white male workers in goods-producing industries.[65,66] Many workers have long been left out of OSHA, such as domestic workers, who are predominantly female and non-white.[67] Most OSHA standards have not been updated since its inception in 1970, and very few have been added.

Since its inception, OSHA has faced challenges in introducing new standards that may apply to a more diverse American workforce, a workforce now largely employed in services-providing industries.[67,68]

Many of the sociodemographic groups found to bear a disproportionate burden of exposure in our analyses are similar to the groups found to be overrepresented in high-risk occupations in the analysis by Baron et al.[33] Together, these studies demonstrate the unequal burden of occupational exposures and risk of injuries and illnesses among the least privileged sociodemographic groups. While our study is not able to estimate the number of workers at risk of injury and illness, the extent to which exposure informs risk of injury and illness could be the subject of future studies.

Agents that disproportionately burden the most workers, measured as the number of excess workers exposed, varied across sociodemographic groups. While many of the sociodemographic groups were found to be disproportionately exposed to the same agent, other agents were unique to each group. Of all the occupational agents examined in this study, cleaning agents were found to disproportionately burden the greatest number of American Indian and Alaska Native workers, Black workers, multiracial workers, BIPOC workers, female workers, workers with less than a high school diploma or equivalent level of education, and workers with some college experience or an associate degree. Quantifying which agents were common exposures across a range of sociodemographic groups highlight where public health research and intervention efforts may have the greatest impact to reduce exposure and health disparities in specific working populations.

The majority of occupations with the greatest exposure burden, as reflected in the EBI, to the five most common exposures based on number of all workers exposed – cleaning agents, engine emissions, organic solvents, biocides, and PAHs from any source – were overrepresented by workers who were BIPOC, had less than a high school level education, and were foreign-born non-citizens. The majority of occupations with the greatest exposure burden to cleaning agents and biocides were also overrepresented by female workers, considered low-wage occupations, and tended to fall under Service Occupations. The majority of occupations with the greatest exposure burden to engine emissions, organic solvents, and PAHs from any source tended to fall under Production, Transportation, and Material Moving Occupations; and Natural Resources, Construction, and Maintenance Occupations. Many of these occupations identified in the EBI were also on the 2014 CSTE list of occupations at high risk of occupational morbidity, defined as occupations with a DAFW nonfatal injury and illness rate of at least twice the national rate of 97.8 cases per 10,000 full-time equivalent employees.[61]

The results from our analyses call particular attention to cleaning agents, many of which are not regulated by OSHA. Cleaning agents was not only the most common exposure based on the total number of US workers exposed, but it was also the most common exposure across sociodemographic groups to disproportionately burden the greatest number of workers. Further, the sociodemographic groups that were found to bear disproportionate burden of exposure to cleaning agents were those with the least amount of power. Overall, these findings suggest that public health research and control efforts for cleaning agents should be made a priority and that these efforts would have a high impact on reducing occupational exposure and health disparities.

In this analysis, we observed that estimates of disproportionate exposure for the aggregated BIPOC group did not necessarily reflect estimates for workers of the disaggregated race/ethnicity groups. For example, although BIPOC workers overall were found to be disproportionately burdened by all the most common occupational exposures, Asian workers were found to be underrepresented in exposure for all the agents, Black workers were found to be underrepresented in exposure to organic solvents and alkanes (C5-C17), and Native Hawaiian/Pacific Islander workers were found to be underrepresented in exposure to engine emissions and aliphatic alcohols. The opposite was also observed; for example, BIPOC workers overall were found to be underrepresented in exposure to nickel fumes (not shown in the tables), but Hispanic/Latino and American Indian/Alaska Native workers were found to be overrepresented in exposure. These examples demonstrate that while the incorporation of a higher aggregated group can be useful, caution must be exercised when it is used in health disparities work. These examples also demonstrate how greater disaggregation of sociodemographic groups can help reveal exposure disparities among specific working populations. The usefulness of incorporating greater and more detailed demographics in health disparities work was also noted in a study by Montoya-Barthelemy et al.[69]

Application of the Exposure Burden Index

Using the EBI, we attempted to identify occupations that may benefit most from public health research and intervention efforts for each agent in this analysis. The EBI identified occupations that not only have a high number of exposed workers, but also have a high likelihood and magnitude of exposure. For example, Registered Nurses (Census code 3255) had the largest number of workers exposed to cleaning agents. However, because Registered Nurses did not rank as high as other occupations in terms of likelihood or magnitude of exposure, it ranked tenth on the EBI. In contrast, Janitors and Building Cleanings (Census code 4220) did not have the highest rank across the three measures of exposure, but it had the highest average rank amongst all occupations, so it ranked first on the EBI. In addition to the overall EBI rank, the characterization of occupations by wage and sociodemographic overrepresentation may help incorporate principles of equity in the prioritization of occupations for research and other intervention measures. For example, although Janitors and Building Cleaners (Census code 4220) had the highest overall EBI rank for cleaning agents, Maids and Housekeeping Cleaners (Census code 4230) must also be prioritized for research and control measures as the workers are low-wage and predominantly female, which are understudied occupational groups. The EBI can help occupational health researchers, practitioners, and policymakers better understand where the greatest burdens of exposure are in the US and where to prioritize their efforts. Further, the EBI can also help inform equitable approaches to their work.

Sensitivity analysis

Our sensitivity analysis demonstrated that using the more stringent reliability exposure rating resulted in a decrease in the estimated number of workers exposed for most agents. The extent to which the exposure estimates changed varied by agent, and while some agents did not change, others decreased by 100%. While the percent change in estimates varied greatly, the agent rankings in terms of number of exposed workers did not change as much, both in the 10 most common agents and overall. Among the most common agents, the top three did not change, and eight remained within two ranks. Among the entire data set, half of all agents remained within 13 ranks, and 75% remained within 24 ranks. These results suggest that the CANJEM expert raters may have been more confident in exposures for some agents than others. Overall, while there was some movement, there were few changes to our main conclusions.

We also investigated whether there was evidence of disproportionate exposure burden for marginalized sociodemographic groups when using the more stringent reliability rating in our analysis. Overall, the number of agents which disproportionately burdened each of the sociodemographic groups decreased, but minimally. Interestingly, the number of agents did not change among Asian workers, and the number of agents increased for non-Hispanic white, female, and native-born workers. We suspect that expert rates were more confident in estimating exposure for agents and occupations that are common to white and native-born populations.

Overall, the sensitivity analysis results generally provide justification for including possible, probable, and definite exposures in the calculation of our exposure estimates. While the estimates from the stringent analysis may be more reliable, they may underestimate the number of workers that may potentially be exposed, especially in occupations that may contain disproportionately high numbers of marginalized workers. By including possible, probable, and definite exposures in our analysis, we aimed to be more protective in our approach with the intention of capturing working populations that might have otherwise been missed or overlooked as having important sources of occupational exposure.

Limitations

This study is subject to several limitations. First, it is important to acknowledge that this analysis does not provide coverage of all workers, occupations, and occupational exposures in the US. Coverage of the US workforce is limited by the CPS, which does not include the military or institutionalized workforce in its labor force statistics, and CANJEM, which does not provide exposure information for a third of the workforce captured in the CPS. Coverage of occupational exposures is limited by those available in CANJEM, which does not contain exposure information for noise, psychosocial, biological, ergonomic, and other important occupational hazards. Additionally, this analysis is based on exposures encountered in a Canadian population from 1985 to 2005, which may not necessarily reflect exposures to US workers in 2019 due to differences in industries, occupations, and regulations between the two countries and changes in materials, technologies, work processes, and regulations over time. The static nature of

CANJEM also limits our ability to measure trends in the magnitude and extent of exposure over time. Any trends seen over time would merely be a factor of occupational trends and the distribution of demographics within those occupations, rather than changes in exposure due to changes in work practices. Despite these limitations, we believe CANJEM to be the most appropriate JEM available for a wide range of occupations and exposures in North America. For this reason, to our knowledge CANJEM is the best available JEM to estimate the burden of occupational exposures at the population level in the US.

As with any other JEM, one of the most important limitations of CANJEM is exposure misclassification.[70] Because CANJEM provides the same probability of exposure for all individuals in an assigned occupation, we are unable to account for intra-occupational exposure differences of individuals or groups. There is ample evidence of workers of different sociodemographic groups experiencing differential exposure to occupational hazards within the same job due to differences in assigned tasks and other occupational inequities.[26,29,71–73] In a cross-sectional study that investigated the sociodemographic distribution of several occupational exposures, Quinn et al.[73] found that sociodemographic variables were associated with differences in occupational exposures independent of the industry or job in which workers were employed. An analysis by Lacourt et al.[74] evaluated the level of agreement of occupational exposures between men and women in two of the case-studies that comprise CANJEM. They found exposures between men and women had good agreement, but there were notable differences in exposure for some occupation-agent combinations, and men tended to be exposed in more jobs than women. Furthermore, Xu et al.[75] characterized the performance reliability of CANJEM in estimating exposures among women in a case-control study using an expert assessment approach. They found that CANJEM's ability to ascertain exposures among females performed well for some agents, but not for others. While this study only focused on the performance of CANJEM for female workers, we can suspect that CANJEM's reliability in estimating exposures may also vary among the other sociodemographic groups in our study. These studies suggest that there could be important intra-occupational differences in exposure among sociodemographic groups that are not captured in our study. We expect this form of misclassification to result in the overestimation of exposures for some combinations of agents and sociodemographic groups and the underestimation of exposure for others. In addition, any identified exposure disparities across sociodemographic groups in our analysis can only be attributed to the differential distribution of workers across occupations, i.e., occupational segregation. Some misclassification may have also been introduced into the study from the use of crosswalks needed to merge the data sources by a common occupation classification system.[43]

There are also some important limitations associated with CPS data to note. Some worker estimates across occupation-demographic strata are small and considered unstable. Despite the unstable nature of these small samples, we decided to include them in our calculations in order to avoid underestimating our exposure estimates, which is more likely for smaller sociodemographic groups, such as Native Hawaiian/Pacific Islanders. Additionally, the demographic information collected in the CPS is limited to a small number of categories and may hinder our ability to identify exposure disparities among more specific sociodemographic groups than those available in the data. For example, data is provided only for binary sex variables, rather than gender. In addition, data is provided only for a limited number of race and ethnicity groups. As demonstrated by Montoya-Barthelemy et al.[69], the collection of greater and more detailed demographics in the CPS may be useful in better identifying and addressing occupational health disparities. Lastly, the extraction of worker estimates for multiple identities at the occupation level is limited in the ELF query system, so we did not explore intersectionality in this analysis. The application of an intersectional approach has demonstrated to be useful in highlighting important social inequities and should be considered in future studies.[76]

Conclusion

The recent availability of CANJEM has provided the opportunity to efficiently and inexpensively characterize the burden and distribution of exposures to a large set of occupational agents in the US. To our knowledge, this is the first study to combine a population-based JEM with employment and demographic data to estimate the burden of occupational exposures and characterize exposure disparities among sociodemographic groups in the US. The findings from this analysis call particular attention to cleaning agents, which was found to be the most prevalent exposure among US workers. This analysis also found an uneven distribution of occupational exposures across sociodemographic groups, with the least privileged groups tending to bear the greatest burden of exposure. The wealth of data generated in this analysis can help identify the extent of work-related exposures, specific populations disproportionately burdened by exposures and at risk of excess injuries and illnesses, and occupations with high exposure burdens that may not otherwise have been identified through current health outcome-based occupational health surveillance systems. This information can then be used to target occupational health research, policy, and intervention efforts aimed at reducing occupational illnesses in the US. The incorporation of sociodemographic information can additionally help inform equitable approaches to reduce occupational exposure and health disparities and ensure occupational justice. Continual improvement to occupational exposure surveillance is vital to the primary prevention of occupational injuries and illnesses and should be made a top priority in the US.

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Supplementary materials

File name	Description
Table S1 CANJEM exposures and definitions	This table contains definitions of CANJEM exposures used in this analysis.
Table S2-S21 Full dataset	R markdown HTML document containing exposure estimates, estimates of exposure disproportionality, exposure burden index, and sensitivity analysis for all 248 agents in the analysis.
Additional Documentation of Methods	Document containing procedures and decisions made to crosswalk between 2010 SOC, 2018 OEWS codes, and 2010 US Census codes.
R code	R code used to run analysis.