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Meta-Analysis of Job Exposure Matrix Data from Multiple Sources

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Abstract

Objectives: To determine the heterogeneity of the data making up a job-exposure matrix (JEM) for occupational noise and to calculate pooled estimates for noise exposure for different job titles.

Methods: The JEM was constructed by collecting noise measurement data – made according to the criteria of the US Occupational Safety and Health Administration (OSHA) – from government databases, private industry and the published literature. The data were organized by job title using the US Standard Occupational Classification (SOC) system. Using data from the literature as a prior, adjusted mean exposure was calculated for both the government and industry data. A meta-analysis was conducted to measure data heterogeneity and to calculate a pooled exposure estimate for each SOC and SOC group.

Results: In total, 715,867 noise measurements across 259 SOCs were analyzed. Using the literature as a prior, 14 out of the 28 applicable SOCs in both the government and industry data had adjusted mean exposures above the OSHA action level of 85 dBA. The meta-analysis showed that 4% of SOCs, and 25% of SOC groups, had moderate to high levels of heterogeneity, Fifty-four percent of the SOCs and 53% of the SOC groups were found to have a pooled estimated exposure >85 dBA.

Conclusions: The low level of heterogeneity suggests that no one source of data contributed measurements that were significantly different from the other sources. The estimates from this JEM predict that workers in 134 out of 259 SOCs (51.7%) were exposed to noise >85 dBA.

Keywords

Noise; Occupational Exposure; Occupational Epidemiology; Heterogeneity

Introduction

Noise is one of the most common occupational exposures in the United States; every year, >22 million American workers are exposed to hazardous noise, that is, noise in excess

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of 85 A-weighted decibels (dBA) over an 8-hr shift (1,2). Hazardous noise can lead to noise induced hearing loss (NIHL) and tinnitus (3). In addition, noise exposure may also be associated with hypertension, cardiovascular disease, and workplace stress, and may increase the risk of injury in the workplace (4-10). These adverse noise-related health outcomes are major contributors to morbidity and mortality in the US and also cost the healthcare system billions of dollars annually (8,9,11).

Epidemiological studies have sought to better characterize and quantify the relationship between occupational noise exposures and adverse health outcomes. However, these studies are challenging to undertake because of the time and costs associated with the detailed and accurate exposure analysis necessary to help elucidate the relationship between an exposure and disease. Conducting such an analysis on individual subjects in an epidemiological study is a highly complex endeavor, particularly for ecological and case-control studies where contact with individual subjects may be limited or impossible (12).

To overcome these challenges, researchers have often used job exposure matrices (JEMs) to efficiently create exposure estimates for groups of workers. In its simplest form a generic JEM consists of two axes, one containing job groups and the other containing qualitative or quantitative exposure information for each job group (13,14). JEMs can be made more complex by adding multiple exposures, various job tasks, or different temporal windows (15). Using a JEM as an exposure assessment tool is attractive because it allows an exposure assessment to be conducted quickly and at a low cost (16). There are numerous examples in the published literature of JEMs that have been used as epidemiological exposure assessment tools (17-24).

The primary limitation of JEMs is measurement error resulting from inaccurate estimates of exposure for a job title or titles. This error arises primarily from the between-worker variation in exposure when grouping workers by job title or other observational grouping strategies. For example, Rappaport et al. (1993) found that only about one-fifth of 183 so-called homogenous exposure groups (HEGs) had less than a two-fold difference among 95% of individual mean exposures for various chemical substances (25). Another potential source of error comes from sampling bias that can arise when an organization purposely chooses to monitor a worker expected to have an exposure significantly higher or lower than other workers with the same job title. For instance, regulatory agencies such as the US Occupational Safety and Health Administration (OSHA) and US Mine Safety and Health Administration (MSHA) that assess compliance with legally enforceable exposure limits may oversample the most highly-exposed workers (26). Conversely, data from industrial sources could have negative bias if measurements were only made on workers expected to have low exposures, or workers with exposures that are otherwise not representative of the overall workforce (12).

Despite the measurement error that can result from using job titles to group workers, this approach is still often used because job titles represent a simple and straightforward way to create groups of workers who may have similar exposure profiles. These standardized job titles can then be linked to company records, health registries, and other datasets. In some large epidemiological studies, JEMs are the only feasible method for assessing exposures due to their comparatively low cost and logistical ease when compared to collecting new measurements. It is also important to consider that as the number of measurements for a specific job title increases the standard error for that job title is reduced, resulting in a more stable and less-biased estimate of group-mean exposures (14).

To date, the only JEM specifically focused on occupational noise was created in Sweden. The JEM was developed for 321 job families using a combination of noise measurements (n=569 from 129 job families) and expert judgment (24). While this JEM represents an important step forward, its utility is limited by the small fraction of job families for which noise measurements were available and the low overall number of measurements. These features substantially increase the likelihood of measurement error within and between job families. Additionally, the job families with exposure estimates based solely on expert judgment are not true quantitative exposure estimates and are subject to potential intra- and inter-rater biases.

The current study is based on a substantially larger dataset of full-shift, quantitative personal noise exposure measurements. Measurement data were obtained from US and Canadian government and industry sources, as well as from the published literature describing noise measurements made in the US and Canada. This study had two goals. The first was to estimate and adjust exposure levels from the data incorporating information from the literature, based on Bayes theorem. Bayesian inference is becoming increasingly popular in epidemiology studies, and was utilized here because it allowed the inclusion of prior knowledge about the data. The second goal of this study was to conduct a meta-analysis to better understand the heterogeneity of the measurements within and between the three sources of data (literature, government, and industry). To our knowledge, this approach has not previously been used to assess the validity and variability of different sources of data used to compile a JEM for noise or any other occupational hazard.

Methodology

JEM Construction

The exposure measurements for the noise JEM were drawn from US and Canadian government occupational exposure databases, private industry, and the published literature. The compilation of the JEM will be described in detail elsewhere (manuscript in preparation). Briefly, only full-shift (i.e., ≥8 hour duration) measurements from the US and Canada were included in the noise JEM. Job and industry titles collected from the original data sources were coded using the 2010 Standard Occupational Classification (SOC) from the US Bureau of Labor Statistics (BLS) and the 2012 North American Industry Classification System (NAICS) from the US Census Bureau, respectively (27,28). Regular and literal expressions were used in STATA 13 (College Station, TX) in conjunction with NAICS codes and over 40,000 unique job titles to assign each job title an appropriate SOC (29). This was a highly labor-intensive process, but was necessary to account for numerous misspellings in text-field job titles and various synonyms used to describe a single common job both within and between industries. All measurements presented here were made using the OSHA noise measurement criteria, e.g., 90 dBA criterion level, 8-hour criterion duration, 5 dB time-intensity exchange rate, 80-130 dB measurement range, A-weighting network, slow response (30). All exposure measurements were converted to an 8-hour time weighted average (8-hr TWA) in A-weighted decibels (dBA) prior to analysis. For comparison, the US Occupational Safety and Health Administration (OSHA) has a legally enforceable 8-hour TWA Permissible Exposure Limit (PEL) of 90 dBA, and an Action Level of 85 dBA as an 8-hour TWA. Workers exposed above these limits must be enrolled in hearing conservation programs to ensure that their hearing is protected from excessive noise exposures.

Data Analysis for Exposure by SOC

To accomplish our first goal, estimation of exposures by SOC, we used exposure data at the SOC level from the published literature as informative priors. We considered *a priori* that the exposure data from the published literature are the most reliable data among the three data sources, and therefore could be considered as the prior knowledge for SOC level exposure. We used this prior to estimate the mean exposure level by SOC based on government data (μ_G), and the mean exposure level by SOC based on industry data (μ_I).

For a particular SOC, we denoted the number of observations, mean, and standard deviation as N_x, $\bar{Y}_x$ and $\bar{S}_x$ respectively. The subscripts L, G, and I correspond to literature, government, and industry data respectively.

Using the Bayes theorem, we estimated the exposure level by SOC based on government data incorporating prior knowledge from the literature ($\hat{\mu}_G$) using equation 1. The industry equivalent ($\hat{\mu}_I$) was calculated using equation 2. Equations 3 and 4 were used to calculate the 95% confidence intervals for the government and industry data, respectively. We calculated the contribution of each source of data to a particular SOC using equations 5 and 6 for the government and industry data respectively. The derivations of these equations can be found in Appendix 1.

Equation 1. Estimated exposure for government data using the literature data as the prior.

$$\frac{\frac{\bar{S}_L^2}{N_L} N_G \bar{Y}_G + \bar{Y}_L \bar{S}_G^2}{\frac{\bar{S}_L^2}{N_L} N_G + \bar{S}_G^2}$$

Equation 2. Estimated exposure for industry data using the literature data as the prior.

$$\frac{\frac{\bar{S}_L^2}{N_L} N_I \bar{Y}_I + \bar{Y}_L \bar{S}_I^2}{\frac{\bar{S}_L^2}{N_L} N_I + \bar{S}_I^2}$$

Equation 3. 95% confidence interval for the government estimate ($\hat{\mu}_G$) using the literature data as the prior.

$$[\hat{\mu}_G - 1.96\sqrt{\frac{\frac{\bar{S}_L^2}{N_L}\bar{S}_G^2}{\frac{\bar{S}_L^2}{N_L}N_G + \bar{S}_G^2}}, \hat{\mu}_G + 1.96\sqrt{\frac{\frac{\bar{S}_L^2}{N_L}\bar{S}_G^2}{\frac{\bar{S}_L^2}{N_L}N_G + \bar{S}_G^2}}]$$

Equation 4. 95% confidence interval (CI) for the industry estimate ($\hat{\mu}_I$) using the literature data as the prior.

$$[\hat{\mu}_I - 1.96\sqrt{\frac{\frac{\bar{S}_L^2}{N_L}\bar{S}_I^2}{\frac{\bar{S}_L^2}{N_L}N_I + \bar{S}_I^2}}, \hat{\mu}_I + 1.96\sqrt{\frac{\frac{\bar{S}_L^2}{N_L}\bar{S}_I^2}{\frac{\bar{S}_L^2}{N_L}N_I + \bar{S}_I^2}}]$$

Equation 5. Contribution of government data to the government estimate ($\hat{\mu}_G$).

$$Contribution_G = \frac{\frac{\bar{S}_L^2}{N_L}N_G}{\frac{\bar{S}_L^2}{N_L}N_G + \bar{S}_G^2}$$

Equation 6. Equation 5. Contribution of industry data to the industry estimate ($\hat{\mu}_I$).

$$Contribution_I = \frac{\frac{\bar{S}_L^2}{N_L}N_I}{\frac{\bar{S}_L^2}{N_L}N_I + \bar{S}_I^2}$$

Data Analysis by Collapsed SOC group

We combined the SOC data by their SOC category. This was done to make it possible to calculate exposure estimates for SOCs that had few measurements and identify which occupational categories have high noise exposure. The SOC codes were collapsed into groups of similar SOCs (“SOC groups”); many groups had more than one occupation while some categories had only one. We used the previously-described meta-analysis procedure to produce estimated exposure values for the SOC groups. Similarly, we used the previously-described Bayesian approach to estimate each SOC group’s exposure from government and industry data using literature data as prior.

Assessing heterogeneity between different data sources

Our second goal was to conduct a meta-analysis of exposure levels by SOC collected from the three different data sources. A meta-analysis of data from all sources for each SOC can also be used to assess whether there is evidence for diverse biases in the three data source, and can be used to identify which SOCs have the highest exposure without evidence of bias.

For the meta-analysis of each SOC, we estimated the summary exposure using a fixed-effects model. We also estimated the 95% CI of this summary exposure. Between-source heterogeneity was assessed using the chi-squared statistic (X^2), and a p-value less than 0.10 was considered to show evidence of heterogeneity. We computed a heterogeneity index (I^2) that represents the percent of total variation (from 0 to 100%) due to variation between data sources; 0% represents no heterogeneity, 25% means low heterogeneity, 50% indicates moderate heterogeneity, and 100% indicates very high heterogeneity (31). Where exposure level data by SOC was available from only one source, we could not calculate the summary exposure, X^2, or I^2, and instead used the mean from this source to represent the summary exposure.

Results

In total 715,867 personal, full-shift noise exposure measurements were analyzed. Of these, government data accounted for 614,284 measurements (85.8%), industry data for 96,349 (13.5%), and literature data for 5,234 (0.7%). In total 259 SOC codes were represented in this analysis, a list of these occupations and their corresponding SOC codes can be found in Appendix 2. Figure 1 shows the number of SOC codes that were present in each the three sources of data, as well as in common between data sources. There were 28 SOCs shared between the government and literature data and 31 SOCs shared between the industry and literature data.

Using the literature data as the prior, the adjusted mean exposure and corresponding 95% confidence interval was calculated for the 28 SOCs present in both the government and literature data. Figure 2 summarizes the adjusted mean exposures and confidence intervals for the government data. Similarly, using the 31 SOCs that were present in both the industry and literature data the adjusted means exposures and 95% confidence interval was calculated for the industry data (Figure 3). Most of the adjusted government and industry values had very narrow 95% CIs; conversely, SOC 39-2021 (Nonfarm Animal Caretakers) had the widest 95% CI in both data sets. Five SOCs (17.8%) from the government data were found to have an adjusted mean exposure in excess of 90 dBA TWA; while 14 (50.0%) had an adjusted mean exposure greater than 85 dBA TWA. In the government data, 3 out of 28 SOCs (10.7%) had a government contribution to the adjusted mean of less than 5%. Seven SOCs (22.5%) from the industry data had an adjusted mean exposure greater than 90 dBA; while 14 (45.1%) exceeded 85 dBA TWA. In the industry data, 4 out of 31 SOCs (12.9%) had an industry contribution to the adjusted mean less than 5%.

Among the 259 SOCs, 235 had measurements from more than one source of data and could be assessed for heterogeneity. A summary of the observed heterogeneity is presented in Table 1. Of the 235 included SOCs, 211 (89.8%) had an I^2 statistic of 0%, indicating that there was no heterogeneity between the different sources of data. Only 10 SOCs (4.3%) were found to have moderate to high levels of heterogeneity (31). Of the 235 SOCs, 126

(53.6%) had a pooled estimated exposure greater than the OSHA AL of 85 dBA, while 27 (11.5%) SOCs had a pooled estimated exposure greater than the OSHA PEL of 90 dBA.

Using the literature as the prior, adjusted mean exposures and 95% CI were calculated for the government data by SOC group (Table 2). Thirteen of 19 SOC groups (68.4%) had a mean exposure >85 dBA TWA and 3 groups (15.8%) had exposures >90 dBA TWA. Unlike the individual SOCs, none of the SOC groups had a government contribution less than 5% (Table 3). When using the literature as the prior with the industry data 10 SOC groups out of 19 (52.6%) had a mean exposure over 85 dBA TWA, and 3 groups (15.8%) over 90 dBA TWA. One SOC group (rail transportation workers) had industry data contribute less than 5% to the estimate.

Heterogeneity was assessed for the 40 SOC groups that had measurements from more than one source of data (Table 4). Like the individual SOCs, a majority (65.0%) of the groups had no heterogeneity. However, 25.0% of groups had moderate to high heterogeneity, compared to only 4.3% when using individual SOCs. Twenty-one (52.5%) groups had a pooled estimated exposure greater than 85 dBA TWA; while 3 (8%) groups had a pooled estimated exposure greater than 90 dBA TWA.

Discussion

By combining noise exposure data from US and Canadian government agencies, industry sources, and the published literature we were able to construct a JEM with hundreds of thousands of measurements. Considerable effort was needed to clean and standardize the job titles from the government and industry data. This was in contrast to the literature data, which had well defined job titles and detailed descriptions of each title making the standardization of job titles very straightforward. In addition, because most of the government data were from regulatory agencies focused on enforcement and all the industry data were voluntarily provided by private companies, the presence of both positive and negative bias was a possibility (32). In order to address these factors we used the literature data as an informative prior to calculate an adjusted mean exposure. This resulted in similar estimated exposures and corresponding confidence intervals for both the government and industry data. Because of number of measurements from government and industry data far exceeded the number from the literature, the contribution of the literature to the exposure estimate was often minimal. However, for SOCs with low government or industry contribution, using this approach can help reduce uncertainty in the estimated exposure.

More than half (53.6%) of the 235 SOCs had a pooled estimate greater than the OSHA AL of 85 dBA TWA. This represents a large number of workers who must be enrolled in a hearing conservation program, including access to hearing protection devices (HPDs) and delivery of baseline and annual audiometric testing (30). Although OSHA does not require workers exposure to <90 dBA TWA to utilize hearing protection, NIOSH recommends protection for workers exposed to >85 dBA (1). Twenty-seven (11.5%) of SOCs had a pooled estimate greater than the OSHA PEL of 90 dBA TWA. Workers in these job titles must use HPDs, and engineering controls should be implemented where feasible to reduce exposures below 90 dBA (30). While the pooled estimates cannot be considered equivalent to, or as desirable as, the results of a single noise monitoring campaign, they can be used to provide guidance for implementing controls when no other exposure information is available.

The results of the meta-analysis found that about 95% of the SOCs had low or no heterogeneity. This suggests that there is not a significant variation in the data from the three different sources. The low heterogeneity and large sample size makes the pooled estimates that were calculated from the available data sources more reliable (see appendix 2 for a complete table).

The only other JEM focused on occupational noise exposure was presented by Sjöström et al. 2013. An experienced group of occupational hygienists used a mixture of noise exposure measurements and professional judgment to estimate the noise exposure for 321 job families from 1970 to 2004 in Sweden. Exposures were estimated in 5-year bins as <75 dBA TWA, 75-84 dBA TWA, or ≥85 dBA TWA (24). The primary limitation in the Swedish JEM is it is based on very sparse quantitative data (only 569 total measurements spread across 129 job families). In contrast, our JEM contains 715,867 OSHA PEL measurements from 256 SOCs. The large number of measurements in our JEM increases the accuracy of the exposure estimates for each SOC compared to the Swedish JEM.

Limitations

One of the greatest weaknesses of any JEM is the potential measurement error that is introduced when job titles are grouped (17). This is especially true for large JEMs such as ours, which had over 40,000 unique job titles before the titles were standardized during our data cleaning process. Since the data used here were primarily collected from the US, we used the US SOC occupational coding system. However, this coding system was designed for tracking economic indicators and not for exposure assessment. Andersson et al. found that developing a specific occupational coding system based around exposures in the pulp and paper industry resulted in better retrospective exposure analysis when compared to using the Canadian Classification and Dictionary of Occupations (CCDO) (33). However, developing specialized coding systems greatly increases the time and resources needed to construct a JEM covering all industries and occupations in a given country, as we have attempted to do here. In addition, the use of highly specialized occupational codes would make the comparison of exposure estimates with health data from large health surveys such as the National Health and Nutrition Examination Survey (NHANES) substantially more complicated.

A second limitation relates to the fact that any changes in exposure trends over time were ignored in the pooled estimates. An analysis of OSHA's Integrated Management Information System (IMIS) demonstrated that from 1979 to 1995 noise levels decreased on average; however, PEL exposures increased slightly from 1995 to 1999 (32). However, because the pooled estimates are based on a large number of samples, from a variety of sources, and collected over 52 years they are likely still a reliable measure of mean exposure for a particular group of workers.

Conclusions

The JEM we have described and analyzed here provides a valuable tool for both researchers and occupational health professionals. By standardizing all the job titles collected to assemble this JEM to the SOC coding system, it is possible to use data from the BLS's O*NET system to further assign each SOC an estimated frequency of exposure to high levels of noise, in addition to the mean exposure levels estimated here. This could supplement previous work that used basic noise exposure information from O*NET to predict noise-induced hearing loss (34). In addition, the data in the JEM will be made available to other researchers to use as an exposure assessment tool, and will also be presented online in a searchable database for occupational health professionals and the lay public to access. The goal of making this information widely available is to help identify occupations for which few data are available, which can help guide further measurement efforts and implementation of exposure controls as needed.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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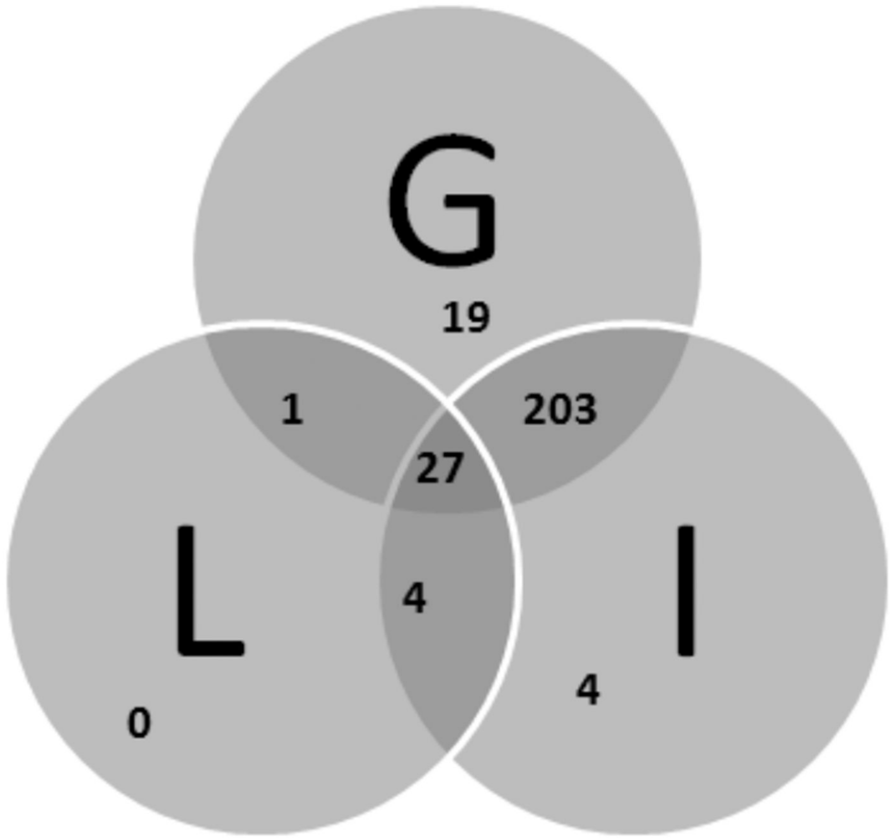

Figure 1.

Relationship of SOC codes between the three sources of data. L,G, and I correspond to literature, government, and industry data respectively.

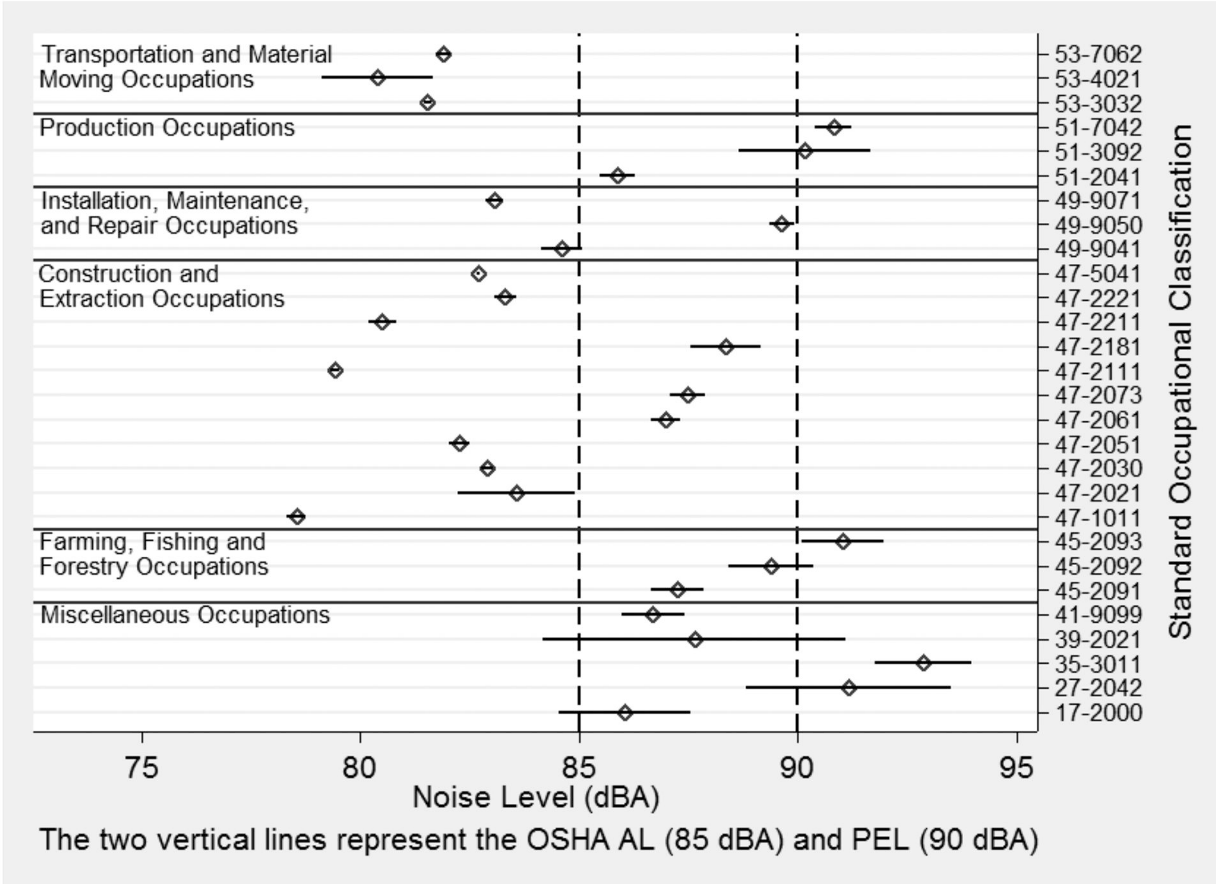

Figure 2.

Adjusted means and 95% CI for government data using the literature data as the prior.

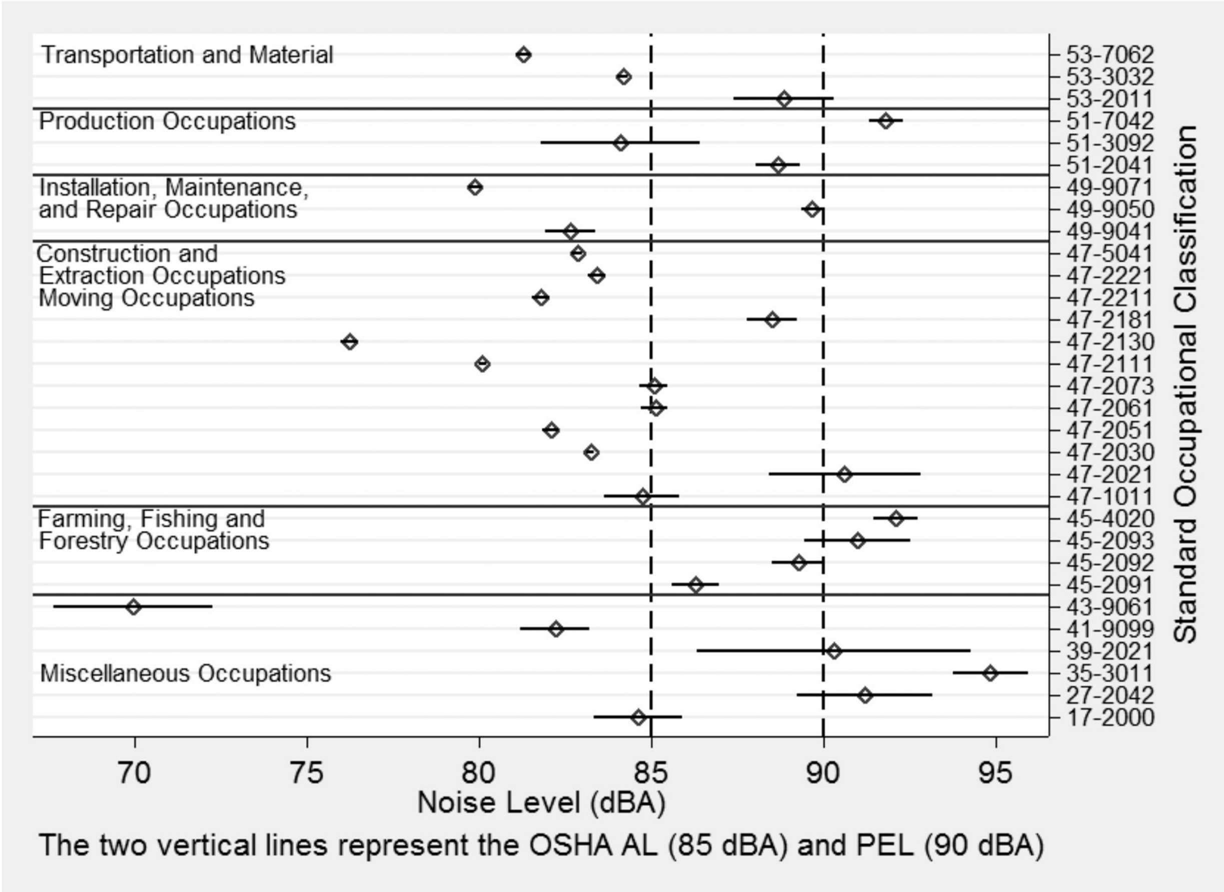

Figure 3.

Adjusted means and 95% CI for industry data using the literature data as the prior.

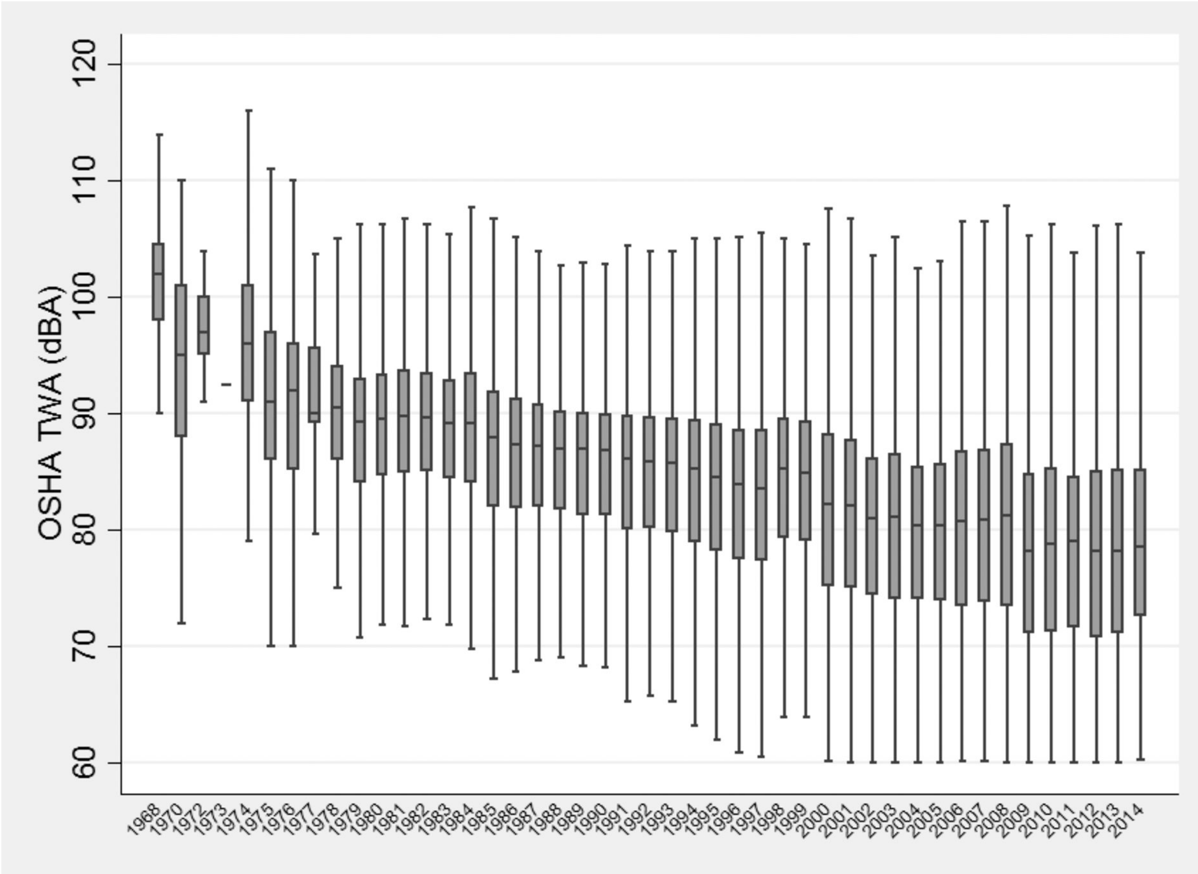

Figure 4.
Distribution of noise measurements from 1968- 2014. The lower bound of the box represents the 25th percentile, the line represents the 50th percentile and the upper bound of the box represents the 75th percentile.

Table 1.

Distribution of data for the OSHA PEL measurements in the JEM.

Source	**Date range (years)**	**Number of samples**
Total	1968-2015	715 867
Government	1979-2014	614 284
OSHA	1979-2013	93 332
MSHA	1979-2014	520 952
Private Industry	1970-2015	96 349
Agriculture, Forestry, Fishing and Hunting	1975-2013	757
Mining, Quarrying, and Oil and Gas Extraction	1979-2014	22 440
Utilities	1979-2014	646
Construction	1978-2014	2 984
Manufacturing	1970-2015	67 155
Wholesale Trade	1978-2014	332
Retail Trade	1977-2014	166
Transportation and Warehousing	1974-2014	392
Information	1978-2008	39
Finance and Insurance	-	-
Real Estate and Rental and Leasing	2013-2013	1
Professional, Scientific, and Technical Services	1980-2012	21
Management of Companies and Enterprises	-	-
Administrative and Support and Waste Management and Remediation Services	1976-2013	52
Educational Services	1974-2013	328
Health Care and Social Assistance	1974-2011	100
Arts, Entertainment, and Recreation	1997-2012	29
Accommodation and Food Services	1976-2012	116
Other Services (except Public Administration)	1979-2013	396
Public Administration	1975-2014	395
Literature[a]	1968-2013	5 234

[a]Refer to appendix 2 for a list of references for the literature data.

Table 2.

Summary of heterogeneity for various SOCs.

I^2 range (%)	Number of SOCs (%)	Examples
0	62 (26.4)	Transportation, storage, and distribution managers; Wholesale and retail buyers, except farm products; Surveyors, etc
>0-25	13 (5.53)	Arts, design, entertainment, sports, and media occupations; Cooks and food preparation workers; Baggage porters and bellhops, etc
>25-50	12 (5.11)	Computer occupations, all other; Engineers; Cargo and freight agents, etc
>50-75	12 (5.11)	Occupational health and safety specialists; Police officers; Gaming change persons and booth cashiers, etc
>75-100	136 (57.9)	Top executives; Industrial production managers; Life, physical, and social science technicians, etc
Total	235 (100.00)	

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Table 3.

Estimated mean exposure for government data using the literature as a prior.

Category Name	N	$\bar{Y}_G$	$\bar{S}_G$	N_G	$\bar{Y}_L$	$\bar{S}_L$	N_L	$\hat{\mu}_G$ [1]	95% CI	Contribution
Agricultural workers	4	91.0	0.3	390	86.7	0.3	325	88.6	88.1-89.0	0.44
Air transportation workers	2	74.7	1.8	10	92.7	0.9	80	89.2	87.7-90.8	0.19
Animal care workers	1	79.5	2.2	12	103.8	3.1	4	87.6	84.2-91.1	0.66
Assemblers and fabricators	6	86.8	0.1	5 574	80.4	2.8	4	86.8	86.6-87.0	1.00
Construction supervisors	1	78.3	0.1	5 846	86.5	0.6	58	78.5	78.3-78.8	0.97
Construction workers	22	82.3	0.1	8 905	81.3	0.0	3 166	81.4	81.4-81.5	0.14
Entertainers	1	86.5	4.0	5	91.6	1.2	18	91.1	88.8-93.5	0.09
Extraction workers	9	82.8	0.0	41 6225	82.3	0.3	134	82.8	82.8-82.9	1.00
Food processing workers	9	90.0	0.1	3 275	90.0	1.7	3	90.0	89.7-90.2	0.99
Food service workers	9	82.9	0.5	209	95.8	0.6	24	87.9	87.1-88.7	0.62
Logging workers	6	93.8	0.4	182	91.8	0.4	255	92.8	92.2-93.4	0.48
Material movers	14	84.6	0.1	15 163	77.5	0.1	612	83.2	83.1-83.3	0.81
Motor vehicle operators	3	81.5	0.0	52 857	83.8	0.3	241	81.5	81.5-81.6	0.98
Office workers	27	84.2	0.2	1296	69.9	1.3	4	83.8	83.3-84.2	0.97
Other installation-maintenance and repair occupations	12	83.7	0.1	14 130	89.8	0.2	147	85.1	84.9-85.2	0.77
Rail transportation workers	2	82.1	1.2	57	79.7	0.8	5	80.4	79.1-81.7	0.29
Retail workers	7	86.3	0.3	711	86.5	2.0	4	86.3	85.7-86.9	0.97
Woodworkers	6	91.9	0.1	7 608	88.0	0.7	7	91.9	91.7-92.0	0.99
NA	14	85.6	0.4	385	83.5	2.5	16	85.5	84.7-86.4	0.97

[1] $\hat{\mu}_G$ represents the estimated mean exposure for government data using the literature as a priors

Table 4.

Estimated mean exposure for industry data using the literature as a prior.

Category Name	N	$\bar{Y}_I$	$\bar{S}_I$	N_I	$\bar{Y}_L$	$\bar{S}_L$	N_L	$\hat{\mu}_I$[1]	95% CI	Contribution
Agricultural workers	4	90.0	0.4	284	86.7	0.3	325	87.9	87.4-88.4	0.35
Air transportation workers	2	82.8	0.8	68	92.7	0.9	80	87.2	86.1-88.4	0.55
Animal care workers	1	79.7	2.7	9	103.8	3.1	4	90.3	86.3-94.3	0.56
Assemblers and fabricators	6	81.6	0.0	15 276	80.4	2.8	4	81.6	81.5-81.7	1.00
Construction supervisors	1	77.3	1.3	41	86.5	0.6	58	84.7	83.6-85.8	0.19
Construction workers	22	83.6	0.1	6 918	81.3	0.0	3 166	81.8	81.7-81.9	0.21
Entertainers	1	90.5	1.7	4	91.6	1.2	18	91.2	89.2-93.2	0.36
Extraction workers	9	83.3	0.1	13 148	82.3	0.3	134	83.2	83.1-83.3	0.95
Food processing workers	9	85.9	0.3	228	90.0	1.7	3	86.0	85.5-86.6	0.97
Food service workers	9	82.7	0.4	87	95.8	0.6	24	86.5	85.8-87.1	0.71
Logging workers	6	91.0	0.3	323	91.8	0.4	255	91.3	90.8-91.8	0.63
Material movers	14	87.0	0.1	5 670	77.5	0.1	612	84.4	84.2-84.5	0.72
Motor vehicle operators	3	84.1	0.1	5 736	83.8	0.3	241	84.1	84.0-84.3	0.92
Office workers	27	79.5	0.2	1 879	69.9	1.3	4	79.4	79.1-79.7	0.99
Other installation-maintenance and repair occupations	12	80.2	0.1	6 765	89.8	0.2	147	82.7	82.6-82.9	0.74
Rail transportation workers	2	88.0	5.8	3	79.7	0.8	5	79.8	78.4-81.3	0.02
Retail workers	7	80.6	0.4	228	86.5	2.0	4	80.9	80.1-81.7	0.95
Woodworkers	6	92.3	0.1	6 094	88.0	0.7	7	92.2	92.0-92.4	0.98
NA	14	80.4	0.3	847	83.5	2.5	16	80.5	80.0-81.0	0.99

[1] $\hat{\mu}_I$ represents the estimated mean exposure for industry data using the literature as a prior

Table 5.

Summary of heterogeneity for various SOC groups.

I^2 range (%)	Number of groups (%)	Examples
0	9 (22.5)	Artists; Electrical and electronic equipment mechanics, installers, and repairers; Entertainers; Healthcare workers; Media; Other transportation workers; Police officers; Supervisors of installation, maintenance, and repair workers; Water transportation workers
>0-25	0 (0.0)	-
>25-50	0 (0.0)	-
>50-75	1 (2.5)	Rail transportation workers
>75-100	30 (75.0)	Agricultural workers; Animal care workers; Construction workers; etc
Total	40 (100.0)	

Table 6.

An example sensitivity analysis using SOC 49-9050 (Line Installers and Repairers).

N_L	$\hat{\mu}_G$	95% CI	Contribution	$\hat{\mu}_I$	95% CI	Contribution
139	89.6	89.3 - 89.9	0.01	89.7	89.4 - 90.0	0.01
100	89.6	89.3 -90.0	0.01	89.6	89.3 - 90.0	0.01
70	89.6	89.2 - 90.0	0.02	89.6	89.2 - 90.0	0.01
40	89.5	88.9 - 90.0	0.03	89.5	88.00 - 90.1	0.02
10	88.9	87.9 - 89.9	0.12	89.0	88.0 - 90.1	0.07
8	88.7	87.6 - 89.9	0.15	88.9	87.7 - 90.1	0.09
6	88.5	87.2 - 89.8	0.19	88.7	87.3 - 90.0	0.11
4	88.0	86.5 - 89.5	0.26	88.2	86.6 - 89.8	0.16
2	87.0	85.1 - 88.9	0.41	87.1	85.0 - 89.3	0.28

$\mu(l) = 89.7$, $\sigma(l) = 1.8$; $\mu(g) = 83.1$, $\sigma(g) = 7.0$, $n(g) = 21$; $\mu(i) = 80.4$, $\sigma(i) = 9.9$, $n(i) = 23$