Factors Associated with Exposure in Occupational Safety and Health Administration Data

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This study investigated the possibility of making compliance data from the public and private sectors more amenable for multiple uses, by studying data from Occupational Safety and Health Administration (OSHA) inspections during 1979–1989. The potential association of five variables with mean and upper-end (in upper quartile) airborne exposures in similar exposure groups was investigated. The exposure groups reflected airborne exposures to lead in the battery manufacturing industry, to perchloroethylene among dry cleaners, and to iron oxide among welders in three metal fabrication industries. Variables examined were year, inspection type and scope, and size and union status of inspected establishments. Multiple linear regression and logistic regression models were used for the analyses. In small battery plants mean exposure levels were higher and the relative frequency of upper-end exposures (>75th percentile) greater than in larger establishments. Evidence suggested a decline in mean lead exposures (5–9% per year). Neither type of inspection nor union status were associated with mean or upper-end levels of lead exposure, although the study's power to detect an association was sometimes modest. Some evidence showed that full scope inspections may be associated with higher mean exposures. Strong evidence showed a decline in mean perchloroethylene exposures among dry cleaners (7% per year), but no temporal trends for welder exposures to iron oxide. With few exceptions, the size, type, scope, and union variables were rarely associated with mean or upper-end exposure levels among dry cleaners or welders, although the power of the analyses to detect associations was at times modest. Results show that OSHA data is amenable to analysis that can provide valuable insights about workplace exposures. Several findings of the study are directly useful to the design of public policy.

Keyword: compliance data

Since the early 1970s there have been increasing demands for exposure data to support many activities related to the management of workplace risks.[1–6] These activities include (a) the conduct of population risk assessments,[7–12] (b) epidemiologic research,[13–16] (c) exposure surveillance and other efforts to measure status and trends in occupational disease risk, and (d) the use of indicators to plan, target, and evaluate corporate and regulatory risk management endeavors.[17–26] In the same period there has also been an explosion in the amount of occupational exposure data collected in both the public and private sectors.

Regrettably, these developments in the supply and demand of exposure data have not been complementary. The increased data are collected primarily for compliance objectives, but they are rarely designed or exploited for other exposure assessment applications, despite the need, their potential for such uses, and the sizable resources that are devoted to their collection. This contradictory situation is, to a large extent, the result of uncertainty about what the available (primarily compliance) data represent. Yet there have been no systematic efforts to investigate the characteristics of compliance data so as to enhance their usefulness, as by designing collection methods or strategies that would make them more amenable to other applications. Research in these areas is necessary to optimize the large investments that will continue to go into compliance data.

The exposure data collected during inspections by the federal Occupational Safety and Health Administration (OSHA) are attractive for this type of research. The OSHA data system is a very large and publicly available source of compliance exposure measurements, gathered in a standardized manner that includes quality assurance on sampling and analytical methods and covering a wide range of substances, industries, and jobs across much of the U.S. economy. These measurements can potentially yield informative estimates of exposure parameters for groups of similarly exposed workers. The OSHA measurements are also accompanied by information about several variables that may serve to answer important questions regarding the representativeness (or lack thereof) of this type of data. Moreover, because OSHA sets the pattern for exposure data collection methods in the United States, research findings on these data also may prove relevant to improving the usefulness of data collected by other institutions.

To help fill this research gap, this study investigated the potential association of five variables with mean and upper-end airborne exposures in several exposure groups drawn from the OSHA data: lead exposures among five exposure groups in the battery industry, exposures to perchloroethylene among dry cleaners, and iron oxide exposures among welders in three metal fabrication industries. Throughout this report, the word "exposure" refers to potential airborne exposures measured at the worker's breathing zone, independent of the use of respirators. The exposure measurements were collected during OSHA inspections in the period 1979–1989, and the variables examined were the year, type and scope of the inspection, and the size and union status of the establishments.

MATERIALS

OSHA Data System

OSHA maintains the records of federal and state inspections in its computerized Internal Management Information System (IMIS).[28] The IMIS is organized as a series of files linked by inspection number. These files contain all the OSHA inspection exposure measurements, accompanied by information about variables such as job titles that may be associated with exposure levels. This study focused on 8-hour time-weighted average (TWA) personal samples of airborne chemicals, which make up the bulk of the measurements recorded in the IMIS (>80%).

The IMIS files contain the name, address, and other descriptors of the establishment where the measurements were made; the date; the type of inspection (e.g., complaint, referral from safety inspector, routinely planned, etc.); the number of employees in the plant and the parent company; the number covered by the inspection; the scope of the inspection (full or partial); and whether or not there is a union in the facility. Information concerning citations, penalties, and other administrative matters are also recorded in the system. Additional description of the OSHA system can be found elsewhere.[12,27–29]

Variables Investigated for Potential Associations with Exposure

Five of the variables recorded in the OSHA data were investigated to ascertain whether, and to what extent, they were associated with estimates of central tendency and upper-end exposure (in upper quartile or greater than the 75th percentile of the data) in several exposure groups (EGs). These variables are important because they are the most likely to cause the OSHA data to be unrepresentative of typical workplaces (e.g., to be biased towards high exposures because OSHA is more likely to visit "dirty" workplaces, or towards low exposures because OSHA visits large, modern, unionized firms). The variables and the rationale for their selection as subjects for study are described below.

The type of inspection is a record of the reason for each inspection. Only two of the nine possible categories—planned and complaint inspections—generally had enough data for analysis. These two categories constitute more than 80% of the OSHA data as a whole (37% planned, 45% complaint). Firms selected for planned inspections from any given industry can be plausibly treated as a random sample of establishments from that industry. Once OSHA designates a given industry as a priority for planned inspections (e.g., battery manufacturing), each area office compiles a list of establishments in those industries in their area and selects sites from that list at random. Complaints arise from requests to OSHA by employees or their representatives, and it is valuable to investigate whether they truly reflect high or "worst-case" exposures, as many assume.

The year an inspection was conducted potentially can be used to investigate temporal trends in exposure levels, which are possible indicators of the impact of factors such as standards on exposure levels. The last two digits of the year were used as the variable of study, which was treated as a continuous variable.

The number of employees in each inspected establishment was used as a measure of the size of the establishment. This variable was treated as categorical by dividing the data into three tertiles (small, medium, large), based on the number of employees per plant in the overall data from each industry. The size of a firm may be related to its ability to maintain low exposures.

Finally, the IMIS records whether or not a workplace was represented by a union and the scope of an inspection (inspection of an entire plant or only a portion of it). These variables, which were treated as categorical, may also tend to make the data unrepresentative of typical workplaces. For example, it may be postulated that the presence of a union may result in "cleaner" firms, or that partial inspections may be susceptible to manipulation of exposures by employers or employees on the day of an OSHA visit.

EGs

The EGs that were the focus of the study are described in this section. EGs were defined as groups of workers assumed to have similar exposures because they performed a task, or a group of tasks, that shared similar sources of exposure, purposes, tools, and other exposure-relevant characteristics.[30–33]

Lead EGs

For the period 1979 to early 1989, the OSHA IMIS contains 2111 samples of 8-hour TWA personal exposures to lead in the lead battery industry (Standard Industrial Classification [SIC] codes 3691, Storage Batteries, and 3692, Primary Batteries, Dry and Wet). A subset of these data were grouped to form the five EGs for this study. The grouping methods are described in detail elsewhere.[34] Briefly, a set of *a priori* job title categories was developed, based on commonly found key words in the job titles reported in the raw OSHA data and in the literature for this industry.[35] These initial categories were collapsed (by computer sorting followed by direct review) into EGs that were judged to share similar activities and sources of exposure.

Five of the EGs formed had enough measurements to support analysis with the linear regression models described in the Methods section. These five EGs are briefly described in the Appendix Table A as Burning, Casting, Mixing, Pasting, and Racking.[35] Table I contains descriptive statistics for them, which

TABLE I. Lead Exposure Groups—Summary Statistics

Exposure Group	Number of Samples	Number of Inspections	GM (mg/m³) (GSD)	Arithmetic Mean (mg/m³)^A (SD)
Mixing	87	77	0.123 (3.3)	0.231 (0.314)
Pasting	131	69	0.099 (3.2)	0.188 (0.250)
Racking	282	65	0.080 (3.7)	0.238 (0.625)
Burning	219	61	0.054 (3.4)	0.144 (0.532)
Casting	120	52	0.040 (2.6)	0.087 (0.363)

^A OSHA permissible exposure limit = 0.050 mg/m³

indicate that exposure levels for these EGs were quite high in relation to the OSHA standard. The table also reports the numbers of measurements and inspections.

These five EGs comprise a sizable proportion of the available data in this industry (approximately 42% of all the available 8-hour TWA measurements in the industry, and 53% of those with classifiable job titles). They are also among the most highly exposed groups of workers in the industry, which makes their study worthwhile from a public health perspective. Because there were only three possible instances of repeat inspections (one was uncertain), no attempt was made to account for this potential source of correlation in the data.

Welder/Iron Oxide EG

This EG included exposures to iron oxide among metal arc welders ("stick welders") in 3 four-digit SIC codes, namely the manufacture of Fabricated Plate Work and Boilers (SIC 3443), Construction Machinery (SIC 3531), and Truck and Bus Bodies (SIC 3713). These industries were selected because they were the four-digit categories within their broad industry groupings (i.e., two-digit SIC groups) with the highest number of welder/iron oxide measurements. The industries are similar because they all involve the fabrication of metal goods. The EGs from each industry were analyzed separately, but it was logical to later contrast the results for the three EGs because of the industry similarities.

The exposure group for each SIC was formed by grouping all the 8-hr TWA exposure measurements for iron oxide whose job titles included the key word "weld" (or slight spelling variations thereof). Job titles that also included the word "mig" (for "metal inert gas") were excluded to enhance the similarity of the EG by grouping only very similar welding processes in it. Arc or "stick welding" is reported to be by far the most frequent in metal fabrication processes.[36,37]

Table II reports the crude geometric means and geometric standard deviations for the three exposure groups. The average exposures are all under OSHA's current permissible exposure limit (PEL) for iron oxide fume of 10 mg/m³, as well as the 1988 proposed reduction to 5 mg/m³, which is also the American Conference of Governmental Industrial Hygienists' threshold limit value (TLV®). Table II also reports the number of measurements and inspections for each EG. Because only a small number of repeat inspections were identified for any of the SICs (1–3%), no effort was made to account for this potential source of correlation in the data.

TABLE II. Welder/Iron Oxide Exposure Groups—Summary Statistics by Industry Group (SIC)

Industry Group (SIC)	Number of Samples	Number of Inspections	GM (mg/m³)^A	GSD
3443	491	159	1.90	3.7
3531	522	124	2.31	2.6
3713	180	69	1.87	3.6

^A OSHA permissible exposure limit = 10 mg/m³

Dry Cleaner/Perchloroethylene Exposure Group

This EG examined perchloroethylene exposures among dry cleaners in the industry group "Laundry, Dry Cleaning & Garment Services" (SIC Code 721). The exposure group included all the 8-hr TWA exposure measurements for perchloroethylene where the job title entry included the key word "cleaner," or slight spelling variations thereof (83% of the group), and/or the key words "washer," "operator," "worker," or "laborer," (remaining 17% of the group). Most of the measurements (79%) came from the four-digit SIC code 7216 (Dry Cleaning Plants, Except Rugs), the remaining 21% from other four-digit SICs within the 721 industry group (SIC 7211, Power Laundries, Family and Commercial [4%]; SIC 7212, Garment Pressing and Cleaners' Agents [3%]; SIC 7213, Linen Supply [2%]; SIC 7215, Coin-Operated laundries and Dry Cleaning [6%]; SIC 7218, Industrial Launderers [6%]).

Only planned, complaint, and referral inspections were included, for a raw total of 147 observations collected in 87 inspections. Ten of these observations, however, were treated as outliers because they seemed implausible (two very high ones and eight nondetectable or zero values). Exclusion of these values also resulted in a better fit of the data to a lognormal model. Nearly all the analyses, however, were also run including these outlier values (assigning the zeroes one-half the lower detectable limit of 0.5 mg/m³ reported by the OSHA laboratory), and the results were fundamentally the same. Only 4% of the observations in the EG (five samples) came from planned inspections, and only 6% (eight samples) came from union establishments. These small numbers weaken any conclusions regarding these variable categories. Most inspections involved only one sample for the EG, and there were no repeat inspections in the same establishment.

Crude geometric mean exposures ranged from 19–83 mg/m³ (for different strata of the variables), suggesting that mean exposures were well below the current PEL of 680 mg/m³ (100 ppm) as well as the current TLV of 340 mg/m³ (50 ppm). The geometric standard deviations hovered around 3.0 (range 1.39–4.95).

METHODS

The data for each exposure group were assumed to be lognormally distributed, which is reasonable[38,39] though not always true for occupational data.[32,39-41] Approximate graphic analyses (stem-leaf, normal probability plots) generally supported the validity of this assumption for all EGs. Figure 1 shows the distribution of the log values of the lead exposures for the EG Casting. The approximately normal plot is typical of those obtained with other EGs.

The analyses of the mean EG exposures relied on three models that treated the (natural) log mean exposures as different linear functions of the five variables. The use of alternate linear regression models sought to strengthen the characterization of the role of the

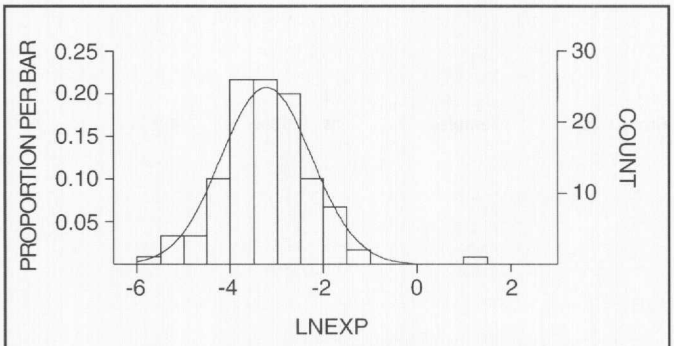

FIGURE 1. Distribution of lead exposure values (log) for EG Casting. Smooth curve represents theoretical distribution with same geometric mean and standard deviation.

five variables, with more confidence placed in those findings that were considered robust because they were observed consistently across all the models (i.e., similar direction or sign of the coefficients). In addition, consistent findings across multiple EGs (in the lead and metal finishing industries) were important in developing conclusions about the effects of specific variables. For example, a consistent finding of negative regression coefficients for the variable year across all the lead EGs (and under all the models) supports a conclusion of declining mean exposures over time, although not all the coefficients were statistically significant. Logistic regression was used to examine the possible relationship of high exposure to the five variables. Ten measurements per independent variable were considered the minimum number of observations required for meaningful analysis. Statistical significance of the coefficients was evaluated through the conventional p-value of 0.05 and the borderline value of 0.10. The models are described below.

Model One: Mean of Establishment Means

Under this model, multiple observations for an EG in the same inspection were first used to estimate establishment means (log). The establishment means for each EG were then modeled as a linear function of the five variables. This approach does not assume that multiple measurements taken for an EG during the same inspection are independent.

Model Two: Linear Regression of Individual Means

Under this model, each observation in an EG was treated as an independent measurement of the group's exposure, even when they were collected in the same establishment and inspection. These individual measurements for each EG were modeled as a linear function of the five variables.

Model Three: Generalized Estimating Equations (GEE)

This model used the generalized estimating equation (GEE) method to estimate linear regression coefficients.[42,43] By accounting for the possible correlation among multiple measurements of the mean exposure for the same EG in the same establishment and inspection, this method should yield answers (regression coefficients) that are intermediate between Models One (assumes high correlation) and Two (assumes independence) and perhaps better estimates of the truth.

Linear Logistic Regression Model: Upper-End Exposures

Logistic regression was used to investigate whether any of the five variables were predictive of upper-end exposures. Specifically, multiple logistic regression was used to study the effect of the five variables on the adjusted odds of exposure in the upper quartile of exposure levels for each EG. The binary characteristic of interest was exposure >75th percentile value of the exposure data aggregated by exposure group, and the regression examined the association between this characteristic and the five independent variables. This approach was applied only under Model One (i.e., for establishment means for each EG). Although the term "upper-end" is used to refer to exposures in the upper quartile of the distribution of each EG, in most instances these exposures are near (iron oxide and perchloroethylene) or above (lead) existing standards and can also be considered "high" in a toxicologic sense, as the means and geometric standard deviations summarized in Tables I–III indicate (the upper quartile of the normal distributions described by the tables encompass values near or above current standards).

TABLE III. Mean Lead Exposures, Effect of Year by Exposure Group, Regression Coefficients (Trends) for Year, Regression of Means of Means (Model One)

Exposure Groups (n)	Regression Coefficient[A]	Standard Error	p-value
Racking (77)	-0.0772	0.0489	0.1191
Burning (69)	-0.0887	0.0434	0.0461
Pasting (65)	-0.0567	0.0447	0.2098
Mixing (61)	-0.0419	0.0498	0.4032
Casting (52)	-0.1446	0.0444	0.0021

[A]Units of regresssion coefficient are ln (mg/m^3)

First-order interaction effects were identified by testing the significance of combined interaction effect terms. When the interaction terms were not statistically significant (defined throughout this report as p>0.05), the analyses were conducted with reduced models (no interaction terms). If significant interactions were found, the data were stratified until first-order interactions disappeared. This sometimes resulted in strata with too few observations for meaningful results. Although it might have been fruitful, no attempt was made to interpret interaction effects. The assumption of equal variance was confirmed by visual examination of residual plots. Colinearity effects under Model One were investigated (and never found) using the criteria described by Kleinbaum et al.[44]

SAS Procedures

The Statistical Analysis System (SAS) for Personal Computers was used for all the analyses (PROC GLM) except the GEE model, which used SAS with an IBM mainframe computer. PROC LOGISTIC was used for multiple logistic regressions. The least square option under the SAS GLM procedure was used to estimate and rank order the mean (adjusted) exposures for the categories of each variable (e.g., to rank order the means for small, medium, and large firms for each EG).

RESULTS

The thrust of this investigation was to examine the results from different models and EGs in a weight-of-the-evidence manner to identify patterns of findings suggestive of associations (or lack thereof) of the five variables with exposure levels. The results described in this section therefore emphasize such patterns, rather than specific associations between variables and exposures observed in individual analyses. Moreover, space would not permit the presentation of the detailed results of the large number of regression analyses performed (many EGs under different models), which can be found elsewhere.[34]

Year

For lead exposures the results from all models consistently suggested an average decline of 5–9% per year in mean exposures in the period 1979–1989 in four of the five EGs examined. The coefficients for the variable year were negative in all the available analyses under all models for these EGs (statistically significant or borderline in one of the five—the EG Casting). The only exception was the EG Pasting, for which contradictory results for the behavior of the regression coefficient for year were observed under Model One (a nonsignificant decline or negative coefficient), Model Two (borderline increase or positive coefficient), and Model Three (nonsignificant positive coefficients for full scope inspections).

Table III illustrates the kinds of results obtained under Model One for the effect of year. The table contains the values of the regression coefficients (in ln mg/m^3), their standard errors, and their p-values. All the coefficients are negative (decreasing exposures with time), and two of them are statistically significant. The table thus strongly suggests a pattern of declining exposures. An almost identical pattern was obtained for year under the other models for this EG (i.e., the coefficients were always negative, and sometimes statistically significant), but the numerical details are not included because of space limitations.

For dry cleaners, all three models strongly suggested that there was a decrease in average perchloroethylene exposures during the decade covered by the study. The coefficients for year were negative in all the analyses and statistically significant in Models Two and Three. The decline in geometric mean exposures was approximately 7% per year.

For welders none of the results indicated a time trend in mean exposures to iron oxide in planned inspections (roughly equivalent to a random picture of welding exposures in the three industries). For complaint inspections, the results were inconsistent across the three EGs and therefore difficult to interpret. There was evidence of a statistically significant increase in mean exposures with time in SIC 3713, but no such effect was observed for SIC 3531, and there were contradictory results under different models for SIC 3443 (i.e., the signs of the regression coefficients were contradictory across models). Detailed numerical regression results are not reported for reasons of space.

Type of Inspection

In the lead battery industry, the coefficients for type of inspection were not statistically significant or borderline in any of the analyses under any model for any of the five EGs, suggesting that this variable was not associated with mean exposures.

For dry cleaners the evidence was strong that mean exposures for complaint and referral inspections were not different. There was no consistent rank ordering for these categories across models and no statistically significant or borderline regression coefficients. These two categories make up the bulk of the available data (96%). While there was some evidence that means for planned inspections were approximately twice those of complaint inspections (Models One and Three), the number of planned observations was too small to make these findings convincing.

The results available for this variable for welder exposures were limited primarily to Model One, because type had to be used as a stratification variable in a number of the other analyses. These results at times suggested a tendency for mean welder exposures in complaint inspections to be greater than the means observed in planned inspections (statistically significant for SIC 3713 and borderline for SIC 3443). This pattern was also observed for SIC 3531 for full scope inspections (in scope-stratified analysis). A reverse and statistically significant pattern was observed (planned means > complaint means), however, for this SIC, for partial scope inspections under Model Two.

Size

In the lead battery industry, size was a clear predictor of mean lead exposures. The findings from all the models consistently indicated an inverse relationship between establishment size (number of employees) and mean exposures for all the EGs examined. Almost without exception, the coefficients for this variable were statistically significant, and the ranking of mean exposures by size nearly always followed the pattern small>medium>large. Geometric mean exposures in both large and medium establishments (which were close) were approximately 30–40% of those in small establishments.

Table IV illustrates the kinds of results obtained under one model (Model Three) for the effect of size, by indicating the rank order of mean exposures for different size plants, as well as the statistical significance of the regression coefficients for the different size plants. The table reports the results for full scope complaint inspections. For the EG Pasting, for example, the largest mean exposures were found in small plants, and the difference in mean exposures between small plants and both medium and large plants were statistically significant (the coefficients had p-values <0.01). Overall, the rank order of mean exposures by size categories in the

TABLE IV. Mean Lead Exposures, Effect of Size by Exposure Group, Model Three (Full Scope, Complaint Inspections), Rank Order for Size Categories and p-values of Coefficients

Exposure Group (N)	Rank Order of Size Category by Mean Exposure[A] (Approximate p-value of Regression Coefficient)	Crude Geometric Mean by Size Category in mg/m^3 (GSD)
Pasting (82)	small[B]	0.257 (0.171–0.316)
	large[C]	0.087 (0.066–0.115)
	medium[D]	0.051 (0.036–0.077)
Casting (69)	medium (NS)[E]	0.034 (0.024–0.049)
	small (NS)	0.034 (0.022–0.053)
	large	0.032 (0.025–0.040)
Burning (141)	small	0.100 (0.076–0.131)
	medium (B)[F]	0.055 (0.032–0.094)
	large	0.037 (0.030–0.046)
Mixing (57)	small	0.260 (0.154–0.437)
	medium	0.099 (0.049–0.200)
	large	0.081 (0.056–0.117)

[A]Size tertiles are based on the size distribution of the entire industry in the OSHA data, as follows: small, 1–60 employees; medium, 61–272 employees; large, > 273 employees.
[B]p=0.05–0.01
[C]p=0.01–0.001
[D]p=<0.001
[E]NS=not significant
[F]B=borderline, p=0.05–0.10

table strongly suggests that small establishments have larger mean exposures (approximately twice the average value of large and medium firms, not shown), and most of the results are statistically significant. Very similar results were observed for size with the other models.

For welders, no persuasive patterns of findings were observed. The rankings by size categories were inconsistent both within and across the three SICs, and regression coefficients were only very rarely significant or borderline ($p<0.10$). A few statistically significant results were observed under Model Three, but the ranking of the size categories was opposite that from the other models in each case.

For dry cleaners the size of the establishment was not a statistically significant (or borderline) predictor of perchloroethylene exposures in any of the analyses. There was, however, a very consistent pattern (nonsignificant) in the ranking of all the analyses suggesting that geometric mean exposures in small establishments may be approximately one half those of medium or large establishments (which were always quite close and statistically indistinguishable).

Union

In the lead industry, the presence of a union was generally not associated with mean exposures. With only one exception (see below), the regression coefficients for the variable union were not statistically significant or borderline. More importantly, the rank order of mean exposures for union and non-union establishments appeared to be quite random across EGs under each model and particularly across different models for each EG. The sole exception to this pattern was the EG Mixing. For full scope inspections in this EG, all the models suggested that firms with a union had higher mean exposures (roughly twice the geometric mean) than non-union firms. However, this result reached statistical significance only under Model Three.

For dry cleaners the presence of a union was not a statistically significant factor in any of the analyses, and the pattern of ranking of mean exposures according to union status did not reveal any suggestive patterns across the models.

For welders no consistent pattern was observed for the effect of this variable across the three EGs. For SICs 3531 and 3443 all but one of the results suggested that union was not a significant predictor of mean exposures. The single exception was a borderline effect observed for union for SIC 3443 under Model One.

For SIC 3713, however, the results of type-stratified analyses under all models suggested that mean exposures for complaints in union firms were statistically greater than the means for complaints in non-union firms. For planned inspections, no statistically significant effects for this SIC for union were observed.

Scope

For the lead industry the results for the variable scope of inspection are mostly drawn from Model One, with no confirmation from other models because interactions forced many of the analyses to be stratified by this variable. For the EGs Racking, Mixing, and Casting the results of Model One did not identify scope as a significant predictor of mean exposures, and no suggestive ranking pattern was observed. For Pasting, Model One yielded a statistically significant effect, with full scope inspections having approximately twice the mean levels of partial scope inspections. A similar but borderline effect was observed for the EG Burning under Model One. Together, these results suggest that scope may sometimes be a predictor of higher mean exposures in this industry.

For dry cleaners the scope of an inspection was not a statistically significant factor in any of the analyses, and there was no consistent ranking pattern in the categories of this variable across the models.

Among welders the results also strongly suggested that scope is not an important predictor of mean exposures for SICs 3531 or 3713. No statistically significant effects or consistent ranking patterns were observed for this variable in these SICs. The evidence points in the same direction for SIC 3443, except for complaint/full scope inspections under Model Two, which had statistically greater mean exposures than partial scope inspections.

Upper-End Exposures

For the lead battery industry logistic regressions under Model One identified a sizable and statistically significant effect of size on the probability of upper-end exposures (upper quartile). The odds of finding upper-end exposures in small establishments were approximately five times those in large firms. This finding is consistent with the results of the analyses of mean exposures. Logistic analyses also weakly suggested that fewer upper-quartile exposures occurred in latter calendar years, although this effect was less clear in this analysis than in the means analysis, for unknown reasons. No association was found between the probability of upper-end lead exposure and type or scope of inspection, or union presence, although the high variability of the data and the resulting modest power of individual analyses does not permit one to rule out associations that may have gone undetected.

Table V illustrates the results obtained under the multiple logistic model for the effect of type for the lead EGs. The table summarizes the adjusted risk (odds ratio and 95% confidence intervals) of a measurement from a complaint inspection being upper-end (upper quartile of exposure levels) versus being in the lower three quartiles of exposure, as an adjusted function of the variable. Four of the five odds ratios in the table are close to and include one, indicating that complaint inspections did not tend to have a higher relative frequency of upper-end exposures than planned inspections.

TABLE V. Upper-End Lead Exposures, "Risk" of Upper Quartile in Complaint Inspections, by Exposure Groups, Adjusted Odds Ratios and 95% Confidence Limits

Exposure Groups				
Racking	Burning	Pasting	Mixing	Casting
0.95 (0.23–3.77)	0.72 (0.19–2.80)	1.06 (0.18–5.58)	1.06 (0.40–4.57)	0.52 (0.09–3.16)

Upper-end (upper-quartile) inorganic lead exposure values in mg/m^3 were: Racking, 0.152; Burning, 0.111; Pasting, 0.236; Mixing, 0.281; Casting, 0.066

For dry cleaners and welders logistic regression analyses did not identify statistically significant associations between any of the five variables and upper-end exposures, although the high variability of the data and the resulting modest power of individual analyses does not permit one to rule out associations that may have gone undetected.

Variability Explained by the Models

In the lead battery industry the models were able to explain a substantial proportion of the variability in the data (average R^2 values of 0.22 and 0.34 for Models One and Two respectively). For the other EGs the average R^2 values were much smaller (0.07–0.09). Model Three did not yield estimates of R^2.

DISCUSSION

Very few investigators have addressed the issue of extracting useful exposure information from the OSHA data. Stewart and Rice qualitatively described the OSHA system as a potential source of data to support epidemiologic research and provided summary statistics for silica exposures as an example of its contents.[29] Mendeloff used multiple regression analysis to examine the effect of several variables on lead and asbestos exposures in the OSHA data, but his study was only able to use semiquantitative exposure measures (multiples of permissible levels), and it examined only crude "industry averages," without grouping the data into exposure groups.[12] Froines et al. examined OSHA lead data in five industries (including much the same battery data as in this study) and similar variables with logistic regression.[28] They reported that inspection type was a significant variable, with complaint inspections having "median severity levels" (ratio of exposures to the standard) greater than 1 much more frequently than planned inspections. There is a very likely reason, however, for this apparent discrepancy with the results for this variable in this report. The Froines et al. data were not analyzed by EGs, so that in all likelihood the median levels for complaint inspections were inflated, because more samples were taken of high-exposure-potential EGs (the focus of the complaints) during such inspections than during planned inspections.

This study expands the scope of previous work on the OSHA data in several important ways. First, unlike previous work it analyzes the data by EGs, which provides a more valid unit for analysis and understanding of the potential factors that may tend to make the OSHA data unrepresentative of typical workplaces. Secondly, it covers a broader scope of EGs and substances than previous research. Finally, the methods used in the study provide the basis for more persuasive findings about the role of several important variables than in the past.

Many of the results of this study are persuasive because they rely on the weight of the evidence from complementary regression analyses using several regression models. This approach maximized the possibility of detecting effect(s) of the variables on exposure levels. The data generally satisfied the normality and equal variance assumptions for linear regression, and the models spanned the possible behavior of the data with regard to the assumption of independence.

Consistency in findings for the same variable across models indicated that findings were robust (i.e., not dependent on a particular model), and consistent findings across multiple EGs (in the lead and welder EGs) served as cumulative evidence for the role of several specific variables. For example, consistent (and often statistically significant) results from all the models strongly suggested a declining temporal trend in mean perchloroethylene exposures. An even stronger conclusion could be drawn for the size effect in the lead battery industry, which was very consistent and also statistically significant across most models and EGs.

Some of the more interesting findings involve the absence of effects for several variables suspected of introducing unrepresentativeness into the data. These null findings are also often the ones that must be interpreted most cautiously. The power to detect associations in many individual analyses (i.e., one EG and one model) varied considerably, depending on the number of data points, the variability of the data, and the degree of balance in the data (the proportion of observations for different categories of a variable). For example, the analysis under Model One for the EG Mixing was among the weakest because of a low number of observations (N=61). Assuming 80% power and a two-sided significance level of 0.10, the minimum standard deviation difference that could be detected for the variable type would be 0.80 in some of the more unbalanced analyses (i.e., those where the proportion of observations for each type of inspection were in the ratio of 20–80%). In contrast, in the analysis of type for individual means (Model Two) for the EG Racking, the minimum detectable standard deviation difference drops to 0.30–0.40, because the split was closer to 50-50 and the analysis had a much larger number of observations (N=222).

It is reasonable to argue that the observation of consistently null findings for a given variable across models, and particularly across several EGs, can provide persuasive evidence of the absence of a strong effect (e.g., the absence of important type or union effects in most analyses for lead and iron oxide, where the number of observations are fairly high). Even with low to moderate power, as was the case in many of the individual analyses in this study, one would expect strong associations to appear in at least some of the analyses.

The study findings are useful for the design of effective public policy and possibly other applications. For example, the declining trend in lead exposures with time may reflect the impact of the 1978 OSHA lead standard (though the levels are still quite high, see Table I). The evidence for declining perchloroethylene exposures suggests that it would be useful for OSHA to identify the reasons in order to sustain and encourage the reduction of exposures throughout the dry cleaning industry. The strong association of size with average and upper-end lead exposures strongly suggests that targeting of small battery plants for intervention would be valuable.

Although the power to detect negative findings was modest in some of the analyses, the apparent absence of a strong effect for type of inspection in most lead EGs is also a potentially valuable finding, albeit in need of confirmation through additional research. Roughly half of OSHA's inspection resources are devoted to complaint inspections (75% for the battery industry data examined), and the absence of a strong relationship between average or upper-end exposure levels and complaint inspections in this study deserves a closer scrutiny. One plausible interpretation, which the author favors, is that complaints were not strong predictors of lead exposure problems, and thus that alternative means to help target inspection resources are advisable. Less likely, though still possible, is that the findings are an artifact of the analysis (i.e., the complaints may not have been prompted by lead exposures), or the result of other undetected bias.

In general, understanding whether any of these variables result in unrepresentative or biased exposure estimates is important, because it can facilitate more informed use of the data in population risk assessments,[10,45,46] epidemiologic analyses, or modeling efforts.[47,48]

In the initial stages of this study, the author identified approximately two dozen additional EGs in the OSHA data to which this type of analysis could be extended (e.g., to other EGs, industries). Doing so would further expand the potential future uses of the data.

A weakness of this study is the absence of certain information in the OSHA system that would allow better grouping of the data for inferential analysis. For example, the data contain only relatively crude job titles, rather than accurate information about the specific tasks, work practices, work instruments, and controls associated with the measurement. The relatively unsophisticated method of grouping undoubtedly contributed to the high variability of the data and the limited power of some of the analyses.

The use of similar exposure groups in this study, however, is consistent with similar grouping approaches described in the literature and with common industrial hygiene practice. Also, the variability of the exposure groups is not unlike that reported in many other studies (geometric standard deviations of 2–4). Finally, the exposure groups, despite their shortcomings, have clearly identifiable counterparts in the real world.

Questions regarding the representativeness of the OSHA data are also a potential obstacle to drawing useful conclusions from the findings of this study. Evidently, estimates of exposure from the OSHA data would be most useful if they could be defensibly extrapolated to their counterparts in the real world. Theoretically, the only way to validate such an extrapolation would be to compare estimates drawn from the OSHA data to estimates from appropriate random samples of the universe of workplaces subject to OSHA inspections. This study could not attempt such a direct comparison, but it did address the issue of representativeness by (a) analyzing the data as similar exposure groups, thus eliminating much of the so-called worst-case exposure bias that the data allegedly contain; and, (b) by examining the role of the type of inspection, the factor most strongly suspected of making the data unrepresentative (i.e., the potential unrepresentativeness or internal bias introduced by a large percentage of complaint inspection measurements). Planned inspections are a roughly random sample of certain high-risk four-digit SIC codes subject to OSHA inspections, so that the measurements for given EGs from them should be representative of typical exposure levels in those EGs and industries (SICs). Therefore, comparisons of data from complaint inspections to data from planned inspections for specific EGs, as was done in this study, should identify any unrepresentativeness due to this factor. The study findings generally did not suggest that complaint measurements were biased in any direction.

Finally, other sources of unrepresentativeness in the OSHA data are possible but unlikely. The lists of establishments from which planned inspection sites are identified may not be representative of their industries. It is also theoretically possible for employers or employees to adjust their activities soon after OSHA arrives to affect the measurements, although it seems unlikely that this could result in a major across-the-board bias in exposure levels. Also, the analysis of the scope of inspection should have identified this effect, if it exists.

CONCLUSIONS

Mean exposure levels for the five exposure groups in the lead battery industry were inversely proportional to size of the plant (measured as number of employees). Geometric mean exposures in large and medium size establishments were approximately 40% of those in small establishments. Small establishments were five times more likely to have upper-end exposures (upper quartile) than medium or large firms. There was also suggestive evidence that mean exposure levels for four of the exposure groups declined at a rate of approximately 5–9% per year over the period of the study. Neither the type of inspection nor the union status of the establishment were associated with mean or upper end levels of lead exposure, although the power of the analyses to detect associations was sometimes modest. There was some evidence that full scope inspections may be associated with higher levels of mean exposure.

Declines in mean perchloroethylene exposures for dry cleaners were observed during the period of study (7% per year), but no temporal trends were observed for welder exposures to iron oxide. The size, type, scope, and union variables were rarely associated with unequivocal effects on mean or upper-end exposure levels among dry cleaners or welders. The exceptions were some evidence that complaint exposures for welding may be higher than those during planned inspections in one SIC, and that small dry cleaners may have lower average exposures than larger plants

Appendix Table A

Lead Battery Manufacturing Brief Descriptions of Exposure Groups Used as Study Data
Burning Workers connect battery plates into cell elements or groups with small connecting parts, and/or attach battery terminal posts. These operations are carried out by "burning" the parts by applying heat or flame. Exposures arise from lead fume generated by excessive heating, plate handling tasks, brushing of parts, and re-entrainment of dust. Different makes of "cast-on-strap" machines are used to carry out these manufacturing steps, and their names were used as index words to form the groupings (e.g., COS, Farmer, Dynacast, MAC, Tiegal, Intercell).
Casting Workers cast lead into battery grids (grid casters) or other battery parts such as posts, straps, or connectors (small parts casters). Exposures arise from excessive heating of lead, feeding and/or drossing lead pots, and re-entrainment of settled oxide dust.
Mixing Workers mix lead oxide dust and sulfuric acid into a paste to be applied to the grids. Exposures arise from the performance of frequent manual cleaning and maintenance tasks in mixing machines, from leaks in conveyance of lead oxide, and from dust re-entrainment.
Pasting Workers apply lead oxide paste to the grids. Although the process is typically automated, exposures arise from the frequent manual interventions needed to keep paste flowing and to clear equipment jams, as well as dust re-entrainment.
Racking Workers move battery plates between workstations and racks. Exposures arise from the manual handling of dry plates, including removal of pasted plates from drying ovens (offbearers), disposal of scrap plates, parting or splitting of plates, "enveloping" of plates with porous membranes, and "stacking" of plates with insulating separators between them.

Note: Based on reference 35

Although the relatively high variability of the data means that many of the individual null findings are consistent with associations that exist but could not be detected, the overall weight of the null evidence across models and EGs often strongly suggests that the factors are not predictors of mean or upper-end exposures. These null findings must be interpreted cautiously, however, and additional research is needed to confirm them.

In the broadest sense, the most important conclusion is that the study was able to describe the associations (or apparent lack thereof) of several factors with exposure levels in nine EGs, despite the imperfections in the data. The findings clarify the role of these variables, shed light on whether the OSHA data may be representative of typical workplaces, and thus facilitate the use of the OSHA data for exposure assessment applications. Finally, the methods of analysis are also applicable to other EGs in the OSHA data.

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