HHS Public Access
Author manuscript
J Occup Environ Hyg. Author manuscript; available in PMC 2017 September 01.

Published in final edited form as:
J Occup Environ Hyg. 2016 September ; 13(9): 668–674. doi:10.1080/15459624.2016.1165913.

Cross-Classified Occupational Exposure Data

Rachael M. Jones[1,*] and **Igor Burstyn**[2]

[1]School of Public Health, University of Illinois at Chicago

[2]Dornsife School of Public Health, Drexel University

Abstract

We demonstrate the regression analysis of exposure determinants using cross-classified random effects in the context of lead exposures resulting from blasting surfaces in advance of painting. We had three specific objectives for analysis of the lead data, and observed: 1) high within-worker variability in personal lead exposures, explaining 79% of variability, 2) that the lead concentration outside of half-mask respirators was 2.4-fold higher than inside supplied-air blasting helmets, suggesting that the exposure reduction by blasting helmets may be lower than expected by the Assigned Protection Factor, and 3) that lead concentrations at fixed area locations in containment were not associated with personal lead exposures. In addition, we found that, on average, lead exposures among workers performing blasting and other activities was 40% lower than among workers performing only blasting. In the process of obtaining these analyses objectives, we determined that the data were non-hierarchical: Repeated exposure measurements were collected for a worker while the worker was a member of several groups, or cross-classified among groups. Since the worker is a member of multiple groups, the exposure data do not adhere to the traditionally assumed hierarchical structure. Forcing a hierarchical structure on these data led to similar within-group and between-group variability, but of precision in the estimate of effect of work activity on lead exposure. We hope hygienists and exposure assessors will consider non-hierarchical models in the design and analysis of exposure assessments.

Keywords

Cross-classified data; hierarchical data; lead; abrasive blasting

INTRODUCTION

The inhalation and dermal occupational exposures of a worker varies from day to day, and systematically among workers. [1,2] Estimating within-worker variability requires repeated exposure measurements for workers, while between-worker variability requires exposure measurements on more than one worker. As reviewed by Burdorf and van Tongeren, [3] the concept of within- and between-worker exposure variability has been extensively used to evaluate classification of workers into similar exposure groups, within which workers have small between-worker variability (and similar exposure groups are distinguished by large

*Corresponding Author: 2121 W Taylor St. (M/C 922), Chicago IL 60612, rjones25@uic.edu, 312-996-1960 (phone), 312-413-9898 (fax).

between-group variability). This application involves a hierarchical structure, in which each worker is a member of one group (i.e. workers are nested in groups) and exposure and risk patterns for a group are assumed to apply more to members of a given group than to members of another group. The models also assume that exposure distributions are time-invariant, though this can be addressed by modeling time trend.[4]

The concept of similar exposure groups imposes a hierarchy, but this hierarchy may not be observed in all occupational exposure assessments. When exposure is measured repeatedly for a worker who changes groups from day-to-day the nesting assumption in the hierarchical model is violated. An example is the promotion of a worker to a supervisory role (presumed low exposure) from frontline work (presumed high exposure) within the same work area. Another example may arise when, one classifies construction painters as working in enclosed versus open spaces but a specific individual paints the machine room of ship on one day and its exterior on another. [5] That is, a worker may belong to more than one group. Workers who participate in more than one group may be unique, and ignoring their participation in multiple groups may result in incorrect representation of group differences. Clearly the definition of a group is not universal, but is driven by the analysis objective.

More formally, a cross-classified scenario is described as follows. Consider a worker of whom four 8-hour TWA exposure assessments were collected. On day d_1, d_2, and d_4 the exposure measure was collected while the worker was in Group 1. On day d_3, the exposure measure was collected while the worker was in Group 2. Group is used here to indicate any type of categorization, such as by work location, work tasks, etc., and does not refer specifically to similar exposure groups as typically defined for epidemiology. These exposure measurements are cross-classified among workers and groups (Figure 1), and no strict hierarchy exists.

Cross-classified models have been applied in education research, and many instructional examples use this context, [6–8] though other examples are available in public health. [9,10] The models are an extension of hierarchical models, and the cross-classified data structure with associated variance components are modeled as random effects. Fixed effects can be added, depending upon the research question. In the context of occupational exposure assessment, regression models used to identify exposure determinants have used a hierarchical structure, [11–13] but need for a cross-classified structure may arise.

The objective of this paper is to describe models for cross-classified occupational exposure assessment data, and illustrate their application to a study of lead exposures during the preparation of bridge surfaces for painting. While cross-classified data involve a different conceptualization of random effects, in practice, the data are modeled similarly to hierarchical data and can be readily implemented in most statistical software. By illustrating modeling cross-classified data so as to obtain similar information about variance components and exposure determinants commonly obtained through hierarchical structures, we hope to improve the analysis and presentation of cross-classified occupational exposure data; and enhance the utilization of naturally arising non-hierarchical exposure assessment strategies.

Author Manuscript

Author Manuscript

Author Manuscript

THE RANDOM EFFECT MODEL

Recall the hierarchical random effects model. Let y_{kij} represent the logarithm of the exposure concentration measured for the *i*th worker in group *k* on the *j*th day. The three-level model is:

$$y_{kij}=\beta_0+\nu_k+\gamma_{ki}+\varepsilon_{kij} \quad \text{Eq. 1}$$

where β_0 is the grand mean of the logarithm of the exposure concentrations, ν_k is the deviation of the mean logarithm of the exposure concentration for group *k*, γ_{ki} is the deviation of the mean logarithm of the exposure concentration for worker *i* in group *k* from the group mean, and ε_{kij} is the residual error representing the deviation of the logarithm of the *j*th exposure concentration from the mean for worker *i* in group *k*. The parameters ν_k, γ_{ki}, and ε_{kij} are independent and normally distributed with mean zero and variances σ_G^2, σ_B^2, and σ_W^2, respectively. The subscripts G, B and W remind us that the variance components reflect between-group, between-worker and within-worker contributions the total variability in exposure concentrations, respectively. The mean of the logarithm of the exposure concentrations for group *k* is $\beta_0 + \nu_k$.

When workers are not exclusively nested within groups, the exposure data are cross-classified. Cross-classified models can be represented using notation similar to Eq. 1, but this notation is ambiguous: Other notations are more explicit, such as the classification notation of Browne et al. [(14)] used herein. Let y_i denote the logarithm of the *i*th exposure concentration, which is cross-classified among workers and groups. Let $group(i) \in \{1, 2, \ldots, k\}$ and $worker(i) \in \{1, 2, \ldots, w\}$ indicate the group and worker associated with the *i*th exposure measurement. The random effects model is:

$$y_i=\beta_0+u^{(3)}_{group(i)}+u^{(2)}_{worker(i)}+\varepsilon_i \quad \text{Eq. 2}$$

where β_0 is the grand mean of the logarithm of the exposure concentrations, $u^{(3)}_{group(i)}$ and $u^{(2)}_{worker(i)}$ are the random effects for the group and worker levels with superscript (2) indicating the worker level, and superscript (3) indicating the groups into which workers are cross-classified, and ε_i is the residual error for the logarithm of the *i*th exposure measurement. The superscripts are not strictly necessary, but are a notational convention to indicate the levels of grouping. The random effects $u^{(3)}_{group(i)}$ and $u^{(2)}_{worker(i)}$ are independent and normally distributed with mean zero and variance σ^2_G and σ^2_B and ε_i is independent and normally distributed with mean zero and variance σ^2_W. The mean of the logarithm of the exposure concentrations for group *k* is $\beta_0 + u^{(3)}_{group(i)}$.

ROLE OF FIXED EFFECTS

It is common in hierarchical analysis of occupational exposure data to use a two-level random effect structure, and incorporate the group variable as a fixed effect to represent the mean of the logarithm of the exposure concentrations for each group, instead of as a random effect. [13] This approach would transform Eq. 1 into

$$y_{kij}=\beta_k+\gamma_{ki}+\varepsilon_{kij} \quad \text{Eq 3}$$

where β_k is the mean of the logarithm of the exposure concentration for group k, and is a fixed effect. This formulation allows for statistical testing of differences in the exposure concentrations among groups, but this may not always be the analysis objective. A three-level random effects structure, such as in Eq. 1 or 2, is appropriate for exploration of exposure determinants common to multiple groups. A model containing n fixed effects with three-levels of random effects with cross classified data is

$$y_i=\beta_0+\sum_{j=1}^{n}\beta_j x_{j,i}+u^{(3)}_{group(i)}+u^{(2)}_{worker(i)}+\varepsilon_i \quad \text{Eq. 4}$$

where β_j is the regression coefficient for the fixed predictor variable $x_{j,i}$, where j ={1, 2,…, n}.

IMPLEMENTATION

Implementation of cross-classified random-effects models is straightforward in most statistical software. The Center for Multilevel modeling has examples in Stata and MLwiN. [8] In the R Project for Statistical Computing, cross-classified data are readily handled in the *lme4* package version 1.1–8. [15] The *lme4* random effects covariance structure used is an identity matrix multiplied by the residual variance, with off-diagonal entries multiplied by an additional random-effect specific coefficient, θ. In R, the *nlme* package has more flexibility for random effect covariance structures, but does not readily implement cross-classified random effects models. In SAS, dummy variables must be added to the data to represent the cross-classified random effects with the MIXED procedure, [16] which was previously the case in R. [6]

The analysis in this study was implemented using the *lmer* function in the *lme4* package as follows: *lmer*(y ~ x_1 + x_2 + (1|group) + (1|worker), data = named.data, REML = TRUE), where named.data is a data frame containing variables x_1 (a fixed effect), x_2 (a fixed effect), y (the outcome of interest), group (indicating the group for each measurement), and worker (indicating the worker for each measurement). The group and worker variables can be factors or numerical, and contain unique identifiers for each worker and group.

AN EXAMPLE

The exploration of cross-classified data structures was motivated by an interest in lead exposures during surface preparation activities, measured at four work areas in Chicago, IL in 1991 and 1992. [17,18] The objectives of the analyses are to: 1) determine the magnitude of within- and between-worker variance, 2) determine the extent to which lead concentrations measured at fixed locations within the containment area explain the personal breathing zone (PBZ) concentration of lead, and 3) determine the effectiveness of supplied-air blasting helmets.

With respect to objective 2, we considered lead concentrations measured at fixed locations may be influenced by the work activity being performed because the work activity may require increased proximity to the point source (e.g., the point of blasting). With respect to objective 3, we were interested to know if through statistical analysis we could verify the protection afforded by supplied-air blasting helmets. Typically, the effectiveness of respiratory protection is defined as the difference between the contaminant concentrations simultaneously measured inside and outside of the respirator while worn under normal (or simulated) working conditions, termed the (simulated) workplace protection factor. This objective, however, was prompted by exploratory analyses indicated the concentration of lead inside blasting helmets was higher than those estimated to be inside half-mask respirators (Table I), even when the lead concentrations at fixed locations within containment were similar and workers performed the same work activity (but had different job titles). Respirator use was determined by job title, not work activity.

This analysis included data from three work areas – Michigan Avenue bridge (MI-Bridge), Michigan Avenue viaduct (MA Viaduct), and Melrose Park bridge (MP-Bridge) – and study days on which lead concentrations were measured at fixed locations in containment. The location of work is important to understanding the exposures because each site had a unique containment structure and the lead content of paint differed by work area. [17]

A total of 117 PBZ exposures were measured among 25 workers at these work areas. Each worker was subject to 1–13 (median 4) measurements. Nine workers had PBZ exposures measured at both the MI-Bridge and MI-Viaduct work areas, indicating that the exposure measurements are cross-classified among work areas, rather than nested in a hierarchy. Simultaneous to the PBZ measurements, lead concentrations were measured at three fixed locations within containment. PBZ and fixed area measurements were collected on 37 mm Millipore mixed cellulose ester filters (closed-face cassette) and analyzed by an IL Video 22 Atomic Absorption/Emission Spectrophotometer consistent with the 1990 NIOSH Manual of Analytical Methods. [17,18] All measurements were above the limit of detection.

Ten workers wore supplied-air blasting helmets, in which case the PBZ exposure was measured inside the helmet. Sixteen workers wore half-mask respirators, in which case the PBZ exposure was measured outside the respirator. Workers had a variety of job titles (blaster/sweeper, foreman, equipment operator, helper, supervisor, tool and inspector), but job titles were not tied closely to work activities performed: The data reflect PBZ exposures during abrasive blasting or power tooling activities.

The PBZ exposure measurements are summarized in Table I, and indicate frequent exposures above the Permissible Exposure Limit at the time, 50 μg/m^3 (29 CFR 1910.1025 promulgated 1978). When the Assigned Protection Factor (APF) of 10 was applied to PBZ exposures measured outside half-mask respirators, [19] 45% of exposure measurements were above the exposure limit (Table I). The 22 unique lead concentrations measured at fixed locations are summarized in Table II.

The objectives were attained using a multiple mixed-effects regression model that predicts the logarithm of the ith lead concentration measured in the worker's breathing zone, y_i:

$$y_i=\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,i}+u^{(3)}_{area(i)}+u^{(2)}_{worker(i)}+\varepsilon_i \qquad \text{Eq. 5}$$

where $x_{1,i}$ is the type of respirator worn during the ith personal exposure measurement ($x_{1,i}$ = 0 when a supplied-air respirator helmet was worn and exposure was measured inside the helmet, and $x_{1,i}$ = 1 when a half-mask elastomeric respirator was worn and exposure was measured outside the respirator), $x_{2,i}$ is the logarithm of the lead concentration measured at the corresponding fixed area location and $x_{3,i}$ is the work activity performed ($x_{3,i}$ = 0 when only abrasive blasting was performed and $x_{3,i}$ = 1 when abrasive blasting and other support activities were performed); β_1 to β_3 are the fixed effects associated with predictors x_1 to x_3.

The random effects structure includes random intercepts for area and worker, $u^{(3)}_{area(i)}$ and $u^{(2)}_{worker(i)}$. Though there were relatively few work areas to include a random effects term, the term was included because the fixed area lead concentration measurements were repeated measures at the work area level and associated with ≥ 1 PBZ measurement. Objective 1, however, involved a model containing only the intercept and random effects of Eq. 5, where the key parameters of interest are σ^2_B and σ^2_W.

Objective 1 was addressed by estimating the magnitudes of σ^2_B and σ^2_W with the random effects model (Table III). The between-worker and within-worker variance components are represented by standard deviations $\hat{\sigma}_B$ = 0.454 (95%CI: <0.001, 0.899) and $\hat{\sigma}_W$ = 1.36 (95%CI: 1.19, 1.59), which correspond to geometric standard deviations of 1.57 and 3.90, respectively. The range of exposures experienced day-to-day between workers and within workers, ${}_BR_{0.95}$ and ${}_WR_{0.95}$ (Kromhout et al., 1993; Rappaport et al., 1993), were estimated span factors of 5.92 and 208, respectively. The within-worker variability was estimated to be high, and ${}_WR_{0.95}$ = 208 falls above the 80th percentile of values observed by Kromhout et al. [1] in an analysis of a large database of chemical exposures. The between-group variability was estimated to have standard deviation $\hat{\sigma}_G$ = 0.538 (95%CI: <0.001, 1.57). Of the total variance in personal exposures $(\hat{\sigma}^2_B+\hat{\sigma}^2_W+\hat{\sigma}^2_G)$, 79% was due to day-to-day variation within workers ($\hat{\sigma}^2_W$). The lower limit of 95%CI for $\hat{\sigma}^2_G$ and $\hat{\sigma}^2_B$ approached zero (Table III), suggesting that the sample size is insufficient to estimate these variance components with precision. These variance components were retained in the model, however, to represent the structure of the data, including the association of fixed area lead concentrations with multiple personal exposure measurements. When fixed effects were added to the regression model (Table III), the magnitude of the between-group and between-worker variance components diminished, which was expected since the variance was now conditioned on the fixed effects that vary primarily between groups and workers.

With respect to objective 2, the coefficient for the logarithm of the lead concentration measured at fixed locations was estimated to be, on average, $\hat{\beta}_2$ = 0.033 (95%CI: −0.154, 0.233) (Table III). This means that there is not statistically significant association between the logarithms of the lead concentrations measured at fixed locations and in the PBZ, conditioned on the other model parameters.

With respect to objective 3, the difference between the logarithm of the lead concentration in the breathing zone outside the half-mask respirator and inside a supplied-air blasting helmet was estimated to be, on average, $\hat{\beta}_1$ = 0.892 (95%CI 0.261, 1.56) (Table III). This means the lead concentration outside a half-mask respirator was 2.4 fold higher than inside a supplied-air blasting helmet (95%CI approximately 1.3-fold to 5-fold higher): This magnitude of difference persists with consideration of the intercept and other terms in the regression model. This effect was separate from the effect work activity, $\hat{\beta}_3$ = −0.896 (95%CI −1.70, −0.097): We tested and verified the interaction between work activity and respirator type was not statistically significant ($\hat{\beta}_{1\text{- }3\text{ interaction}}$ = −0.880 (95%CI −2.55, 0.674)). The mean logarithm of exposure during performance of blasting and other support activities was 40% (exp $\hat{\beta}_3$) of the level during performance of only blasting activities.

The standard hierarchical model, which is miss-specified for these data, was fitted to the data (Table III), where the most-frequent work location was assigned as the group. Worker 1, for example, had four PBZ measurements at the MI-Bridge location and one PBZ measurement at the MI-Viaduct location and so was assigned to MI-Bridge for all five measurements. The hierarchical model yielded similar, if slightly smaller, estimates for $\hat{\sigma}_G$ and $\hat{\sigma}_B$, and consequently a slightly larger estimate for $\hat{\sigma}_W$. The interferences for the primary analysis objectives, were similar with both the hierarchical and cross-classified models, but the effect work activity was not statistically significant in the hierarchical model ($\hat{\beta}_3$ = −0.729 (95%CI −1.61, 0.078)).

The residuals of the cross-classified model showed no evidence of heteroscedasticity in plots.

DISCUSSION

The primary objective of this study was to introduce the concept of data cross-classification in occupational exposure assessment, illustrating that these data can be readily analyzed to explore exposure variability and determinants similarly to more traditional hierarchical modeling of data. Consequently, we reviewed the regression models for cross-classified data, and illustrated its application characterization of determinants of exposures to lead during surface preparation activities for painting. Contemporary statistical methods readily surmount the increased complexity in the non-hierarchical data, which may arise naturally in sampling campaigns designed for objectives other than characterizing similar exposure groups.

The secondary objective of this study was to explore lead exposures during blasting activities in surface preparation for painting. A key finding in the analysis of the blasting data was that lead exposures measured outside half-mask respirators were 2.4-fold higher than lead exposures measured inside supplied-air blasting helmets, on average (97.5th percentile of the effect estimate on the order of 5-fold). This is an imperfect measure of respirator performance, but suggests that air-supplied blasting helmets may not perform as expected, reducing exposures by 2.4-fold, on average. Workers in this study wore CE-type supplied-air abrasive blasting helmets, [(18)] which have an APF ≥ 25, depending upon the fit of the hood and delivery of fresh air. [(19)] A respirator that achieves a protection factor of 25 should reduce the lead concentration inside the respirator 25-fold relative to the concentration outside the respirator, a much greater reduction than predicted in the statistical model. Virji et al., [(20)] analyzing data very similar to these data, also observed that lead exposures were higher than expected when measured inside blasting helmets, but described instances when workers took off their blasting helmets between blasting sessions while in the presence of other dust-generating activities, and at the end of shift. This could explain some of the limited performance of the supplied air helmets, but it is important to focus on real-life performance of the control measures (which we estimated). Certainly, another explanation for this result is that workers performed different activities when wearing the two respirator types, resulting in different near-field exposure, but work activity was found to be associated with lead exposures (Table III). A strength to this result, however, was that in this study, workers wore air-supplied blasting helmets and half-mask respirators while performing the same activities (blasting or blasting with other activities like setting up, cleaning, moving containment and painting) in the same work areas: Respirator type was determined by job title, not activity or containment area. All workers who wore half-mask respirators had job title “blaster/sweeper”, while only air-supply blasting helmets were worn by foremen, equipment operators, helpers and supervisors.

The second finding was that lead concentrations measured at fixed locations were poor predictors of PBZ lead exposures: The confidence interval around $\widehat{\beta_2}$ is wide and includes zero, indicating that the positive association may be due to random chance. To our knowledge, lead concentrations at fixed locations in containment have not been used to predict PBZ exposures in the context of blasting operations. Virji et al., [(20)] consistent with this study, observed lead concentrations measured at fixed locations inside containment to vary several orders of magnitude, but did not compare fixed location and PBZ lead concentrations. It makes sense that there should be some positive association between the lead concentration in the work area and in the PBZ, since air exchanges between these two locations, but the applicability of simple mass-balance models – e.g., the two-zone or well-mixed models, [(17,21)] to this scenario is unclear owing to the presence and movement of multiple workers, each of who creates a source of lead, and potential non-linearity of the relationship.

The lead content of the paint and thickness of paint should be associated with the lead concentration in the work area during blasting operation as these factors affect total lead emission. [(17)] While Booher[(22)] found relatively poor correlation between the lead content of paint and lead concentrations in air during sanding (Person’s $\rho = -0.27$) and chipping

(Pearson's ρ = 0.44) during ship overhaul, Zedd et al. [23] reported a stronger correlation, with Spearman's ρ between 0.4 and 0.6, depending on work activity. This and other location-specific factors like containment ventilation and efficiency were not specifically explored in this work because of limited number and variability in location-specific data, but these analyses would be possible if more locations were studied. The absence of these factors in the models may have left some residual confounding in our estimates.

Cross-classified data represent a first step beyond strictly hierarchical structures for occupational exposure data, but another related data structure involves membership in multiple groups. [14] That is, the exposure measurement was collected while the worker was a member in multiple groups. An example of multiple membership data in this work is the PBZ exposures measured for three workers who moved around at Michigan Avenue work areas, and spent time in both the MI-Bridge and MI-Viaduct work areas during a single exposure measurement. Multiple-membership can occur when exposure assessment strategies are tasked-based, but may be more common in the context of long-term exposure assessment campaigns, or when detailed observations about tasks performed during a full-shift are made but the exposure is integrated through shift-duration sampling. For example, radiation dosimeters are worn for months at a time, and workers may change job activities or job titles during the monitoring period resulting in membership of multiple similar exposure groups or work area; and biological markers of chronic exposure may similarly reflect occupational exposures occurring in multiple groups and/or environmental exposures occurring in multiple microenvironments.

CONCLUSIONS

In this example, we found that the incorrectly specified hierarchical model, which required re-classification of work areas for some workers on some days, yielded similar inferences to the cross-classified model, but underestimated the between-worker and between-group variance and the estimates of fixed effects, representing determinants of exposure, were estimated less precisely. The cross-classified model, however, correctly represents the variance structure of the exposure assessment strategy. Through this demonstration, we hope hygienists and exposure assessors will consider non-hierarchical models in the design and analysis of exposure assessments.

Acknowledgments

This work was supported by the award 1K01OH010537-01 from the National Institute for Occupational Safety and Health. We thank Lorraine Conroy for sharing the lead exposure data, and Donald Hedeker for constructive discussions about non-hierarchical data and mixed-effects regression models.

References

1. Kromhout H, Symanski E, Rappaport SM. A comprehensive evaluation of within- and between-worker components of occupational exposure to chemical agents. Ann Occup Hyg. 1993; 37:253–270. [PubMed: 8346874]
2. Kromhout H, Vermuelen R. Temporal, personal and spatial variability in dermal exposure. Ann Occup Hyg. 2001; 45:257–273. [PubMed: 11378147]
3. Burdorf A, van Tongeren M. Variability in workplace exposures and the design of efficient measurement and control strategies. Ann Occup Hyg. 2003; 47:95–99. [PubMed: 12581994]

4. Symanski E, Kupper LL, Kromhout H, Rappaport SM. An investigation of systematic changes in occupational exposure. AIHA J. 1996; 57:724–735.
5. Burstyn I, Kromhout H. Trends in inhalation exposure to hydrocarbons among commercial painters in the Netherlands. Scand J Work Environ Health. 2002; 28:429–438. [PubMed: 12539803]
6. Lockwood JR, Doran H, McCaffrey DF. Using R for estimating longitudinal student achievement models. R News. 2003; 3(3):17–28.
7. Goldstein, H. Multilevel Statistical Models. Hoboken, NJ: John Wiley & Sons, Ltd; 2011.
8. Module 12: Cross-Classified Multilevel Models. 2015. [Online] Available at: http://www.bristol.ac.uk/cmm/learning/course.html
9. Muntaner C, Li Y, Xue X, Thompson T, Chung HJ, O'Campo P. County and organizational predictors of depression symptoms among low-income nursing assistants in the USA. Social Science & Medicine. 2006; 63:1454–1465. [PubMed: 16765496]
10. Young RL, Weinberg J, Vieira V, Ascengrau A, Webster TF. A multilvel non-hierarchical study of birth weight and socioeconomic status. Int J Health Geographics. 2010; 9:36.
11. Preller L, Kromhout H, Heederik D, Tielen MJM. Modeling long-term average exposure in occupational exposure-response analysis. Scand J Work Environ Health. 1995; 21:504–512. [PubMed: 8824757]
12. Burstyn I, Teschke K. Studying the determinants of exposure: a review of methods. AIHA J. 1999; 60:57–72.
13. Peretz C, Goren A, Smid T, Kromhout H. Application of mixed-effects models for exposure assessment. Ann Occup Hyg. 2002; 46:69–77. [PubMed: 12005135]
14. Browne WJ, Goldstein H, Rasbash J. Multiple membership multiple classification (MMMC) models. Statistical Modelling. 2001; 1:103–124.
15. Package 'lme4' Version 1.1–7. [Online] Available at: http://cran.r-project.org/web/packages/lme4/lme4.pdf
16. Rasbash J, Goldstein H. Efficient analysis of mixed hierarchical and cross-classified random structures using a multilevel model. J Ed Behav Stat. 1994; 19:337–350.
17. Conroy LM, Menezes Lindsay RM, Sullivan PM. Lead, chromium and cadmium emission factors during abrasive blasting operations by bridge painters. AIHA J. 1995; 56:266.
18. Conroy LM, Menezes-Lindsay RM, Sullivan PM, Cali S, Forst L. Lead, chromium and cadmium exposure during abrasive blasting. Arch Environ Health. 1996; 51:95–99. [PubMed: 8638970]
19. Occupational Safety and Health Administration. Assigned Protection Factors for the Revised Respiratory Protection Standard. OSHA. 2009; 2009:3352–02.
20. Virji MA, Woski SR, Pepper LD. Task-based lead exposures and work site characteristics of bridge surface preparation and painting contractors. J Occup Environ Hyg. 2008; 6:99–112.
21. Nicas M. Estimating exposure intensity in an imperfectly mixed room. AIHA J. 1996; 57:542–550.
22. Booher LE. Lead exposure in a ship overhaul facility during paint removal. AIHA J. 1988; 49:121–127.
23. Zedd HC, Walker YP, Hernandez JE, Thomas RJ. Lead exposures during shipboard chipping and grinding paint-removal operations. AIHA J. 1993; 54:392–396.

Author Manuscript

Author Manuscript

Author Manuscript

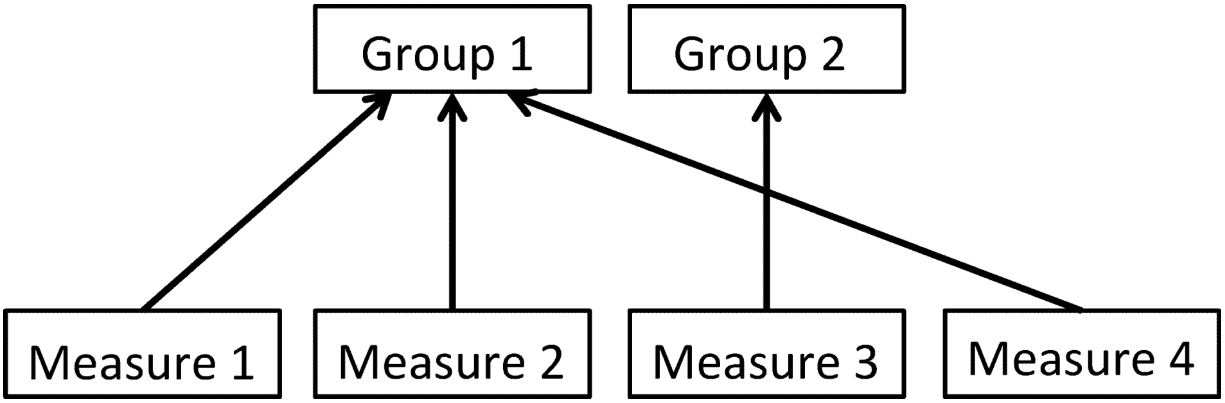

Figure 1.

Cross-classified exposure data for an individual worker for whom four exposure measurements were collected while the worker was in one of two groups.

Table I

Personal breathing zone lead exposure (μg/m^3) measured during blasting activities summarized by location of work and respirator type (exposure measured inside air-supplied helmet and outside half-mask respirator), and compared to the OSHA PEL, 50 μg/m^3.

Location	Respirator Type[A]	Sample Size	Lead Exposure Mean	Lead Exposure GM	Lead Exposure GSD	% > 50 μg/m^3[B]	Mann-Whitney Test p-value[B]
MI-Bridge	Half-Mask	37	1,170	559	4.17	95 (54)	0.003 (0.015)
	Helmet	24	479	180	4.15	75	
MI-Viaduct	Half-Mask	31	507	215	3.71	87 (29)	0.506 (<0.001)
	Helmet	20	188	137	2.69	85	
MP-Bridge	Half-Mask	5	2,126	853	9.39	80	–
	Helmet	0	–	–	–	–	
All	Half-Mask	73	953	383	4.52	90 (45)	0.002 (<0.001)
	Helmet	44	347	159	3.45	80	

[A] When half-mask respirator was worn, lead exposure was measured outside the respirator. When helmet was worn, lead exposure was measured inside the helmet.

[B] Values in parenthesis consider the assigned protection factor of a half-mask respirator, APF = 10, in the comparison with the exposure limit

Table II

Lead concentrations (μg/m^3) measured at fixed locations in the containment structures.

Location	Sample Size	Lead Exposure Mean	GM	GSD
MI-Bridge	11	11,089	5,644	4.58
MI-Viaduct	8	6,268	3,582	3.32
MP-Bridge	3	15,554	14,224	1.70
All	22	9,942	5,427	3.84

Table III

Regression model predicting the logarithm of the lead concentration (*log*(μg/m^3)) in the breathing zone of workers.

Parameter	Cross-Classified Model				Hierarchical Model	
	Point Estimate	95%CI	Point Estimate	95%CI	Point Estimate	95%CI
Random Effects (standard deviations)						
Between-groups σ_G	0.538	<0.001,1.57	0.425	<0.001,1.25	0.412	<0.001,1.19
Between-workers, σ_B	0.454	<0.001,0.899	0.367	<0.001,0.756	0.271	<0.001,0.707
Within-workers, σ_W	1.36	1.19,1.59	1.82	1.16, 1.56	1.37	1.18, 1.58
Fixed Effects						
Intercept, β_o	–	–	4.91	3.12, 6.62	4.49	2.76, 6.22
Respirator type, β_1	–	–	0.892	0.261, 1.56	0.959	0.324,1.58
Lead concentration in area (logarithm), β_2	–	–	0.033	−0.154, 0.233	0.079	−0.119,0.272
Work activity, β_3	–	–	−0.896	−1.70, −0.097	−0.729	−1.61,0.078