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Application of Mixed Models to Assess Exposures Monitored by Construction Workers During Hot Processes

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Particulate exposures were assessed among construction workers engaged in hot processes in four jobs (boilermakers, ironworkers, pipefitters and welder-fitters) at nine sites in the U.S. After being trained by occupational hygienists, the workers obtained shift-long personal samples at each site for total particulates (TP). Selected samples were also assayed for manganese (Mn), nickel (Ni), and chromium (Cr). Workers provided information about process- and task-related covariates that were present on the days of monitoring. Data were investigated with mixed-model regression analyses that designated the jobs and covariates as fixed effects and the worker and error terms as random effects. Results indicated that the within-worker variance components, but not the between-worker variance components, could be pooled among jobs. Mean air levels for a given agent varied by roughly six to 100 fold among the jobs, with boilermakers and ironworkers experiencing much higher levels of TP and Mn than pipefitters and welder-fitters. Limited data also suggested that welder-fitters were exposed to greater levels of Ni and Cr than pipefitters. Sufficient sample sizes were available to evaluate the effects of covariates upon exposures to TP and Mn. As expected, processes involving more than 50% hot work led to substantially higher levels of TP and Mn than those involving shorter durations of hot work. Local-exhaust or mechanical ventilation reduced exposure to TP (but not Mn) by as much as 44%, and shielded or manual arc welding increased exposure to Mn (but not TP) by about 80%. Parameters estimated with these mixed models were used to calculate probabilities that workers were exposed at levels above U.S. occupational exposure limits (OELs). Regarding TP and Mn, these calculations suggested that 26–95% of exposures to boilermakers and pipefitters and 2–13% of exposures to pipefitters and welder-fitters exceeded the current Threshold Limit Values. Among welder-fitters, limited data also pointed to probabilities of 2–50% for exceeding particular OELs for Ni and Cr. Using the significance of the estimated random-worker effects as a gauge for the uniformity of exposure within a job, administrative or engineering changes appear appropriate for reducing exposures to boilermakers and ironworkers, while individual personal environments should be investigated for pipefitters and welder-fitters.

Keywords: particulates; manganese; hot processes; mixed models; exposure assessment methods

INTRODUCTION

It has become clear that occupational exposures vary greatly both within workers over time and between workers in the same job (Kromhout *et al.*, 1987, 1993; Spear *et al.*, 1987; Rappaport, 1991; Heederik *et al.*, 1991; Kumagai *et al.*, 1996;

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Tornero-Velez *et al.*, 1997; Peretz *et al.*, 1997). Such variability complicates assessments of exposure because repeated measurements must be obtained from several workers to evaluate the effects of the job and other covariates upon exposure (Kromhout *et al.*, 1994; Woskie *et al.*, 1994; Preller *et al.*, 1995; Lagorio *et al.*, 1998). Large organizations, employing full-time health professionals, should have the resources to conduct such evaluations, particularly for exposures at fixed production facilities. However, smaller organizations and those engaged with production at diverse locations face difficulties in obtaining sufficient data. Thus, new approaches are needed to facilitate the collection of exposure data at modest cost.

A promising avenue for increasing sample sizes involves self-monitoring by workers as part of the survey design (Rappaport, 1991; Rappaport *et al.*, 1995). Such an approach was successful in a large study of electric field exposures among electric utility workers by employing direct reading monitors that were inexpensive and simple to use (Loomis *et al.*, 1994; Kromhout *et al.*, 1995). However, in situations involving exposures to airborne chemicals, particularly aerosols, measurement devices are expensive, people must be trained to apply the methods, and laboratory analysis is required. We are unaware of any previous studies in which workers have measured their own exposures to airborne particles.

We wished to evaluate exposures to airborne particles among construction workers engaged in hot processes throughout the United States. Such exposures occur routinely among construction trades including boilermakers (BM), ironworkers (IW), pipefitters (PF), sheet metal workers and glaziers. Our goal was to obtain sufficient data from the principal welding trades to make inferences about the effects on exposure of the job, as well as of process- and task-related covariates, and to predict the probabilities of exceeding particular occupational exposure limits (OELs). Because journeyman workers are an important resource for defining process variables associated with their trades and to enhance the collection of data, workers were trained to collect personal samples and to obtain information about covariates as measurements were made (Susi *et al.*, in press).

The tasks and activities involved in the three construction trades have been summarized in a set of generic job definitions (AGCA, 1992). Briefly, BM (generic title 'Boilermaker I', 805.261-014) assemble, repair or dismantle pressure vessels, tanks and vats using a variety of torches and welding equipment. IW (generic title 'Structural-Steel Worker', 801.361-014) assemble girders, columns, etc. into large steel structures, making use of torch-cutting equipment to make alterations. PF (generic title 'Pipe Fitter', 862281-022) install and maintain pipe systems for steam, heating and cooling, refrigeration, etc.; this often involves precision welding of structural or stainless steel. Among members of the pipefitter trade it is common for certain individuals to specialize in welding procedures, in which case the work could be designated under other generic titles, particularly 'Arc Welder' (810.384-014) or 'Welder-Fitter' (819.361-010).

In evaluating the various effects of important variables upon exposure, we recognized the inherent advantage of mixed effects statistical models that can be used to estimate both fixed effects, associated with different jobs and covariates, as well as the within- and between-worker variance components, associated with the random effects. Yet, despite this advantage, we are unaware of published applications of mixed effects models in this context. Indeed, previous investigations relied upon a two-step process, in which random effects were estimated separately from fixed effects, using models which were probably not optimal for either type of analysis (Kromhout *et al.*, 1994; Woskie *et al.*, 1994; Preller *et al.*, 1995; Lagorio *et al.*, 1998).

In what follows we will describe a study in which construction workers obtained personal samples of exposures to particulate matter during hot processes and obtained information about potentially significant covariates. We will then apply mixed models to evaluate the fixed effects of jobs and covariates upon levels of exposure to total particulates (TP) and manganese (Mn) and the effect of job (but not covariates) upon exposure to nickel (Ni) and chromium (Cr). Then, we will use the estimated fixed effects and variance components to estimate probabilities of exceeding OELs. Finally, we will use the predicted random worker effects to explore the uniformity of exposure as well as the options for controlling exposures in the various jobs.

MATERIALS AND METHODS

Data collection

Data were collected as part of a systematic investigation of the construction industry, which has been described elsewhere (Susi *et al.*, in press). Briefly, field surveys were conducted at nine construction sites. One site involved boilermakers welding inside a process vessel at a refinery as part of a turn-around project. Another site involved ironworkers engaged in torch cutting as part of a bridge rehabilitation project. Seven sites involved pipefitters engaged in both industrial and commercial new construction and rehabilitation. All measurements were performed during 1995 and 1996. Participating workers were trained by occupational hygienists in validated methods for particulate sampling and for gathering information about covariates in a standardized manner. After initial supervision by occupational hygienists at each site, participating

Table 1. Process- and task-related covariates

Covariate	Code	Values
Type of Work	TW	1: Welding 0: Brazing & thermal cutting
Continuous/Intermittent	CI	1: $\leq$50% hot work 0: $>$50% hot work
Ventilation	VE	1: Local exhaust or mechanical 0: natural
Welding Process	WP	1: Shielded or manual arc 0: Other[a]
Indoor/Outdoor	IO	1: Indoor work 0: Outdoor work
Degree of Confinement	DC	1: Enclosed space 0: Open space

[a]The following other welding processes were included: flux core, gas-metal arc, gas-tungsten arc, plasma arc and resistance.

workers were responsible for all sampling and observational activities conducted during the surveys.

It was emphasized that measurements should be obtained during 'typical' work rather than during work attendant with 'worst' or 'best' exposures. Workers were selected for monitoring when they were expected to engage in hot processes for at least 60 cumulative min during a workday. Air samples were sent to a laboratory for analysis, by validated methods, of TP and up to three constituent metals. Mn was measured for processes involving carbon steel, and Ni and Cr for those employing stainless steel. The following numbers of measurements were obtained: TP—198, Mn—136, Ni—27 and Cr—24. The duration of measurement ranged from 62 to 525 min per day. Sometimes multiple measurements were obtained during the day in which case results were adjusted to time-weighted averages (TWAs) over the cumulative times sampled. A few measurements were found to be below the analytical limit of detection (LOD); these were assigned a value of 2/3 LOD prior to statistical analysis.

In order to differentiate between welding and non-welding procedures among PF, the workers identified those work shifts in which they had been engaged primarily in welding; and, based upon that information, we defined a separate job as 'welder-fitter' (WF) consistent with the generic title (AGCA, 1992). With one exception, all persons identified as welder-fitters did not have additional measurements during non-welding work shifts, that is, as pipefitters. The sole exception was classified as either a WF or PF depending upon the nature of work on the days monitored.

Throughout the work shift, workers conducting surveys documented variables associated with the tasks and types of processes that were operative on those days (Susi *et al.*, in press). For the current analyses, several covariates were dichotomized, as shown in Table 1, coded and entered into the database. On some occasions, information about covariates was either unavailable or incomplete; thus, sample sizes for the combined analyses were smaller than those for evaluating only the effect of job upon exposure. The numbers of observations are listed by agent and job in Table 2. In cases involving exposures to Ni and Cr, the data were extremely limited and permitted only preliminary investigation of PF and WF.

Statistical models

Nested mixed effects models were used to investigate the effects upon exposure of either the job [Model(1)] or the job plus covariates [Model (2)]. Model (1) is defined as follows:

$$Y_{h(ij)} = \ln(X_{h(ij)}) = \mu_y + \alpha_h + \beta_{h(i)} + \varepsilon_{h(ij)}$$

for $h = 1, 2, \ldots, g$ jobs,
for $i = 1, 2, \ldots, k_h$ workers in the h-th job, and
for $j = 1, 2, \ldots, n_{h(i)}$ measurements of the i-th worker in the h-th job,

(1)

where $X_{h(ij)}$ represents the exposure level on the j-th day for the i-th worker in the h-th job, and $Y_{h(ij)}$ is the natural logarithm of the individual measurement $X_{h(ij)}$. The logged variate $Y_{h(ij)}$ represents the sum of the effects consisting of: μ_y representing the true underlying fixed mean (logged) exposure level averaged over all jobs [that is, $\mu_y = \frac{1}{g}\sum_{h=1}^{g}\mu_{y,h}$, where $\mu_{y,h}$ is the true underlying fixed mean (logged) exposure level for the h-th job]; α_h representing the fixed effect of the h-th job (that is, $\alpha_h = \mu_{y,h} - \mu_y$); $\beta_{h(i)}$ representing the random effect of the i-th worker [that is, $\beta_{h(i)} = \mu_{y,h(i)} - \mu_{y,h}$ where $\mu_{y,h(i)}$ is the random mean of the (logged) exposure level for the i-th worker in the h-th job]; and, $\varepsilon_{h(ij)}$ representing the random effect of the j-th day for the i-th worker (that is, $\varepsilon_{h(ij)} = Y_{h(ij)} - \mu_{y,h(i)}$). It is assumed under Model (1) that $\sum_{h=1}^{g}\alpha_h = 0$, that

Table 2. Numbers of observations used for mixed models[a]

Agent	Job	Model	No. measurements	No. workers	No. workers with $n > 1$	Max. No. measurements per worker	No. measurements < LOD
TP	BM	1	22	5	5	7	0
	BM	2	22	5	5	7	0
	IW	1	41	16	6	14	0
	IW	2	35	16	5	11	0
	PF	1	72	21	16	8	0
	PF	2	52	17	14	8	0
	WF	1	63	20	15	6	2
	WF	2	63	20	15	6	2
Mn	BM	1	18	5	5	5	0
	BM	2	13	4	4	4	0
	IW	1	13	7	2	4	0
	IW	2	13	7	2	4	0
	PF	1	45	14	11	8	0
	PF	2	43	13	11	8	0
	WF	1	60	19	14	6	0
	WF	2	60	19	14	6	0
Ni	PF	1	8	5	2	3	0
	WF	1	10	4	3	3	1
Cr	PF	1	8	5	2	3	0
	WF	1	10	4	3	3	0

[a]n—number of measurements per worker, BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters, TP—total particulates, Mn—manganese, Ni—nickel, Cr—chromium, LOD—limit of detection; Model (1) was used to evaluate the effect of job upon exposure and Model (2) the combined effects of job and covariates.

$\beta_{h(i)}$ and $\varepsilon_{h(ij)}$ are normally distributed with means of zero and variances of $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$, respectively (representing the between- and within-worker components of variance, respectively, for the h-th job), and that the $\beta_{h(i)}$s and $\varepsilon_{h(ij)}$s are all statistically independent. Thus, $\sigma^2_{y,h} = (\sigma^2_{B,h} + \sigma^2_{W,h})$ is the variance of each logged exposure $Y_{h(ij)}$ in the h-th job, and $Y_{h(ij)}$ is normally distributed with mean $\mu_{y,h} = (\mu_y + \alpha_h)$, and variance $\sigma^2_{y,h}$.

It is implicit under Model (1) that each daily exposure ($X_{h(ij)}$) for a worker in the h-th job is lognormally distributed with mean $\mu_{x,h,} = e^{(\mu_{y,h}+0.5\sigma^2_{y,h})}$, and variance $\sigma^2_{x,h} = \mu^2_{x,h}(e^{\sigma^2_{y,h}} - 1)$. Thus, the mean and variance of the lognormally distributed exposures (that is, $\mu_{x,h}$ and $\sigma^2_{x,h}$) can easily be related to the mean and variance of the normally distributed (logged) exposures (that is, $\mu_{y,h}$ and $\sigma^2_{y,h}$). Further, the worker-specific mean exposures in a given job, that is, the values of $\mu_{x,h(i)} = e^{(\mu_{y,h(i)}+0.5\sigma^2_{W,h})}$, are themselves lognormally distributed, each with mean $\mu_{x,h}$ and variance $\mu^2_{x,h}(e^{\sigma^2_{B,h}} - 1)$.

Model (2) differs from Model (1) only in its inclusion of additional fixed effects for task- and process-related covariates. Thus,

$$\begin{aligned} Y_{h(ij)} &= \ln(X_{h(ij)}) \\ &= \mu_y + \alpha_h + \sum_{m=1}^{p} \delta_m C_{mh(ij)} + \beta_{h(i)} + \varepsilon_{h(ij)} \qquad (2) \end{aligned}$$

for $m = 1, 2, \ldots, p$ covariates,

where all common terms are defined as for Model (1) and the regression coefficients $\delta_1, \delta_2, \ldots, \delta_p$ represent the fixed effects of the p process- and task-related covariates $C_1, C_2, \ldots, C_p$ (given in Table 1). The same assumptions hold as for Model (1), except that $Y_{h(ij)}$ is now assumed to be normally distributed with mean $\mu_{y,h} = \mu_y + \alpha_h + \sum_{m=1}^{p} \delta_m C_{mh(ij)}$ and variance $\sigma^2_{y,h}$.

Models (1) and (2) were applied to the exposure data using the MIXED procedure available with SAS statistical software (SAS, Inc., Cary, NC) to obtain restricted maximum likelihood (REML) estimates of the parameters μ_y (the overall mean of the logged exposures), $\mu_{y,h}$ (the mean of the logged exposures for the h-th job), $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$ (the between and within-person variance components for the h-th job), which are designated $\hat{\mu}_y$, $\hat{\mu}_{y,h}$, $\hat{\sigma}^2_{B,h}$ and $\hat{\sigma}^2_{W,h}$, respectively. These estimated parameters were then used to obtain $\hat{\mu}_{x,h} = e^{(\hat{\mu}_{y,h}+0.5\hat{\sigma}^2_{y,h})}$ (the estimated mean of $X_{h(ij)}$ for the h-th job) and $\hat{\sigma}^2_{y,h} = \hat{\sigma}^2_{B,h} + \hat{\sigma}^2_{W,h}$ (the estimated variance of $Y_{h(ij)}$ for the h-th job).

When applying Model (1) to the data, the following three alternative variance structures were evaluated:

1. Model (1A): $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$ assumed to be distinct for all jobs (Proc MIXED: **class** = worker, **random int/subject** = worker, **by** jobcode);
2. Model (1B): $\sigma^2_{B,h}$ assumed to be distinct for each job and $\sigma^2_{W,h}$ assumed to be common for all jobs (Proc MIXED: **class** = jobcode & worker, **random int/subject** = worker **group** = jobcode); and,
3. Model (1C): $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$ assumed to be com-

mon for all jobs (Proc MIXED: **class** = jobcode & worker, **random int/subject** = worker).

Model (1A) is the least restrictive of the three models, since it allows both the within- and the between-person variance components to be distinct among jobs. Models (1B) and (1C) add restrictions in the form of common within- or within- and between-person variance components, respectively, thereby reducing the total number of model parameters. Since the goal of model building is to select the most parsimonious model (the one with the fewest parameters) consistent with the data, likelihood ratio tests were applied at a significance level of 0.05 to compare different versions of Model (1). The tests compared the more restrictive Models (1B) or (1C) to Model (1A) so as to examine the effect of pooling $\sigma^2_{W,h}$ and/or $\sigma^2_{B,h}$ among jobs. The likelihood ratio test comparing Models (1A) to Model (1B) is testing the null hypothesis: H_0: $\sigma^2_{W,1} = \ldots = \sigma^2_{W,g}$, and is testing the null hypothesis of equality of both within- and between-person variance components for comparing Model (1A) to Model (1C). [The p-values for these tests were approximated by comparing -2 times the log likelihoods to a Chi-square distribution with either (g$-$1) d.*f.* for testing Model (1A) vs. (1B) or 2(g$-$1) d.*f.* for testing Model (1A) vs. (1C)]. Predicted random effects and standard errors were produced under Model (1B) (Proc MIXED: using the **solutions** option for the **random int** statement).

The fits of Models (1B) and (2) were evaluated using an ad hoc graphical procedure based upon the work of Dempster and Ryan (1985) and Lange and Ryan (1989) which examine the normality assumption of the random effects. This involved computing standardized random effects [the predicted random effects ($\hat{\beta}_{h(i)}$) from Proc MIXED divided by their standard errors of prediction] for each job having a non-zero between-person variance component and then plotting the corresponding quantiles against the observed quantiles in q–q format. In each case the test for normality was not rejected, indicating adequate fit for the models. We had previously applied similar procedures to evaluate the goodness of fit of the one-way random effects model to occupational exposure data (Rappaport *et al.*, 1995).

The uniformity of exposure within each job was examined in terms of the number of predicted random effects [$\hat{\beta}_{h(i)}$, obtained under Model (1B)] which were significantly different from zero ($P < 0.05$) (via Proc MIXED). This approach is similar to one based upon an *ad hoc* test of predicted random effects obtained from a one-way random effects model (Rappaport *et al.*, 1995; Lyles *et al.*, 1997).

Applications of Model (2) assumed distinct $\sigma^2_{B,h}$ parameters and a common $\sigma^2_{W,h}$ parameter based upon results from evaluation of Models (1A), 1(B) and (1C). A forward selection method was used for model building in which each dichotomous covariate (see Table 1) was considered separately in a model and only those covariates with P-values of less than 0.10 were used to obtain final models. In each case two variables were retained [TP exposure: continuous/intermittent (CI), $P = 0.083$ and ventilation (VE), $P = 0.066$; Mn exposure: continuous/intermittent (CI), $P = 0.011$ and welding process (WP), $P = 0.031$]. Final models were constructed by including pairs of these variables and any significant interactions ($P < 0.10$).

Estimation of probabilities relative to OELs

Since occupational exposures vary both within and between workers in each job, two probabilities were computed with reference to OELs, consistent with earlier work (Tornero-Velez *et al.*, 1997). The probability that a single measurement (that is, a TWA concentration measured for a randomly selected worker in the h-th job on a randomly selected day) would exceed the OEL is referred to as the 'exceedance' (γ_h, which is related to the parameters of the exposure distribution as follows:

$$\gamma_h = P\{X_{h(ij)} > \text{OEL}\} = 1 - \Phi\left\{\frac{\ln(\text{OEL}) - \mu_{y,h}}{\sqrt{\sigma^2_{B,h} + \sigma^2_{W,h}}}\right\}, \quad (3)$$

where $\Phi\{z\}$ denotes the probability that a standard normal variate would fall below the value z. The second probability defines the likelihood that a randomly-selected worker's mean exposure in the h-th job, i.e., $\mu_{x,h(i)}$, would be greater than the OEL; this is referred to as the probability of overexposure (θ_h) which is given by:

$$\theta_h = P\{\mu_{x,\,h(i)} > \text{OEL}\} = 1 - \Phi\left\{\frac{\ln(\text{OEL}) - \mu_{y,\,h} - \frac{\sigma^2_{W,\,h}}{2}}{\sigma_{B,\,h}}\right\}. \quad (4)$$

From Equations 3 and 4 we see that, whereas γ_h relates to the probability that a worker in the h-th job would be exposed above the OEL on a single day, θ_h relates to the likelihood that he or she would be exposed, on average, above the OEL. The estimated probabilities of exceedance and overexposure, designated $\hat{y}_h$ and $\hat{\theta}_h$, respectively, were obtained by substituting $\hat{\mu}_{y,h}$, $\hat{\sigma}^2_{B,h}$ and $\hat{\sigma}^2_{W,h}$ for the corresponding parameters, $\mu_{y,h}$, $\sigma^2_{B,h}$, and $\sigma^2_{W,h}$, respectively, in Equations 3 and 4. Note that $\hat{\theta}_h$ is undefined when $\hat{\sigma}^2_{B,h}$ equals zero.

The relationship between γ_h and θ_h is complicated because it depends upon the particular values of the within- and between-person variance components in

Table 3. Estimated parameters of exposure distributions for particular agents and jobs. [based upon Models 1A (distinct and $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$), 1B (distinct $\sigma^2_{B,h}$ and common $\sigma^2_{W,h}$) and 1C (common $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$)][a]

Agent	Job	Between-person Variance Components For Job (Logged Data, $\hat{\sigma}^2_{B,h}$)			Within-person Variance Components For Job (Logged Data, $\hat{\sigma}^2_{W,h}$)			Mean exposure for job (logged data, $\hat{\mu}_{y,h}$)			Mean exposure for job (raw data, $\hat{\mu}_{x,h}$)		
		1A	1B	1C	1A	1B	1C	1A	1B	1C	1A	1B	1C
TP	BM	0.000	0.000	0.238	0.254	0.354	0.401	2.57	2.57	2.560	14.8	15.5	17.8
	IW	0.131	0.155	0.238	0.417	0.354	0.401	1.82	1.84	1.848	8.15	8.09	8.74
	PF	0.148	0.168	0.238	0.449	0.354	0.401	0.799	0.790	0.682	3.00	2.86	2.72
	WF	0.884	0.739	0.238	0.228	0.354	0.401	0.411	0.432	0.580	2.63	2.66	2.46
		Likelihood ratio test: 1B vs. 1A, P = 0.091; 1C vs. 1A, P = 0.001											
Mn	BM	0.000	0.000	0.379	0.829	0.996	1.06	−1.16	−1.16	−1.146	0.474	0.515	0.652
	IW	0.000	0.000	0.379	0.508	0.996	1.06	−2.26	−2.26	−2.222	0.134	0.171	0.222
	PF	0.597	0.750	0.379	1.51	0.996	1.06	−3.38	−3.42	−3.378	0.097	0.078	0.070
	WF	0.614	0.464	0.379	0.775	0.996	1.06	−3.48	−3.44	−3.427	0.062	0.066	0.067
		Likelihood ratio test: 1B vs. 1A, P = 0.080; 1C vs. 1A, P = 0.046											
Ni	PF	1.10	0.773	3.77	0.240	0.828	0.859	−5.62	−5.62	−5.621	0.007	0.008	0.037
	WF	7.67	8.04	3.77	1.16	0.828	0.859	−4.55	−4.58	−4.511	0.874	0.862	0.111
		Likelihood ratio test: 1B vs. 1A, P = 0.150; 1C vs. 1A, P = 0.085											
Cr	PF	2.37	2.42	4.52	0.93	0.853	0.863	−4.47	−4.48	−4.483	0.059	0.058	0.167
	WF	7.48	7.43	4.52	0.811	0.853	0.863	−4.30	−4.29	−4.250	0.861	0.862	0.210
		Likelihood ratio test: 1B vs. 1A, P = 0.888; 1C vs. 1A, P = 0.654											

[a]Mn—manganese, TP—total particulates, Ni—nickel, Cr—chromium; $\hat{\mu}_{yh}$ is the mixed model estimate of the mean of the logged exposure concentrations (exposures given in mg m^{-3}) for the h-th job; $\hat{\sigma}^2_{W,h}$, and $\hat{\sigma}^2_{B,h}$ represent REML estimates of the within- and between-worker variance components, respectively, of the logged exposure concentrations (exposures given in mg m^{-3}) for the h-th job; $\hat{\mu}_{xh}$ represents the estimated mean exposure (mg m^{-3}) for the h-th job.

Table 4. Final models relating job and covariates to exposure. Effects estimated under Model (2)[a]

Agent	Effect	Estimate	P-value
TP	Job BM ($\hat{\mu}_y + \hat{\alpha}_1$)	2.659	0.0001
	Job IW ($\hat{\mu}_y + \hat{\alpha}_2$)	1.959	0.0001
	Job PF ($\hat{\mu}_y + \hat{\alpha}_3$)	0.960	0.0001
	Job WF ($\hat{\mu}_y + \hat{\alpha}_4$)	0.654	0.0056
	Local-exhaust or Mechanical Ventilation (VE) ($\hat{\delta}_1$)	−0.0498	0.0390
	Hot work ≤ 50% (CI)($\hat{\delta}_2$)	−0.0712	0.0317
	Interaction (VE × CI) ($\hat{\delta}_3$)	−0.4642	0.0588
Mn	Job BM ($\hat{\mu}_y + \hat{\alpha}_1$)	−1.698	0.0010
	Job IW ($\hat{\mu}_y + \hat{\alpha}_2$)	−2.372	0.0002
	Job PF ($\hat{\mu}_y + \hat{\alpha}_3$)	−3.691	0.0001
	Job WF ($\hat{\mu}_y + \hat{\alpha}_4$)	−3.676	0.0001
	Hot work ≤ 50% (CI) ($\hat{\delta}_1$)	−0.523	0.0427
	Shielded or manual-arc welding (WP) ($\hat{\delta}_2$)	0.593	0.115

[a]BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters, CI—'continuous/intermittent' (1: ≤ 50% hot work; 0: > 50% hot work), VE—'ventilation' (1: local exhaust or mechanical; 0: natural), WP—'welding process' (1: shielded or manual arc welding; 0: other), $\hat{\mu}_y$—estimated fixed effect for the overall mean (logged data), $\hat{\alpha}_1$—estimated fixed effect for the i-th job, and $\hat{\delta}_1$—estimated fixed effect for the i-th covariate.

the particular job (Tornero-Velez *et al.*, 1997). In general, $\gamma_h > \theta_h$ when γ_h is 'small' and $\gamma_h < \theta_h$ when γ_h is 'large'. However, what constitutes a 'small' or 'large' value of γ_h is a function of the overall variability (the sum of $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$) which covers a remarkably large range in occupational settings (Tornero-Velez *et al.*, 1997). For this and other reasons we discourage occupational hygienists from relying exclusively upon γ_h in evaluating exposures relative to OELs (for further discussion, see Rappaport *et al.*, 1998).

The particular OELs which were applied to these data have been summarized by the ACGIH (ACGIH, 1991). They consist of Threshold Limit Values (TLVs) recommended by the ACGIH, Permissible Exposure Limits (PELs) promulgated by the U.S. Occupational Safety and Health Administration (OSHA), and Recommended Exposure Limits (RELs) proposed by the U.S. National Institute for Occupational Safety and Health (NIOSH). Note that all of these OELs refer to 8-h TWA exposures. Even though some of the data used in this study were obtained over intervals shorter than 8 h, they were obtained under conditions of 'typical' work and were therefore assumed to represent valid estimates of shift-long exposure. Because all particulate exposures in this study involved aerosols generated by hot processes, the TLV for welding fumes (designated TLVw) of 5 mg m^{-3} was applied rather than that for nuisance dusts.

RESULTS

Effects of job upon exposure (Model 1)

Results from fitting Models (1A), (1B) and (1C) to the data sets are summarized in Table 3. In each case, the fixed effects of the job and the within- and between-worker variance components were estimated. The pooling of variance components among jobs was evaluated based on the difference in REML log likelihoods between Model (1A), which assumes distinct variance components for each job, and Models (1B) and (1C), which allow for pooling of either the within- or both the within- and between-worker variance components, respectively. Regarding exposures to TP and Mn, there was evidence that the variance components estimated under 1C (common $\sigma^2_{B,h}$ and $\sigma^2_{W,h}$) differed from those under 1A (P < 0.001), suggesting that it would be inappropriate to pool both variance components across jobs. On the other hand, when only $\sigma^2_{W,h}$ was assumed to be common to all jobs (1B), the fits were only marginally different from those of 1A (P = 0.080 or 0.091), suggesting that it was reasonable to pool $\sigma^2_{W,h}$ across jobs. Regarding exposures to Ni and Cr, very small samples of data were available for analysis (see Table 2) and the likelihood ratio test had limited power to detect differences among models. Thus, despite the fact that significant differences were not detected among Models (1B) or (1C) relative to (1A), we chose to pool only $\sigma^2_{W,h}$ for exposures to Ni and Cr, consistent with the larger data sets.

It should be noted that the values of $\hat{\mu}_{y,h}$ were essentially the same under Models (1A), (1B), and (1C) (Table 3), suggesting that the choice of model had little impact upon estimation of the fixed job effects. However, because the estimated mean exposures of each job depend upon the estimates of both the fixed job effects and the variance components (that is, $\hat{\mu}_{x,h} = e^{[\hat{\mu}_{y,h}+0.5(\hat{\sigma}^2_{W,h})]}$), Model (1C) sometimes exerted a large effect upon values of $\mu_{x,h}$, notably for exposures to Ni and Cr. Little difference was observed between estimates of $\mu_{x,h}$ obtained from Models (1A) and (1B). Relying upon the values of $\hat{\mu}_{y,h}$, $\hat{\sigma}^2_{B,h}$, and $\hat{\sigma}^2_{W,h}$, obtained under Model (1B), the impact of job upon exposure can be

Table 5. Estimated parameters of exposure distributions for jobs and significant covariates (Under Model 2 assuming distinct between-worker variance components and a common within-worker variance component among jobs)[a]

Agent	Job	$(\hat{\sigma}^2_{W,h})$	$(\hat{\sigma}^2_{B,h})$	$(\hat{\mu}_{y,h})$	Estimated mean exposure ($\hat{\mu}_{x,h}$), mg m^{-3})			
					VE = 1		VE = 0	
					CI = 1	CI = 0	CI = 1	CI = 0
TP	BM	0.325	0.000	2.66	9.36	16.0	15.6	16.8
	IW	0.325	0.060	1.96	4.79	8.18	8.01	8.60
	PF	0.325	0.016	0.960	1.73	2.95	2.89	3.10
	WF	0.325	0.626	0.654	1.72	2.94	2.88	3.09
					WP = 1		WP = 0	
					CI = 1	CI = 0	CI = 1	CI = 0
Mn	BM	1.02	0.000	−1.70	0.326	0.550	0.180	0.304
	IW	1.02	0.000	−2.37	0.166	0.281	0.092	0.155
	PF	1.02	0.369	−3.69	0.053	0.090	0.030	0.050
	WF	1.02	0.383	−3.68	0.056	0.095	0.031	0.052

[a]TP—total particulates, Mn—manganese, BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters, $\hat{\mu}_{y,h}$, $\hat{\sigma}^2_{W,h}$, and $\hat{\sigma}^2_{B,h}$ represent REML estimates of the mean and the within- and between-worker variance components, respectively, of the logged exposure concentrations (exposures given in mg m^{-3}) for the *h*-th job, $\hat{\mu}_{x,h}$ represents the estimated mean exposure of the *h*-th job given the effects of CI and either WP (for Mn) or VE (for TP), CI—'continuous/intermittent' (1: $\leq$ 50% hot work; 0: $>$50% hot work), VE—'ventilation' (1: local exhaust or mechanical; 0: natural), and WP—'welding process' (1: shielded or manual arc welding; 0: other).

gauged by the range of mean exposures (that is, the $\hat{\mu}_{x,h}$s) among jobs for a given agent. The results indicate pronounced differences in exposure among jobs, with ranges between 5.8 fold and 107 fold, depending upon the agent. The two most complete data sets, representing TP and Mn, showed consistent trends towards increasing exposure levels (in the order WF < PF < IW < BM), with ranges of 5.8 fold and 7.8 fold, respectively. The smaller data sets, representing Ni and Cr, indicated that WF experienced much higher exposures than PF, with ranges of 14.8 fold and 107 fold, respectively.

Effects of job and covariates upon exposure (Model 2)

Models were constructed to determine which of the estimated regression coefficients representing process- and task-related covariates, i.e., values of $\hat{\delta}_m$, were significant (at P < 0.10). The final models are summarized in Table 4. Only two pairs of covariates added significantly to the effect of job in explaining the variability of exposures to TP and Mn. In the case of TP, the effects of the type of ventilation (VE), the percentage of hot work (CI) (see Table 1), and their interaction had significant effects. That is, exposures were significantly lower when less than half of the day involved hot processes (CI = 1) and when either local-exhaust or mechanical ventilation was used (VE = 1). The interaction is manifested by a greater than additive reduction in exposure when VE and CI are both one (Table 4). For exposures to Mn, CI exhibited the same type of effect as it did for TP and, in addition, shielded or manual arc welding (WP = 1) produced higher air levels than other types of welding (note that this effect was only marginally significant in the final model with P = 0.115).

The finding that ventilation (VE) affected exposures to TP but not Mn was surprising because we had expected exposures to Mn and TP to be highly correlated. However, when we examined the correlation of exposures to Mn and TP among the 25 workers with at least three daily measurements, only eight had significant positive correlation coefficients (P < 0.05), suggesting that exposures to the two agents were not highly correlated for most persons. Furthermore, when we examined the cross-classification of ventilation (VE) and welding process (WP) for exposures to TP and Mn, we found no empty cells (smallest cell size had n = 6), suggesting that WP and VE were not kept out of either model simply due to collinearity. Finally, to determine whether the severe imbalance in the VE data for the jobs BM and IW affected the results (virtually none of the BM had VE = 0 and all of the IW had VE = 1) we reran Model (2) with the single covariate VE, using only data from the jobs PF and WF. For Mn exposures, the estimated coefficient for VE was still not significant (P = 0.980); and, for TP, the estimated coefficient was again significant (P = 0.054), consistent with prior results for all jobs. Thus, we conclude that the observed effect of VE upon TP exposure was not an artifact of the data, but cannot rule out the possibility that the nonsignificant effect of VE on Mn exposure was artifactual. This should be a topic of further investigation.

The magnitudes of the effects of the above pairs of covariates upon exposure to TP (that is, VE and CI) and to Mn (i.e., CI and WP) are illustrated in Table 5, which lists the estimated mean exposures of each job (values of $\hat{\mu}_{x,h}$) and combination of covariates. Looking first at exposures to TP, the results indicate about a two-fold range of exposure within a job depending upon the values of VE and CI. For example, among boilermakers, job means varied from 9.36 mg m^{-3} with local exhaust or mechanical ventilation and less than 50% hot work (VE = 1 and CI = 1) to 16.8 mg m^{-3} with natural ventilation and more than 50% hot work (VE = 0 and CI = 0). Due to the interaction between VE and CI, the contrast among cells was greatest with local exhaust or mechanical ventilation (VE = 1); that is, VE had relatively little effect upon exposure when more than 50% hot work was performed (CI = 0). The reason for this disparity should be investigated further. For exposures to Mn, the range of mean exposures within a job was about three fold for the various pairs of CI and WP. In this case, CI exerted an effect similar to that for TP (under conditions with local exhaust or mechanical ventilation), and shielded or manual arc welding (WP = 1) produced about 80% higher exposures than other welding procedures (WP = 0).

Probabilities of exceedance and overexposure

The values of $\hat{\theta}_h$ and $\hat{\gamma}_h$, estimated from the parameters obtained under Models (1A), (1B) and (1C), are given in Table 6. The results suggest that, although the probabilities estimated under Model (1A) (distinct variance components) and Model (1B) (common $\sigma^2_{W,h}$) were quite similar, those estimated under Model (1C) (common variance components) sometimes differed by a factor of two or more, particularly for exposures to Ni and Cr. Focusing upon the values of $\hat{\theta}_h$ and $\hat{\gamma}_h$ obtained under Model (1B), several of the probabilities were large enough to be of concern, that is, where $\hat{\theta}_h$ and/or $\hat{\gamma}_h$ were greater than 5–10%. Indeed, exposures of BM and IW to both TP and Mn were estimated to exceed the TLVs between 26 and 95% of the time, suggesting unacceptable levels. Although PF and WF had lower exposures than BM and IW, the estimated probabilities of exceeding the TLVw for TP were in the range of 12–13% for WF and, of exceeding the TLV for Mn, were 6–8% for PF. Regarding exposures to Ni and Cr, exposures of WF to both metals were much more likely to exceed the OELs than those of PF. In fact, welder-fitters' exposures exceeded the TLVs and

Table 6. Probabilities of exceedance and overexposure estimated under models (1A), (1B) and (1C)[a]

Agent	Job	OEL (mg m^{-3})	(Source)	Exceedance ($\hat{\gamma}_h$)			Overexposure ($\hat{\theta}_h$)		
				1A	1B	1C	1A	1B	1C
TP	BM	15	(PEL)	0.390	0.406	0.426	Und.	Und.	0.543
	BM	5	(TLVw)	0.971	0.946	0.883	Und.	Und.	0.991
	IW	15	(PEL)	0.116	0.111	0.141	0.031	0.039	0.088
	IW	5	(TLVw)	0.614	0.625	0.617	0.879	0.847	0.816
	PF	15	(PEL)	0.007	0.004	0.006	< 0.001	< 0.001	< 0.001
	PF	5	(TLVw)	0.147	0.128	0.123	0.064	0.058	0.068
	WF	15	(PEL)	0.015	0.015	0.004	0.010	0.007	< 0.001
	WF	5	(TLVw)	0.128	0.130	0.010	0.124	0.122	0.045
Mn	BM	1	(REL)	0.101	0.122	0.170	Und.	Und.	0.158
	BM	0.2	(TLV)	0.689	0.673	0.650	Und.	Und.	0.947
	IW	1	(REL)	0.001	0.012	0.032	Und.	Und.	0.003
	IW	0.2	(TLV)	0.180	0.257	0.305	Und.	Und.	0.446
	PF	1	(REL)	0.010	0.005	0.002	< 0.001	< 0.001	< 0.001
	PF	0.2	(TLV)	0.111	0.085	0.070	0.093	0.064	0.022
	WF	1	(REL)	0.002	0.002	0.002	< 0.001	< 0.001	< 0.001
	WF	0.2	(TLV)	0.056	0.065	0.065	0.029	0.025	0.018
Ni	PF	1	(TLV & PEL)	< 0.001	< 0.001	0.004	< 0.001	< 0.001	0.004
	PF	0.015	(REL)	0.110	0.131	0.254	0.107	0.126	0.305
	WF	1	(TLV & PEL)	0.063	0.062	0.018	0.076	0.071	0.018
	WF	0.015	(REL)	0.453	0.449	0.442	0.533	0.505	0.524
Cr	PF	0.5	(TLV & REL)	0.019	0.018	0.051	0.016	0.015	0.057
	PF	1	(PEL)	0.007	0.007	0.027	0.005	0.005	0.028
	WF	0.5	(TLV & REL)	0.106	0.106	0.063	0.121	0.122	0.071
	WF	1	(PEL)	0.068	0.068	0.034	0.078	0.078	0.036

[a]TP—total particulates, Mn—manganese, Ni—nickel, Cr—chromium, BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters, TLV—Threshold limit Value (ACGIH) (note that TLVw refers to the TLV for welding fumes), PEL—Permissible Exposure Limit (OSHA), REL—Recommended Exposure Limit (NIOSH), $\hat{\gamma}_h$—the estimated exceedance (the probability that a work shift exposure exceeds the OEL), $\hat{\theta}_h$—the estimated probability of overexposure (the probability that an individual worker's mean exposure exceeds the OEL). Note that 'Und.' Indicates that $\hat{\theta}_h$ is undefined due to a REML estimate of $(\hat{\sigma}^2_{B,h}) = 0$.

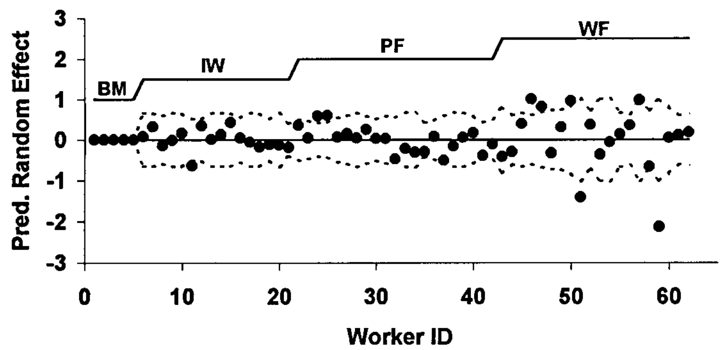

Fig. 1. Predicted random effects for 62 construction workers exposed to particulate matter (TP) during hot processes. Each point represents the predicted random effect ($\hat{\beta}_{h(i)}$) obtained under Model (1B). The dashed curves represent ± 1.96 times the standard error of prediction for each random effect; thus, observations lying outside these bounds represent predicted effects which were significantly different from zero (solid line) ($P < 0.05$). Legend: BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters. Note that all predicted random effects for BM were zero because $\hat{\sigma}^2_{B,h} = 0$ for that job.

PELs for Ni and Cr about 6–12% of the time and exceeded the REL for Ni about half the time. Overall, these results indicate that construction workers engaged in the hot processes investigated in this study were routinely exposed to levels of air contaminants above operative OELs.

Uniformity of exposure within jobs

In an effort to categorize uniform vs. non-uniform exposure within jobs we determined the number of predicted random effects ($\hat{\beta}_{h(i)}$) that were significantly different from zero for each sample of workers in the four jobs. Figure 1 shows the predicted random effects obtained under Model (1B) for exposure to TP and the 95% confidence interval suggesting when $\beta_{h(i)} \neq 0$. The variability of the random effects increased greatly from boilermakers (with none of five random effects being significant), to ironworkers (1/16 significant), to pipefitters (2/21 significant), and finally to welder-fitters (5/20 significant). Table 7 summarizes the numbers of significant random effects for all contaminants. The results indicate that exposures to Mn were fairly uniform among all jobs but that exposures to TP, Ni and Cr were non-uniform among welder-fitters and pipefitters.

DISCUSSION

The evaluation of hazardous chemical exposures generally requires measurements of airborne contaminants. Traditionally, the role of measuring such exposures has been assigned to occupational hygienists, who have been constrained in their abilities to visit workplaces very frequently. Thus, sample sizes have been small (typically no more than one or two measurements per job per year, Tornero-Velez *et al.*, 1997) and have rarely included repeated measurements from the same workers. This inability to obtain sufficient data prior to making decisions has motivated hygienists to focus upon what were perceived to be worst-case exposures and to rely upon professional judgement rather than quantitative data in many cases (for example, Hewett, 1997a,b). Given the many documented variables that can affect exposures, such attempts at pragmatism are arguably counterproductive since they provide little objective information with which to determine cause and effect, to develop intervention strategies, or to conduct epidemiological investigations.

If reliance upon a small cadre of professionals has, indeed, contributed to the paucity of exposure data, then other avenues for monitoring should be sought, including self-monitoring by workers. Likewise, if occupational exposures represent the combined effects of many different variables, then modern methods of multivariable analysis should be brought to bear on the problem. The study described herein presented an opportunity to test both of these conjectures by relying upon workers to measure exposures and upon mixed model regression analysis to evaluate the various effects upon exposure levels.

Results from this study suggest that workers can, indeed, gather sufficient data to allow inferences to be made about exposure which are intuitively reasonable. By enlisting the assistance of the unionized construction trades, it was possible to efficiently train workers to measure aerosol exposures during hot processes at nine sites in the U.S. Since the sampling equipment had to be shared by all participants, measurements could only be committed to a particular site for two weeks during each survey. Nonetheless, this was sufficient time to obtain repeated measurements from some workers in each job, thereby assuring estimation of the

Table 7. Number of predicted random-person effects ($\hat{\beta}_{h(i)}$) which are significantly different from zero ($p < 0.05$). [random effects predicted under model (1B)][a]

Agent	Job	$\hat{\sigma}^2_{B,h}$	Sig. $\hat{\beta}_{h(i)}$/No. workers
TP	BM	0	0/5
	IW	0.155	1/16
	PF	0.168	2/21
	WF	0.739	5/20
Mn	BM	0	0/5
	IW	0	0/6
	PF	0.750	1/14
	WF	0.464	1/20
Ni	PF	0.773	1/6
	WF	8.04	2/6
Cr	PF	2.42	1/6
	WF	7.43	2/6

[a]TP—total particulates, Mn—manganese, Ni—nickel, Cr—Chromium, BM—boilermakers, IW—ironworkers, PF—pipefitters, WF—welder-fitters, $\hat{\sigma}^2_{B,h}$ represents the REML estimate of the between-worker variance component of the logged exposure concentrations (exposures given in mg m^{-3}) for the h-th job, $\hat{\beta}_{h(i)}$ represents the predicted random effect of the i-th worker in the h-th job.

within- and between-worker components of variance. The workers also recorded the tasks and activities during each workday in a manner that permitted straightforward abstraction of the information about selected covariates.

Application of mixed models to the data generated estimates of the within- and between-worker variance components for several combinations of agent and job. We observed that pooling $\sigma^2_{W,h}$ among the four jobs [Model (1B)] led to results that were quite similar to those obtained when each job was allowed to have distinct variance components [Model (1A)]. This is important, because some increase in statistical efficiency due to application of mixed models to the problem can be achieved when $\sigma^2_{W,h}$ is assumed to be homogeneous among jobs. Since $\sigma^2_{W,h}$ tends to reflect the combined effects of process and environment upon exposure (Kromhout *et al.*, 1993; Peretz *et al.*, 1997), the fact that Models (1A) and (1B) led to similar estimated values of this parameter suggests that the various construction sites shared important general characteristics. Certainly, work involving hot processes in the construction industry tends to be intermittent and to involve common types of cutting equipment; so, perhaps, this is a reasonable finding. On the other hand, our analysis indicated that the assumption of common within-*and* between-worker variance components among all jobs [Model (1C)] sometimes led to quite different results from those of Models (1A) and (1B), particularly for exposures to Ni and Cr. Thus, we conclude that it was inappropriate to pool $\sigma^2_{B,h}$ among these jobs, since factors related to the personal environments of workers in the four jobs were probably different. This finding could be an artifact of our database because seven of the nine construction sites provided measurements for only pipefitters and welder-fitters. More work is needed to determine the extent to which $\sigma^2_{W,h}$ and $\sigma^2_{B,h}$ can legitimately be pooled among jobs in construction as well as other industries, and we are currently extending our analyses to other datasets.

The effect of job upon exposure was highly significant. Indeed, based upon the mean levels for each job, we observed that exposures varied roughly six to 100 fold for a given agent. This points to potentially large differences in contaminant levels among the construction trades, with boilermakers and ironworkers exposed to much higher levels of TP and Mn than pipefitters and welder-fitters. We temper this conclusion with the knowledge that our coverage of boilermakers and ironworkers was restricted to only one site for each job, and in both cases the nature of the projects suggested that exposures would be high. That is, the boilermakers were working inside a process vessel and the ironworkers were involved with a rehabilitation project involving a great deal of torch cutting of painted steel. Within the pipefitter trade our preliminary results suggest that welder-fitters were exposed to higher levels of Ni and Cr than were pipefitters. This points to potential hazards associated with welding of stainless steel as opposed to other hot work tasks common to both pipefitters and welder-fitters.

An important advantage of mixed models for analysis of occupational exposure is the ability to evaluate fixed effects while controlling for random effects of the worker and the error term. If the models indicate that particular jobs and covariates significantly affected exposure, then logical control strategies can be developed. We evaluated covariates for exposures to TP and Mn among the four jobs. In both cases, the percentage of hot work (CI) significantly affected air concentrations since situations involving more than 50% hot work led to substantially higher exposures than those involving less than 50% hot work. Since CI is an indirect measure of the source strength, this finding was expected. The other important effects were not common to both agents since ventilation (VE) affected exposure to TP (but not Mn) and the type of welding process (WP) affected exposure to Mn (but not TP). The finding regarding VE requires further study because portable ventilation equipment reduced particulate exposures by 44% in cases where less than 50% hot work was performed but by only 5% otherwise (see Table 5).

Given the wide range of exposures among jobs, it is not surprising that some construction workers were much more likely to be exposed at levels above the operative OELs than others were. This is reflected by values of $\hat{\theta}_h$ and $\hat{\gamma}_h$ for TP and Mn which were much larger among boilermakers and ironworkers (26–95%) than among pipefitters or welder-fitters (2–13%) (Table 6). Certainly such large probabilities of exceeding OELs suggest unacceptable exposures to TP and Mn among boilermakers and ironworkers at the sites investigated, and arguably among pipefitters and welder-fitters as well. Regarding the limited data gathered for exposure to Ni and Cr, our results pointed to potentially hazardous exposures in the pipefitter trade, predominately among welder-fitters, who were more likely to weld stainless steel components.

Since some exposures evaluated in our study were clearly unacceptable, the question logically arises of how best to reduce air levels among the various jobs. We had previously suggested that the variability of the random-worker effects be used as a gauge for the uniformity of exposure within jobs and, by extension, to appropriate intervention strategies (Rappaport *et al.*, 1995; Lyles *et al.*, 1997). That is, jobs with uniform exposure among the workers should lend themselves to general controls (related to the process and environment), while those with non-uniform exposure should shift attention to individual workers (tasks, equipment, location, practices, etc.). Using the number of random effects ($\hat{\beta}_{h(i)}$) that were significantly different from zero as a measure of uniformity, Fig. 1 provides some insight into how controls might be optimized for particulate exposures. The predicted random effects for welder-fitters' (WF) varied tremendously about zero (non-uniform exposure), while those for boilermakers' (BM) were all essentially equal to zero (uniform exposure). This difference between the two jobs indicates that broad environmental changes (engineering or administrative controls) should be explored for BM, but not necessarily for WF, where individual factors (including such variables as equipment, location, and work practices) must be important contributors to exposure. Extending this analysis to all jobs and contaminants (see Table 7), it seems reasonable to conclude that control of TP exposures among boilermakers and ironworkers and of Mn exposures for all jobs should focus upon administrative or engineering controls. Based upon results of the covariate analysis, a reasonable suggestion would be to make greater use of mechanical or local exhaust ventilation to reduce exposures of TP (among boilermakers and ironworkers) and to explore options for reducing emissions of Mn during procedures involving shielded or manual arc welding (see Table 5). On the other hand, efforts at controlling exposures to TP, Ni and Cr among welder-fitters and pipefitters should initially be directed at identifying the sources of the interindividual differences of exposures prior to instituting controls.

In summary, this study provides alternative avenues for obtaining and evaluating occupational-exposure data. Preliminary results suggest that workers can be relied upon to gather sufficient exposure data with which to make inferences about the occupational environment. Likewise, the application of mixed models to the problem offers a particularly convenient and powerful tool for addressing important questions about the magnitude, variability, and sources of exposure.

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