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The CONSTANCES Job Exposure Matrix Based on Self-Reported Exposure to Physical Risk Factors: Development & Evaluation

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Abstract

Objectives: Job exposure matrices (JEMs) can be constructed from expert-rated assessments, direct measurement, and from self-reports. This paper describes the construction of a general population JEM based on self-reported physical exposures, its ability to create homogenous exposure groups (HEG), and the use of different exposure metrics to express job-level estimates.

Methods: The JEM was constructed from physical exposure data obtained from CONSTANCES. Using data from 35,526 eligible participants, the JEM consisted of 27 physical risk factors from 407 job codes. We determined whether the JEM created HEG by performing non-parametric multivariate analysis of variance (NPMANOVA). We compared three exposure metrics (mean, bias-corrected mean, median) by calculating within- and between- job variances, and by residual plots between each metric and individual reported exposure.

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Competing interests. None declared.

Consent. Consent was obtained from all participants as part of the CONSTANCES project.

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Results: NPMANOVA showed significantly higher between-job than within-job variance among the 27 risk factors ($F[253,21964] = 61.33$, $p < 0.0001$, $r^2 = 41.1\%$). The bias-corrected mean produced more favorable HEG as we observed higher between-job variance and more explained variance than either means or medians. When compared to individual reported exposures, the bias-corrected mean led to near-zero mean differences and lower variance than other exposure metrics.

Conclusions: CONSTANCES JEM using self-reported data yielded homogenous exposure groups, and can thus classify individual participants based on job title. The bias-corrected mean metric may better reflect the shape of the underlying exposure distribution. This JEM opens new possibilities for using unbiased exposure estimates to study the effects of workplace physical exposures on a variety of health conditions within a large general population study.

Keywords

Ergonomics; Exposure Assessment; Occupational Biomechanical Exposure; Musculoskeletal Disorders

INTRODUCTION

A job exposure matrix (JEM) is a common method used in occupational epidemiology research to estimate workers' exposures to chemical or physical risk factors based on job titles, industry information, and population exposure data. There is a surge in JEMs to estimate physical exposures such as posture, repetition, and force in the study of work-related musculoskeletal disorders [1–9]. JEMs can be constructed from four sources of data, or their combination: direct exposure measurements in a subset of the population [10], direct observations of workers [10], expert-ratings of exposure [1], and self-reported exposures from individual workers in different jobs [11].

Expert-rated assessments are often used in the construction of JEMs for industry-specific studies of chemical risk factors, and rely on assessors with accurate knowledge of rated jobs. For general population studies, knowledge of many different jobs is required, and individual assessors may or may not have direct knowledge of the very broad range of jobs. Inter-rater agreement has been reported as fair to moderate when ranking job categories in a general population JEM for risk factors for lower limb MSD [7]. Other studies have found substantial variation between raters in assigning exposures [12].

Direct measurement of worker exposures and detailed observational assessments are precise, but may misclassify exposures in jobs where exposures vary over a longer time than the period of observation [13,14]. Direct measurement and observation are expensive and time-consuming, potentially limiting their application to larger groups of workers [15,16].

Alternatively, JEMs can be constructed using self-reported exposures, which makes use of workers' knowledge of their jobs. Reported exposures from all workers are then pooled and exposures assigned at the job-level. Use of a JEM to combine self-reported exposures at the job level reduces information biases due to individual variation in reporting. The use of self-reported physical exposures provides an efficient method to estimate cumulative exposure [2]. Although this approach has been used in a few studies of work-related psychosocial

[3,17], physical [2–4], and chemical exposures [5], there are fewer general population JEMs built primarily from self-reported data for a large range of physical risk factors.

The aim of this study was to create a general population JEM based on self-reported physical exposure estimates within a large prospective cohort study. This JEM will contribute to the growing array of job exposure matrices for physical risk factors, enabling large-scale studies of associations between workplace exposures and chronic diseases, including MSD. In this paper, we report: (1) the creation of a new JEM, (2) a validation of its ability to create homogenous exposure groups, and (3) a comparison between different exposure metrics to express job-level exposures.

METHODS

JEM data source

Physical exposure data were obtained from the CONSTATANCES project (*“Cohorte des consultants des Centres d’examens de santé”*), a large (expected $n = 200,000$) prospective French cohort study investigating occupational and social determinants of health in the general population [18]. CONSTATANCES was designed to create a representative sample of French salaried workers. Detailed information on CONSTATANCES is available at: www.constances.fr. CONSTATANCES participants answered questions estimating 27 different physical risk factors in each participant’s current job. Exposure questions were patterned after the SALTSA criteria [19] and other sources [20]. Overall intensity of physical workload was assessed with the Borg rating of perceived exertion (RPE) scale, ranging from 6 (No Effort at All) to 20 (Exhausting). Questions pertaining to the duration or frequency of performing specific actions, including postures, repetitive motion, and the use of vibrating tools, were evaluated on a 4-point Likert scale (text of each question listed in Table 2). Generally, the Likert scale was formatted with the following anchor points: “Never or nearly never”, “Rarely (< 2 hours per day)”, “Often (2 to 4 hours per day)”, and “Always or nearly always”. Questions pertaining to regular handling, moving, or carrying loads asked participants to report whether they handle objects greater than 1 kg [yes/no], and if yes, asked the frequency of handling objects based on different ranges of weights, following the 4-point Likert scale above.

JEM development

We used data from the first 81,425 CONSTATANCES participants. Reported job titles were assigned a French 4-digit PCS (Profession et Catégorie Sociale) job code using the SiCore automated coding system [21]. The PCS classification system involves three nested levels of classification, from the 1-digit socio-professional job categories (Table 1) to the 4-digit PCS job code. This assignment resulted in 418 PCS job codes. Participants who were not currently working ($n = 35,466$), those who did not report a job title or who were not assigned a PCS job code through automatic coding ($n = 10,396$), and those who had missing exposure data ($n = 30$), were excluded.

To produce reliable estimates, we required a minimum of 10 valid responses for each risk factor within each PCS job code. PCS jobs with fewer than 10 responses were grouped with

other similar PCS jobs to create adequately sized groups (a minimum of 10 valid responses for each exposure for each PCS code). This method has been previously applied in grouping American standard occupational classification (SOC) codes [22]. To create groups of similar jobs, we first used a PCS to ISCO-88 (International Standard Classification of Occupations) crosswalk (Codage Assisté des Professions et Secteurs d'activité) and an existing French auto-coding system tool [23]. Many PCS codes share a single ISCO-88 code, thus creating natural groupings. To group the remaining PCS job codes with few respondents, we used an ISCO-88 to ISCO-08 crosswalk, and an ISCO-08 to SOC crosswalk. All such groupings were reviewed, and PCS job codes that were not successfully grouped via crosswalks were grouped manually based on consensus opinions from three of the authors (BE, AD, AMD). PCS codes with a small sample size that could not be meaningfully merged with other jobs were excluded (n=7 participants). After all exclusions and job code grouping, the JEM was comprised of 27 physical exposures assigned to 407 PCS codes from 35,526 eligible participants.

JEM participant inclusion: Full cohort vs. asymptomatic cohort—We conducted preliminary analyses to determine whether exposure data from both symptomatic and asymptomatic workers should be included in the JEM. Since workers with symptoms of MSD may overestimate physical exposures compared to asymptomatic workers [24,25], reporting bias is a potential concern. Symptomatic workers were defined as those reporting a pain level of 6 or more (on a scale from 0 to 10) in one or more of six body regions in the previous 7 days. We first used linear mixed models to compare self-reported exposure levels between symptomatic and asymptomatic individuals. Separate models were produced for each of 26 risk factors (the variable *Work Outdoors* was not analyzed, we expected this risk factor was unrelated to physical pain). A second analysis examined whether a JEM consisting of only asymptomatic workers led to more favorable homogenous exposure groups than a JEM with both symptomatic and asymptomatic participants (full cohort); for this analysis, the within-job pooled variance was compared between the full cohort and the asymptomatic cohort for each risk factor.

All statistical analyses were carried out with R statistical software (R Foundation for Statistical Computing, Vienna, Austria). The significant main effect was set at an alpha level of 0.05.

JEM evaluation

We computed descriptive statistics to assess the demographics of the cohort, the overall distributions of each of the 27 risk factors, and proportion of symptomatic and asymptomatic participants. To better enable interpretation of JEM assigned exposure estimates and comparison with exposures based on other methods, the ordinal questionnaire responses were re-coded to time-based variables (i.e., minutes of activity per day). We selected the median value of the questionnaire time interval: 0 minutes (ordinal rating of 0 on the 5-pt ordinal scale), 5 minutes (ordinal rating of 1 = “Never or nearly never”), 60 minutes (rating of 2 = “Rarely (< 2 hours per day)”), 180 minutes (rating of 3 = “Often (2 to 4 hours per day)”), and 360 minutes (rating of 4 = “Always or nearly always”).

Validity of JEM classification—We assessed the homogeneity of exposures classified by PCS codes by calculating within- and between- job variance, which is a common approach to determine if workers within the same job title were uniformly exposed [26]. We performed non-parametric multivariate analysis of variance (NPMANOVA) to compare within-job and between-job exposure variance for all 27 exposures. NPMANOVA is a robust alternative to multivariate analysis of variance (MANOVA), and computes the sums of squares using metric distance matrices [27]. Since there was a relatively large number of dependent variables (27 risk factors), we selected Manhattan distances, which is the sum of the absolute value of the differences among vector coordinates. Manhattan distances are particularly appropriate for high-dimensional data [28], providing significantly higher relative contrast between different points and a more meaningful indication of proximity than Euclidean distance metrics. Because the process of merging jobs reported in “JEM development” resulted in overlapping job groups, we first combined overlapping PCS codes to create 229 mutually exclusive job groupings. Each exposure was then scaled by rank transformation; the Manhattan distance between two groups was then the sum of the absolute differences between ranks among the 27 exposures. Univariate Kruskal Wallis tests were performed for each of the 27 exposure variables to evaluate between-job and within-job variance for each exposure variable.

To help visualize within- and between- PCS job code groupings, we created a multi-dimensional scaling (MDS) plot with confidence ellipses to depict the Manhattan distances between exposure vectors. The radiiuses of the confidence ellipses represent the upper 95% confidence bound of within-group distances from the group centers computed from Monte-Carlo simulations.

JEM exposure metrics

When reporting JEM-assigned exposure values, studies have used different exposure metrics [29,30]. MSD-focused JEMs have typically reported arithmetic means [1] and medians [31], therefore we reported both metrics. We also corrected the JEM mean value using empirical quantile mapping (EQM) methods [32] to adjust the group-level data to better reflect the distributions of individual-level exposure estimates. Using EQM, JEM mean values falling within every 1% quantile range were adjusted to reflect respective 1% quantiles of the individual-level self-reported values; this adjusted JEM mean is referred to as *bias-corrected mean*.

To compare exposure metrics, we calculated the within-job variance, between-job variance, and r-squared values for these three exposure metrics for all 27 physical exposures. Within-job variance was defined as the average of the squared deviation from group metric values (Eq. 1). Between-job variance was the average of the squared deviation of metric values from the global mean (Eq. 2).

$$\text{Within-job variance} = \frac{1}{N - K} \sum_{j=1}^K \sum_{i=1}^N (X_{ji} - \bar{X}_j)^2 \quad (\text{Eq. 1})$$

$$\text{Between-job variance} = \frac{1}{K-1} \sum_{j=1}^K n_j (\tilde{X}_j - \bar{X})^2 \quad (\text{Eq. 2})$$

where \tilde{X}_{ji} is the estimated metric value for the j^{th} group.

JEM exposure estimate versus individually reported exposures—For each physical risk factor, we created residual plots of the differences between individually reported exposures and exposures estimated by each of the three JEM metrics. We calculated the average of differences, the average absolute difference, and difference in variance between individually reported and JEM estimated exposure values.

RESULTS

JEM development

Eligible participants represented 407 PCS job titles nested within six broad socio-professional categories. Twenty-three percent of the cohort reported musculoskeletal pain in one or more body regions (Table 1). A linear mixed model compared exposure values between symptomatic and asymptomatic participants; 23 of 26 risk factors demonstrated statistically significant differences (Table 2). Positive beta coefficients from these models indicated that symptomatic individuals reported higher exposure values than asymptomatic individuals within the same PCS job code. Of the 26 linear mixed models, 21 exposures variables had statistically significant positive beta estimates. Eleven exposure variables had beta estimates greater than 0.2. Negative beta estimates indicated that symptomatic workers reported lower exposures than asymptomatic workers. Significant negative beta estimates were observed with two variables: *Change Task* ($\beta = -0.11$) and *Rest Eyes* ($\beta = -0.18$).

The asymptomatic cohort (range: 0.15 to 6.13) demonstrated lower within-job variance than the full cohort (range: 0.16 to 6.65), resulting in more favorable homogenous exposure groups (Table 2). As a result, only exposure estimates from asymptomatic workers were included in the JEM.

JEM evaluation

As expected for the general population in an industrialized country, the risk factors with the highest mean and median duration of daily activity were related to computer or office work, with much lower daily durations of heavy lifting or hand exertion (Table 3). Examining individually reported exposures at the level of the job, NPMANOVA analysis showed significantly higher *between-job* variance than *within-job* variance among the 27 exposures (229 PCS Groupings; $F[228,21989] = 67.18$, $p < 0.0001$). PCS job codes explained 41.4% of the variance in individual self-reported exposures in the overall model. The univariate analysis (Table 3) for each risk factor variable revealed r-squared values ranging from 5% (*Reaching for Items Behind Back*) to 55% (*Standing*). This indicates that the amount of variance explained by PCS job codes was different between risk factor variables; of the 27 risk factors, 12 variables achieved r-squares greater than 30%, while three variables resulted in explained variance less than 10%. Despite the large range of explained variance, all univariate models were statistically significant (all $p < 0.0001$) indicating a relationship

between exposures estimated by PCS code and self-reported exposure variables among asymptomatic workers.

Taking all reported risk factors into account, we observed non-overlapping relationships between individual PCS codes (shown by ellipses in Figure 1), indicating separation between different jobs. We also noted clustering of PCS codes within the same socio-professional categories (represented by color).

JEM exposure metrics

We observed minimal differences between the three exposure metrics (mean, median, bias-corrected mean) based on the within-job variance (Supplement, Table 1). Trends indicate a comparable within-job variance using the means (variance = 0.15 to 6.13), medians (variance = 0.18 to 6.73), and bias-corrected means (variance = 0.22 to 7.62). In contrast to the *within*-job variance, the bias-corrected mean (variance = 25.60 to 1193.55) showed markedly higher *between*-job variance than means (variance = 2.35 to 492.03) or medians (variance = 5.93 to 764.15). R-square values of the 27 physical risk factors ranged from 0.06 to 0.57 (JEM mean), 0.17 to 0.64 (JEM median), and 0.38 to 0.65 (JEM bias-corrected mean). Thus, compared to means or medians, use of bias-corrected means resulted in more homogenous exposure groups at the job level (greater contrast of within- and between-job variance), and explained more of the variance in individually-reported exposures.

Examination of residual plots shows increasing differences between individually reported versus group-level exposure estimates with increasing exposure level (Example: Figure 2; For all physical risk factors see Supplement, Figures 1–27). JEM-assigned exposure estimates were attenuated as the exposure level increased; this effect was most pronounced when assigning individual exposure values based on group-level mean values. Use of the bias-corrected mean led to smaller differences at all exposure levels compared to the JEM mean and median plots. A representative example of these box-plots for JEM mean, bias-corrected mean, and median exposure metrics is shown in Figure 2.

When using job-means, the mean differences were near-zero for all exposure variables [−0.002 (*Repetition*) to 0.003 (*Drive Car or Truck*)]; job-medians led to a mean difference ranging from −0.27 (*Rest Eyes*) to 0.40 (*Repetition*) [Supplement, Table 2]. JEM bias-corrected mean ranged between −0.05 (*Handle Objects 1–4 kg*) and 0.007 (*Repetition* and *Drive Car or Truck*). The bias-corrected mean also led to lower variance differences compared to JEM median values.

DISCUSSION

Assessment of workplace physical exposures is critical for the prevention of MSD and other conditions that may be affected by workplace physical activity [33,34]. The purpose of this study was to develop and evaluate a JEM using individual-level self-reported physical exposure data from a prospective general population cohort study in France. After clustering the PCS codes into 229 groups, we found significantly higher *between*-job variance than *within*-job variance among all 27 exposures tested. Our MDS plot (Fig. 1) supported the interpretation that the CONANCES JEM created homogenous exposure groups, with

distinct separation of exposures between jobs and some clustering of exposures within broad job categories. We also found that using a bias-corrected mean led to the most favorable homogenous exposure groups while best approximating individual-level exposure reports at the level of the job.

The CONSTANCES JEM was constructed using self-reported data from asymptomatic workers. Symptomatic study participants reported higher workplace physical exposures than asymptomatic participants; previous studies have shown differential reporting of exposures by symptomatic workers due to higher perception of exposures [24] or altered work behaviors [35]. It is also possible that higher exposures were accurately reported by those with MSD symptoms, because of actual exposure differences between individuals within the same jobs. While using only the exposures reported by asymptomatic workers created more homogenous exposure groupings, this approach somewhat reduced the overall mean exposures estimated for each job. Future analyses will compare this JEM with other JEMs created from expert-rated exposure estimates or direct measurement, and internal comparison with a new cohort of CONSTANCES participants, to investigate the impact of excluding exposure data from symptomatic workers.

Several metrics have been used to express the central tendency in JEMs. For example, median exposure values were used in a study constructing a JEM to study workplace psychosocial factors [31], means were used in a JEM for shoulder disorders based on expert-rated job exposure estimates [1], and geometric means were used in a JEM for magnetic field exposures [36]. In this study, we compared a bias-corrected mean to the arithmetic mean and median exposure values. We observed that bias-corrected mean values led to comparable within-job variance but larger between-job variance and therefore more homogenous exposure measures at the job level. These methodological differences show a need to further investigate the ability of different exposure metrics to approximate individual-level exposures. Our results suggest that use of empirical quantile mapping methods may correct biases and better reflect the shape of the underlying exposure distribution.

Although we demonstrated that the CONSTANCES JEM, based on self-reported physical exposure data, may be an effective tool to estimate individual workers' job exposures, there are several potential limitations to this JEM relating to the source population, the coding of job titles, and the ordinal nature of the self-reported exposure estimates. The CONSTANCES study does not include self-employed workers, who are affiliated with other health insurance funds in France [18]. This raises the question of the generalizability of the JEM. However, the source population represents more than 85% of the general population, including individuals living and working in diverse settings, individuals from different regions and different population density areas, and individuals that represent a broad range of socioeconomic status and occupations [18]. We developed this JEM using a traditional non-gendered approach. Given evidence that sex and gender influence the reported frequency and magnitude of awkward postures and physical workload within the same job title and task [37], future work will evaluate the differences in individual-level reports within each PCS group, and consider sex/gender-specific stratification.

Reported job titles in our study were assigned a standardized PCS job code using the automated SiCore coding system. This process coded 87% of provided job titles, consistent with coding results in previous surveys [38]. Accuracy of the SiCore system has been shown to be greater than 90% [38]. Manual coding of the currently un-coded jobs will allow future adjustments to the CONSTANCES JEM in case these un-coded jobs were substantively different than those automatically coded.

To aid the interpretation of ordinal scale exposure ratings, we expressed the ordinal values with time-based variables using the median value of the time intervals indicated in the CONSTANCES questionnaire. Future sensitivity analysis will inform the optimal values of these time intervals for assessing exposure-disease associations. In future work, we will also assess this JEM's convergent validity with other multi-occupation sources of exposure information. We will compare CONSTANCES JEM exposure estimates with other JEMs. We will also evaluate its predictive validity through its ability to reproduce known exposure-response associations obtained using other exposure methods.

CONCLUSION

JEMs can be constructed using self-reported data; this method of obtaining data utilizes workers' knowledge their jobs, while pooling this information at the level of the job reduces information bias. We developed a JEM using self-reported data for 27 physical risk factors. Our results demonstrated the ability of this novel JEM to create homogenous exposure groups of physical risk factors that discriminated between different jobs. This JEM provides a potentially robust assessment method for assigning current or cumulative workplace physical exposures in general population studies. Although these preliminary results indicate that the developed JEM may be a promising tool for physical exposure assessment in epidemiology studies, there remains a need for further validation, including comparisons with other exposure assessment methods and demonstration of exposure – disease associations using this JEM.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Key Messages:**What is already known about this subject?**

- A job exposure matrix (JEM) is a cost effective method to assess workplace physical risk factors (e.g. repetitive motion, force exertion, posture).
- JEMs can be built from expert-rated assessments, direct measurement, self-reports, or a hybrid of these methods.

What are the new findings?

- We constructed a general population JEM from self-reported physical exposures, which make use of workers' knowledge of their usual job exposures. The JEM classified individuals into homogenous exposure groups based on job title.
- By using bias-corrected mean exposures, which allow the job-level estimates take into account the shape of the underlying exposure distribution, we found a greater between-job variance in exposures when compared to use of mean or median exposures.

How might this impact on policy or clinical practice in the foreseeable future?

- A JEM is a low cost tool that can be useful for estimating current and past job-level exposures at a population level while minimizing information bias.
- This new JEM constructed from self-reported exposures contributes to the growing literature on JEMs for physical risk factors, and will be used in future studies relating multiple health outcomes to workplace exposures within a large prospective cohort study (CONSTANCES).
- JEMs may also be useful for clinical or compensation assessments among individuals when more detailed exposure data are not available.

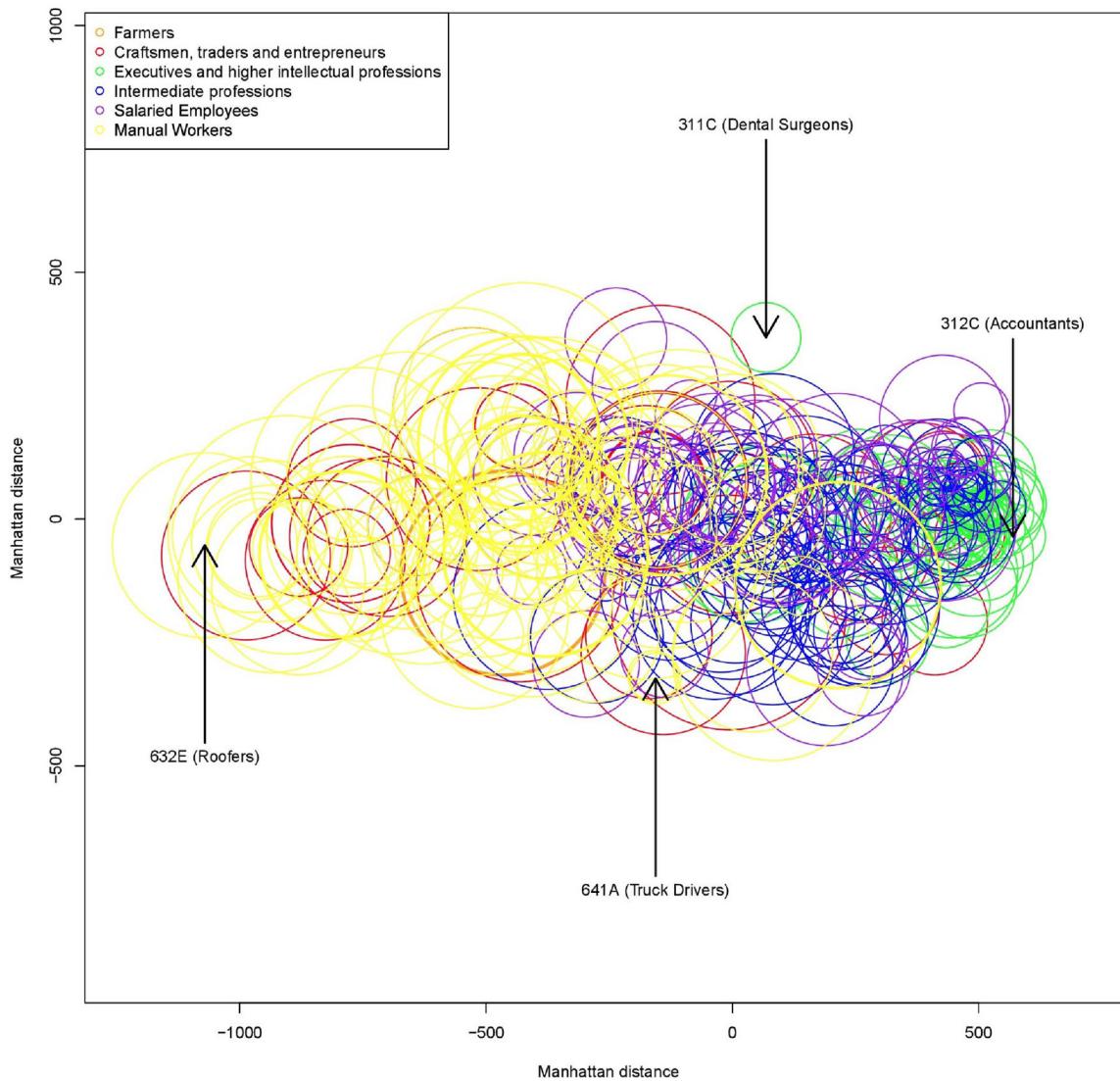


Figure 1.

Multi-dimensional scaling plots of exposure vectors for all PCS codes with 95% confidence ellipses based on Monte-Carlo simulations. Colour coded by PCS subgroup [First digit of PCS].

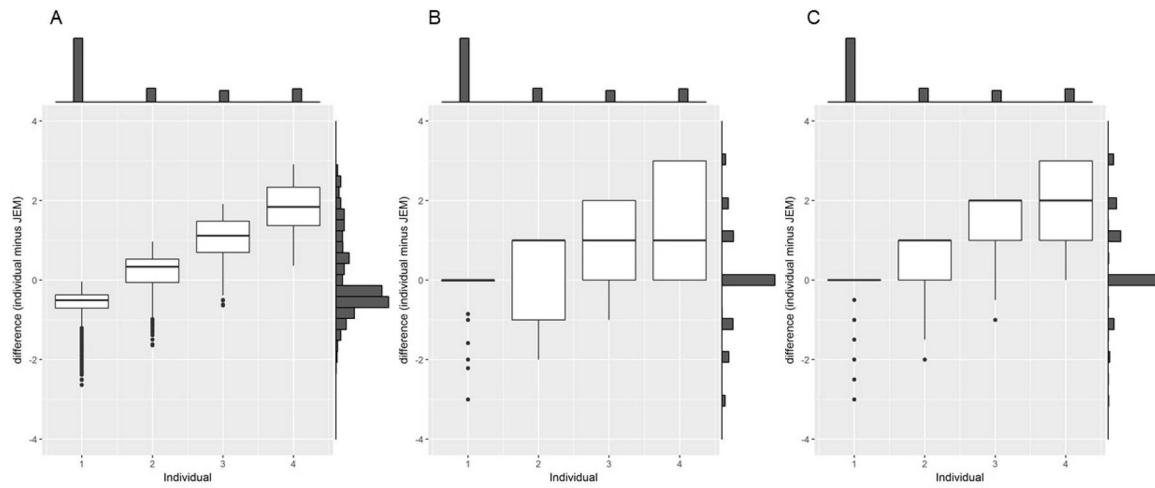


Figure 2.

Example box-plots of the differences between individual-level reports and group-level exposure estimates (individual – JEM) at each exposure intensity level for three exposure metrics: (A) JEM Mean, (B) JEM Bias-Corrected Mean, and (C) JEM Median. Distributions of individual (top axis) and JEM (right axis) are plotted. Bias-corrected mean determined using empirical quantile mapping methods (EQM). The exposure variable in this example is “Repetition”.

Table 1.

Eligible Participants from CONSTANCES Population Cohort Study (N = 35,526)

	n	%*
Socio-Professional Category		
Farmers	13	0.04
Craftsmen, traders and entrepreneurs	534	1.50
Executives and higher intellectual professions	12192	34.32
Intermediate professions	11039	31.07
Salaried Employees	8008	22.54
Manual Workers	3740	10.53
Sex		
Male	15800	44.47
Female	19726	55.53
Age		
18–24 years old	763	2.15
25–34 years old	6470	18.21
35–44 years old	9162	25.79
45–54 years old	10617	29.89
55–64 years old	6546	18.43
65 years and older	1968	5.54
Musculoskeletal Symptoms (Pain in past 7 days & current pain level 6 or more)		
Hand	1656	6.06
Knee	2576	9.29
Neck	2744	9.81
Elbow	1009	3.76
Lower back	4151	14.74
Shoulder	2166	7.85
1 or More Regions	8181	23.03

* Percent of non-missing responses.

Table 2. Comparison Between Exposure Estimates for Symptomatic (Pain >6) and Asymptomatic (Asymp.) Individuals. Within-Job Pooled Variance Between Full Cohort (Symptomatic + Asymptomatic Workers) and Asymptomatic Cohort. Linear Mixed Model (Beta Estimates and P-Values). Included are Descriptions of CONSEQUENCES Exposure Questions.

Exposure Variable	Description	N (Asymp.)	N (Full)	Within-Job Variance (Asymp.)	Within-Job Variance (Full)	Beta Estimate	p-value
Physical intensity	• How would you describe the intensity of the physical efforts of your work during a typical day?	26821	34788	6.13	6.65	0.85	0.00
Stand	• During a typical day of work: Are you standing?	29597	35017	0.55	0.56	0.09	0.00
Repetition	• On a typical day of work: Do you repeat the same actions more than 2 to 4 times per minute?	26424	34297	0.97	1.05	0.27	0.00
Change tasks	• On a typical day of work: Can you interrupt your work or change tasks or activities for 10 minutes or more each hour?	26581	34520	1.11	1.13	-0.11	0.00
Rest eyes	• During a typical day of work: Can you rest your eyes for a few seconds outside of work breaks?	31848	34510	1.00	1.01	-0.18	0.00
Kneel or squat	• During a typical day of work: Do you kneel or squat?	29574	34963	0.51	0.55	0.18	0.00
Bend trunk	• During a typical day of work: Do you lean forward or sideways regularly or for prolonged periods?	30853	34920	0.62	0.66	0.27	0.00
Drive machinery	• On a typical day of work: Do you drive construction machinery, a tractor, a self-propelled forklift or other mobile machinery at your workplace (except car or truck)?	29385	34984	0.15	0.16	0.01	0.09
Drive car or truck	• On a typical day of work: Do you drive a vehicle (automobile, truck, bus, ambulance, motorcycle, etc.) on public roads, excluding commuting?	29357	34951	0.49	0.50	0.04	0.00
Handle objects 1–4 kg	• How much time do you spend doing the following tasks or activities: Handling or regularly moving a load, a part, an object weighing between 1 and 4 kg?	31116	34644	1.34	1.38	0.25	0.00
Handle objects >4 kg	• How much time do you spend doing the following tasks or activities: Handling or regularly moving a load, a part, an object weighing more than 4 kg?	28306	34555	0.91	0.98	0.21	0.00
Carry loads <10 kg	• How much time do you spend doing the following tasks or activities: Carry a load that weighs less than 10 kg?	28240	34475	0.83	0.89	0.19	0.00
Carry loads 10–25 kg	• How much time do you spend doing the following tasks or activities: Carry a load that weighs 10 to 25 kg?	28297	34568	0.54	0.60	0.17	0.00
Carry loads >25 kg	• How much time do you spend doing the following tasks or activities: Carry a load that weighs more than 25 kg?	28271	34533	0.41	0.45	0.14	0.00
Use vibrating tools	• On a typical day of work, do you use: Vibrating tools or place your hand(s) on vibrating machines?	28437	34747	0.16	0.19	0.06	0.00
Use computer screen	• During a typical day of work, do you use: A computer screen or control panel?	31017	34792	0.55	0.56	0.01	0.19

Exposure Variable	Description	N (Asymp.)	N (Full)	Within-Job Variance (Asymp.)	Within-Job Variance (Full)	Beta Estimate	p-value
Use keyboard or scanner	• During a typical day of work, do you use: A keyboard, a mouse, or similar device (optical pen, scanner) to enter data?	28437	34735	0.61	0.63	-0.01	0.98
Bend neck	• How long do you spend in the following posture during a typical day of work: Bending your head forward regularly or for a prolonged period?	32048	34732	1.14	1.14	0.36	0.00
Arms above shoulder	• How long do you spend in the following posture during a typical day of work: Work with one or two arms in the air (above the shoulders) regularly or for a prolonged period?	32712	34834	0.41	0.43	0.23	0.00
Reach behind	• How long do you spend in the following posture during a typical day of work: Reaching regularly for items behind your back?	29482	34839	0.30	0.34	0.15	0.00
Arms abducted	• How long do you spend in the following posture during a typical day of work: Working with one or two arms separated from the body regularly or for a prolonged period?	32634	34758	0.49	0.52	0.24	0.00
Bend elbow	• How long do you spend in the following posture during a typical day of work: Flex the elbow repeatedly or keep the elbow flexed against resistance?	33722	34703	0.55	0.57	0.45	0.00
Rotate forearm	• How long do you spend in the following posture during a typical day of work: Twist your forearm as if you are using a screwdriver?	32647	34786	0.26	0.28	0.15	0.00
Bend wrist	• How long do you spend in the following posture during a typical day of work: Bending the wrist?	32599	34721	0.50	0.53	0.30	0.00
Press base of hand	• How long do you spend in the following posture during a typical day of work: Press/tap with the base of the hand on a surface or on a tool?	33127	34736	0.19	0.20	0.11	0.00
Finger pinch	• How long do you spend in the following posture during a typical day of work: Pinch objects with your thumb and forefinger.	33128	34738	0.69	0.71	0.30	0.00
Work Outdoors	• How long do you spend working outdoors during a typical day of work?	-	35187	-	-	-	-

Table 3.

Descriptive Statistics of Twenty-Seven Risk Factor Variables in JEM. Kruskal Wallis Test for Each Exposure (R-Squared) Reported for 27 Risk Factor Variables to Determine Amount of Variance Explained by PCS Job Code.

Exposure Variable	Scale	N	Mean	SD	P05	P25	Med	P75	P95	Minutes/Day		R ²
										Mean	SD	
Physical intensity	6—20	26821	9.80	3.20	6	7	9	12	15	-----	-----	0.39
Stand	1—4	29597	2.59	1.12	1	2	2	4	4	168	143	0.55
Repetition	1—4	26424	1.75	1.09	1	1	1	2	4	90	130	0.18
Change tasks	1—4	26581	2.94	1.11	1	2	3	4	4	204	142	0.10
Rest eyes	1—4	31848	3.10	1.13	1	2	4	4	4	232	145	0.19
Kneel or squat	1—4	29574	1.58	0.91	1	1	1	2	4	62	101	0.39
Bend trunk	1—4	30853	1.66	0.97	1	1	1	2	4	70	107	0.35
Drive machinery	1—4	29385	1.10	0.46	1	1	1	1	2	15	51	0.27
Drive car or truck	1—4	29357	1.41	0.88	1	1	1	1	4	46	99	0.29
Handle objects 1—4 kg	0—4	31116	1.03	1.46	0	0	0	2	4	69	119	0.36
Handle objects >4 kg	0—4	28306	0.80	1.24	0	0	0	2	4	48	100	0.38
Carry loads <10 kg	0—4	28240	0.72	1.15	0	0	0	1	3	39	89	0.36
Carry loads 10—25 kg	0—4	28297	0.58	0.94	0	0	0	1	3	24	69	0.37
Carry loads >25 kg	0—4	28271	0.51	0.83	0	0	0	1	2	17	57	0.36
Use vibrating tools	1—4	28437	1.11	0.47	1	1	1	1	2	17	55	0.30
Use computer screen	1—4	31017	3.15	1.12	1	2	4	4	4	240	146	0.55
Use keyboard or scanner	1—4	28437	3.11	1.15	1	2	4	4	4	231	149	0.52
Bend neck	1—4	32048	2.45	1.11	1	1	3	3	4	149	133	0.08
Arms above shoulder	1—4	32712	1.39	0.73	1	1	1	2	3	38	74	0.23
Reach behind	1—4	29482	1.27	0.57	1	1	1	1	2	26	53	0.05
Arms abducted	1—4	32634	1.39	0.79	1	1	1	1	3	41	85	0.21
Bend elbow	1—4	33722	1.42	0.85	1	1	1	1	4	45	91	0.23
Rotate forearm	1—4	32647	1.22	0.62	1	1	1	1	3	25	66	0.30
Bend wrist	1—4	32599	1.36	0.79	1	1	1	1	3	40	87	0.22
Press base of hand	1—4	33127	1.14	0.49	1	1	1	1	2	17	51	0.23
Finger pinch	1—4	33128	1.45	0.88	1	1	1	1	4	48	97	0.13
Work outdoors	1—4	35187	1.38	0.78	1	1	1	1	3	38	81	0.31