Spatial Clustering of Occupational Injuries in Communities

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Objectives. Using the social-ecological model, we hypothesized that the home residences of injured workers would be clustered predictably and geographically.

Methods. We linked health care and publicly available datasets by home zip code for traumatically injured workers in Illinois from 2000 to 2009. We calculated numbers and rates of injuries, determined the spatial relationships, and developed 3 models.

Results. Among the 23 200 occupational injuries, 80% of cases were located in 20% of zip codes and clustered in 10 locations. After component analysis, numbers and clusters of injuries correlated directly with immigrants; injury rates inversely correlated with urban poverty.

Conclusions. Traumatic occupational injuries were clustered spatially by home location of the affected workers and in a predictable way. This put an inequitable burden on communities and provided evidence for the possible value of community-based interventions for prevention of occupational injuries. Work should be included in health disparities research. Stakeholders should determine whether and how to intervene at the community level to prevent occupational injuries. (*Am J Public Health.* 2015;105:S526–S533. doi:10.2105/AJPH.2015.302595)

Low wage, minority, and immigrant workers experience an inequitable share of traumatic workplace injuries, in the form of higher rates, compared with their counterparts.[1–6] Reported causes include employment in hazardous sectors and manual labor jobs,[6,7] precarious and insecure employment,[8] limited educational attainment,[9] lack of English proficiency, and low occupational health literacy.[10]

The Occupational Safety and Health Act (OSHA; Pub. Law No. 91-596, 1970) legally mandates that employers provide a healthful and safe work environment to their employees and specifically requires that employers communicate hazards,[11] provide training[12] and personal protective equipment,[13] and record workplace injuries and illnesses.[14] The inequitable distribution of occupational illnesses and injuries suggest that these measures are not being taken. In part, because of unstable employment arrangements, the workforces who bear a disproportionate burden of work-related injuries are difficult to reach. Furthermore, the limitations in the enforcement capacity of OSHA because of inadequate funding call for alternative interventions.[15]

Occupational health surveillance entails the tracking of occupational injuries, illnesses, hazards, and exposures with the ultimate goal of prevention. There is a growing body of peer-reviewed and gray literature that demonstrates significant underreporting of adverse health outcomes to national and state-based health surveillance systems.[16,17] Workers may be reluctant to report illnesses and injuries because of workplace safety contests or bonuses, job instability, and fear of retaliation by their employers. Lack of knowledge about their rights and about the systems in place to provide primary, secondary and tertiary prevention also play a role.[18] Employers also have disincentives to report injuries, because severe occupational injuries increase costs and make them vulnerable to scrutiny by enforcement agencies and the public.[19] Lack of reporting limits the ability to target industrial sectors and workplaces for prevention.

Adults generally live where there are opportunities for employment and housing. Low wage, immigrant, and minority workers, and other persons employed in dangerous jobs are likely to cluster in areas with similar sociodemographic characteristics, influenced by the need for affordable housing, the familiarity of neighbors who are ethnically and linguistically similar, and services that cater to their cultural preferences. Because segments of low wage, minority, immigrant, and contingent workforces, small business employees and others who are at high risk for injury are difficult to reach in their workplaces, we sought to determine whether the need for occupational health and safety interventions could be identified at the community level. We hypothesized the following: (1) there is geographic clustering of traumatic occupational injuries by residential zip code, and (2) geographic clustering of the residential zip codes of workers at risk for traumatic occupational injuries could be predicted based on the sociodemographic characteristics of communities.

METHODS

We performed a retrospective analysis of work-related traumatic injuries that occurred between 2000 and 2009 as reported to the State of Illinois trauma registry (ITR); the ITR includes all level 1 and 2 trauma centers in the state.[20] All reliability and cleaning operations were previously performed on the ITR, and the registry was found to meet the highest quality control criteria as assessed by the North American Association of Central Cancer Registries.[21]

Inclusion Criteria

We reported on Illinois residents, ages 15 years and older, who experienced work-related traumatic injuries within Illinois. We included patients with a workers' compensation payer and those who self-reported work-related injury in the analysis. We considered an injury to be work-related if the injury occurred on an employer's premises or off the employer's premises if the employee was there to work; this included traveling for work (but not traveling to work). Injuries that occurred to the self-employed at home, on a farm, or other location were also considered work-related if the patients reported them as such. Trained record keepers were required to ascertain if an injury occurred on the job, and there was a mandatory field on the database form. Workers' compensation was listed as the primary payer for 71.2% (n = 16 525) of the identified cases, and the remaining cases were identified as work-related by the medical staff, but these cases did not have a workers' compensation payer listed.

Cumulative sums of work-related cases identified in the ITR were aggregated by year for each postal zip code. A complete list of valid zip codes in Illinois for 2000 to 2009 was obtained from the US Census Bureau.[22] If no cases of work-related injuries were identified in a given year within a zip code, a value of zero was inserted.

Community-Level Data

We collected the following sociodemographic and employment data for each zip code from the US Census Bureau,[22] and we merged these data with the aggregated injury data: male-to-female ratio; percentage of African Americans; percentage Hispanic; percentage with an education of a high school diploma or less; percentage military veterans; percentage foreign-born; percentage below the poverty line; percentage of housing stock that was vacant; home ownership rates (percentage of owner-occupied housing units divided by total housing units); and employed-to-population ratio (number of residents employed divided by population in the zip code). Because zip code level data are collected by the census every 10 years, we used year 2000 Census data for 2000 to 2004 trauma registry data and 2010 census data for 2005 to 2009 trauma registry data.

We collected total violent crime rate data from the Federal Bureau of Investigations Uniform Crime Reports.[23] "Total violent crime" was reported at the city level. We cross-matched city to zip code to calculate the violent crime rate. Before 2010, the methods for reporting specific violent crimes did not conform with requirements and, therefore, were unavailable. We used 2010 data for each year. We did not use alternative data sources, such as the American Community Survey, census small area estimates, and the American Housing Survey, because these data sources either did not capture community information at the zip code level, were unavailable beginning in 2000, or did not capture the wide range of community characteristics needed for our study. We wanted to use a limited number of sources to minimize the known variability in the estimates reported by various data sources.[24]

Statistical Analysis

We calculated the frequencies of injury and illness (overall) and distributions by gender, age, ethnicity, year of hospitalization, and measures of injury severity. We used appropriate parametric (Pearson χ^2) and nonparametric tests (Wilcoxon rank sum) to evaluate bivariate relationships. We used the Student *t*-test to compare mean differences in continuous metrics.

We analyzed the data by both absolute counts and rates. We used the sum of injured patients for each year for absolute counts within each zip code. To calculate crude injury rates, we divided the sum of injuries that resulted in treatment in hospitals with specialized trauma care within each zip code for a given year by the total number employed in all industrial sectors based on US Census Data for the specific zip code. "Total employed" was chosen, rather than only those employed in high-risk industries, because of the growing sector of workers employed as temporary employees, consultants, subcontractors, and part-time workers ("contingent" workers) who might have worked in hazardous jobs within a low-risk sector or who were simply not classified as working in a high-risk sector.

In addition to identifying communities with high numbers and rates of residents who experienced work-related injuries, we conducted a spatial cluster analysis to identify groups of communities with greater than expected rates of injury (high rates only, i.e., hotspots). Spatial cluster analysis allowed assessment of the distribution of cases across geographic areas, not simply by individual and arbitrary (postal) geographic areas. We conducted the spatial cluster analysis using SaTScan version 9.2 (Martin Kulldorff, Boston, MA). As parameters for the cluster analysis, we allowed up to a 50-kilometer distance between centroid points of zip codes to avoid excluding rural communities whose postal boundaries cover much larger geographic areas. We ran models using a circular window of shorter distances (25 and 10 km), but these models only identified clusters in more populous areas where the geographic size of the zip codes were smaller, although there was overlap between the clusters in the models. The models that used shorter radii tended to omit zip codes with lower populations around a populous area or completely omit rural clusters. We used total number of employed for the denominator in all the cluster analyses. We used latitude and longitude for the centroid.[25] For the spatial cluster analysis, we used a P value of $<.01$ for each individual cluster to determine statistical significance. The null hypothesis for each individual cluster was tested in a hierarchical manner. The global spatial autocorrelation test was significant ($P<.001$; Moran's I = 0.002; Z = 45.0).

We developed 3 multivariable models to look at the association between injuries and demographic characteristics: (1) continuous count data, (2) crude injury rates excluding zip codes with fewer than 1 injury per year, and (3) the dichotomous variable of zip codes included in spatial clusters of occupational injuries compared with zip codes not included in a spatial cluster. For the count data, we used a zero inflated negative binomial model with random effects for repeated measures within zip codes. We selected this model because there was a high proportion of zip codes without any injuries (n = 0), the data were not normally distributed and overdispersed, and there were repeated measures across the 10 years of observation for each zip code. For the rate data, we also used a zero inflated model with random effects for repeated measures within zip codes. The dispersion test indicated that the Poisson distribution was adequate for this series of data, which excluded rates based on less than 10 cases over the 10 years of observation. We did not use a multilevel logistic regression for the data that evaluated the specific zip codes in which spatial clusters were identified because it was not indicated by the diagnostic tests that assessed the adequacy of a random effects model. The data were already based on spatial clusters that were predefined using a spatial analysis; therefore, we used a single-level fixed effects logistic regression model. We used statistical evaluation of covariates, along with a priori knowledge, to determine the inclusion of covariates in the final models. For the final interpretation, we converted parameter estimates from the negative binomial model into incidence rate ratios, and these were presented as percent change. We developed all of the multivariable models using SAS software version 9.2 (SAS Institute Inc., Cary, NC).

Our analysis of the covariates showed that there was a very high level of collinearity between the variables. Diagnostic tests for tolerance and variance of inflation strongly indicated multicollinearity. We used principal components analysis to group collinear variables; we used principal components analysis (factor analysis), which is a data reduction method used for studying multiple variables by identifying underlying linear dependencies among the variables. The coefficients of the linear combinations represented the degree of correlation between the variable and the principal component (i.e., category), which was derived from the eigenvectors of the correlation matrix. The first combination of variables accounted for the greatest possible variance within the sample. The subsequent principal components represented the combination of variables that accounted for the highest degree of variance and were uncorrelated with previously defined groups. We included only principal components with eigenvalues of the correlation matrix greater than the Kaiser cutoff of 1.0 in the analysis.[26,27] Varimax rotation was performed, which produced a simplified structure by redistributing the explained variance for the principal components (i.e., categories). Variables with a factor loading coefficient greater than 0.30 for a component were considered to be associated with that component and were therefore grouped together. We weighted demographic variables at the zip code level by multiplying the coefficient attributed to the variable in each principal component (i.e., factor loading scores).

The principal component analysis of demographic variables, which are shown in data available as a supplement to the online version of this article at http://www.ajph.org, identified 2 principal components, which were labeled with thematic descriptors. (1) Urban poverty included the following individual variables: violent crime rate, percentage vacant housing units, percentage below the poverty line, and percentage African American. (2) Immigrants included these individual variables: percentage foreign-born, percentage veterans in US military (inversely correlated), and percentage Hispanic. We viewed some demographic variables that were not correlated with a principal component as important for the analysis; home ownership rates and employed-to-population ratio were analyzed as independent variables.

RESULTS

Table 1 presents a summary of the 23 200 residents of Illinois who experienced work-related injuries between 2000 and 2009, reported to the ITR. For the study period, the mean new injury severity score (NISS)[28] was 8.1 ±8.4; the percentage of patients with an NISS of 16 or greater, which indicated serious injuries, showed a continuous increase each year from 11.9% in 2000 to 17.2% in 2009. Surgical intervention was required for 50.9% of cases, and 14.5% were treated in the intensive care unit. The demographic characteristics of the patients treated in trauma units in Illinois were comparable to those reported

TABLE 1—Demographic Characteristics and Measures of Injury Severity Among Persons Experiencing Work-Related Injuries: Illinois Trauma Registry, 2000–2009

Demographic and Other Characteristics	Work Related Injuries (n = 23 200) No. (%) or Mean ±SD
Gender	
Male	19 863 (85.6)
Female	3 337 (14.4)
Age, y	42.0 ±14.2
15–19	756 (3.3)
20–29	4 798 (20.7)
30–39	5 254 (22.6)
40–49	5 676 (24.5)
50–59	4 297 (18.5)
≥ 60	2 419 (10.4)
Race/ethnicity	
Non-Hispanic African American	1 827 (7.9)
Hispanic White	5 191 (22.4)
Non-Hispanic White	14 919 (64.3)
Other/unspecified	1 263 (5.4)
Penetrating injuries	2 826 (12.2%)
Length of hospitalization, d	3.8 ±9.6
Treated in intensive care unit	3 358 (14.5)
Required mechanical ventilation	936 (4.0)
Required surgical intervention	11 806 (50.9)
NISS ≥ 16 (severe injuries)	3 388 (14.6)
Died during course of hospitalization	353 (1.5)
Year	
2000	2 366 (10.2)
2001	2 453 (10.6)
2002	2 314 (10.0)
2003	2 466 (10.6)
2004	2 546 (11.0)
2005	2 425 (10.5)
2006	2 538 (10.9)
2007	2 627 (11.3)
2008	1 620 (7.0)
2009	1 845 (8.0)

Note. NISS = new injury severity score.

in a previous study of injuries that occurred in Illinois between 1995 and 2003.[21]

Communities With the Most Work-Related Traumatic Injuries

Figure 1 presents the 25 zip codes in Illinois with the highest counts and rates of work-related injuries. In the 25 zip codes with the highest number of work-related injuries, we identified a total of 4914 injuries, which represented 21.2% of all work-related injuries among Illinois residents captured in the ITR between 2000 and 2009. In the 20% of zip codes with the highest number of work-related injuries, a total of 18 409 injuries occurred (79.3% of the total). No work-related injuries were reported in 283 zip codes (20.5% of all zip codes) for the entire period of observation.

In the 25 zip codes with the highest rates of work-related injuries per 1000 employed (Figure 1), we identified a total of 88 injuries, which represented 0.4% of all work-related injuries among Illinois residents captured in the ITR between 2000 and 2009. In the 20% of zip codes with the highest rates of work-related injuries, a total of 2748 injuries occurred (11.8% of total work-related injuries). In looking at rates among zip codes with a minimum of 10 injuries during the 10 years of follow-up (n = 422 zip codes), a total of 715 injuries occurred (3.1% of all injuries) within the 25 zip codes with the highest rates of injuries per 1000 employees.

The spatial cluster analysis identified 10 significant spatial clusters composed of 265 zip codes (19.2% of all zip codes in Illinois). Within the 10 spatial clusters, 8361 traumatic injuries (36.0% of all injuries) occurred between 2000 and 2009. Figure 2 shows the 10 clusters, which were located predominately in midsized towns in Illinois. Approximately 23.4% of the state's population lived within the 10 clusters, and the average population of the zip codes within the 10 spatial clusters was 11 592 (interquartile range = 918–18 097); this was comparable to a mean in the remainder of the state of 8982 persons (interquartile range = 713–10 015) in nonclustered zip codes. In addition, almost a quarter of the state's employees lived within these 10 spatial clusters (1.39 million; 23.8%).

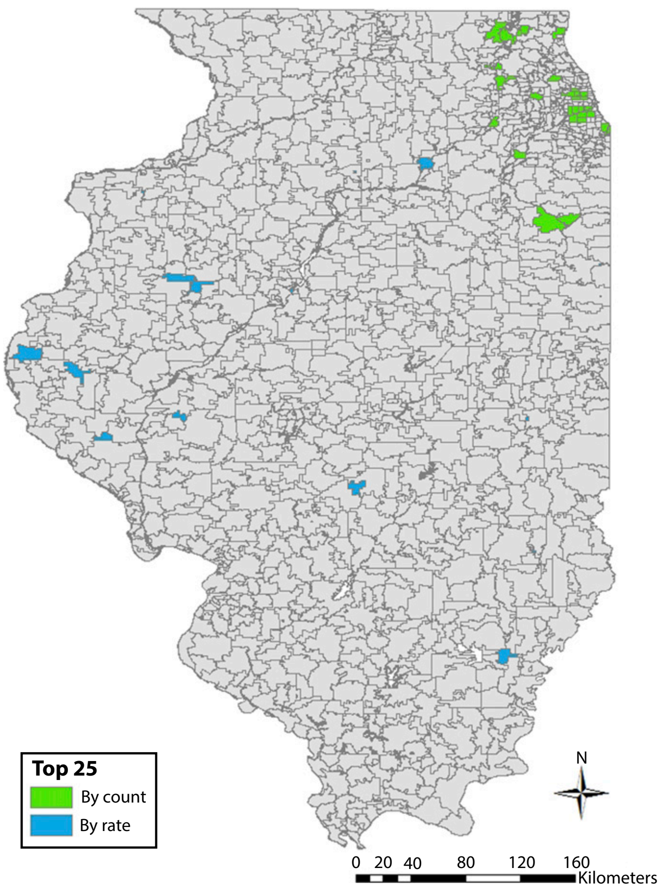

FIGURE 1—The 25 zip codes with the highest counts and rates of work-related injuries: Illinois Trauma Registry, 2000–2009.

Description of Communities With Elevated Occupational Injuries

The 3 multivariable models we developed to characterize the communities with high absolute numbers of work-related injuries (model 1), high rates of work related injuries (model 2), and spatial clusters of work-related injuries (model 3) are shown in Table 2. The direction and magnitude of the parameter estimates of the count model (model 1) and spatial cluster (model 3) data were the most similar. Both of these models demonstrated an inverse relationship between home ownership and occupational injuries, a positive relationship between total employment and injuries, and a strong, positive relationship among zip codes that more strongly adhered to the immigrants component with workplace injuries. Adherence to the urban poverty component was inversely related to the rate of injuries and spatial clustering. Spatial clusters predominately occurred in mid-sized towns, and the communities with the highest rates were found outside of cities, in zip codes with very small populations. The model based on injury rates (model 2) contradicted the other 2 (number, cluster) models because the rate model identified zip codes in rural Illinois and small- to medium-sized towns; in contrast, the spatial cluster model identified clusters in industrial mid-sized towns, and the count data identified zip codes in mid- to large-sized industrial cities. The parameter estimates from each of the models reflected these inherent differences. A more detailed description of the meaning of the parameter estimates can be found in the box on page S531.

DISCUSSION

The social-ecological framework (SEF) suggests that health outcomes are determined by

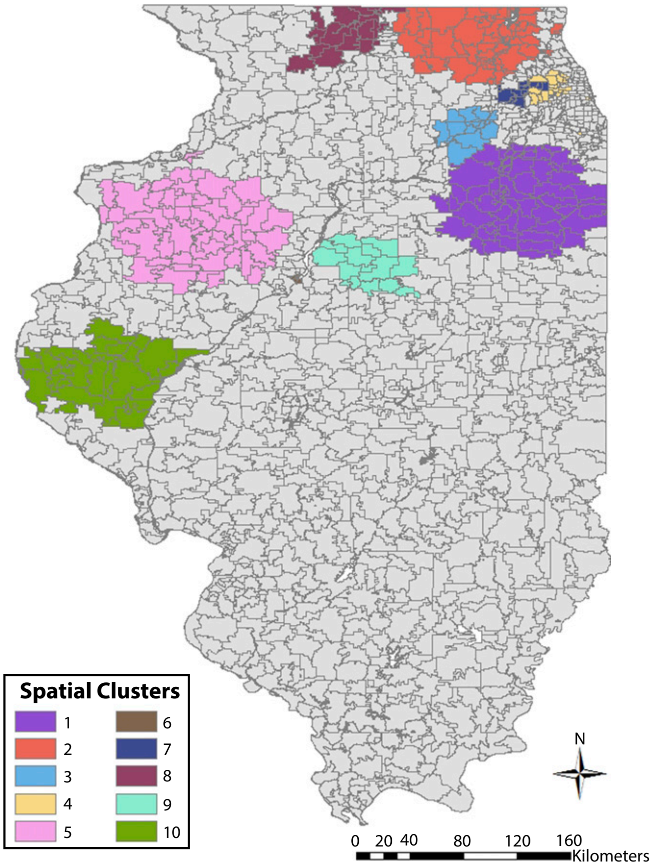

FIGURE 2—Spatial clusters of traumatic occupational injuries by zip code of worker-patient home residences, based on number injured per total employed in the zip code: Illinois Trauma Registry, 2000–2009.

the interaction among intrapersonal, interpersonal, institutional, community or society, and policy levels of influence.[29–32] There are epidemiological and case studies that demonstrate associations between socioeconomic status (e.g., wages, race/ethnicity) and rates of workplace injury and illness.[33] Our investigation, which used existing health surveillance data,[34] suggests that some neighborhoods might be disproportionately affected by traumatic occupational injuries. On a practical level, predictors of vulnerability to workplace injury at a community level allow public health practitioners to reach at-risk workers in their neighborhoods.

We consistently observed the following pattern for the count data: the 25 zip codes (1.6% of the zip codes) with the highest number of cases accounted for approximately 20% of all the cases, and 80% of the cases occurred in 20% of the zip codes. This provides a clear demonstration of spatial clustering of occupational injuries in communities. Count data identified communities that had the greatest absolute burden in terms of number of cases, whereas data based on crude rates identified small communities (i.e., small populations) with a few cases. Because of the limited resources in state government, universities, and social service organizations, consideration must be given to the number of people potentially affected by an intervention. Injury rates, alone, identified communities with a high relative burden of occupational injuries, but only a small number of individuals were affected. The spatial cluster analysis provided a middle ground between count and rate data in this study. More than one third of the injuries occurred in 10 spatial clusters, with 23.5% of the population of the state.

Our focus on the spatial clusters achieved what the count data did not: relying on counts alone targeted only the epicenter of communities that experienced a disproportionate burden of occupational injuries, whereas spatial clusters included surrounding communities, with relatively high numbers of injuries, as well. Furthermore, implementation of effective community-based interventions would require flexibility in determining venues, target audiences, injury types, occupations, and employment sectors; flexibility is better afforded by considering broader geographic areas.

Occupational illness and injury surveillance is critical to identifying emerging hazards, focusing resources, and evaluating intervention activities. Occupational health surveillance in the United States is limited by the lack of a comprehensive system[17] and underreporting to existing data collection systems.[16,19] Severely injured workers are generally transported to hospitals and trauma centers, where the cases are automatically recorded in health records. With variables to identify work-related injuries, it is possible to utilize health care databases for occupational illness and injury surveillance.

On a grander scale, the findings in our study should spur a greater appreciation of the relationship between work and health. There is flourishing interest in the relationship among neighborhood (place) and health, with race/ethnicity, gender, immigration status, income and poverty, social capital, food deserts, crime, housing, transportation availability, environmental injustice, greenspace availability, and other factors modifying this relationship.[35–38] In addition, there is a growing appreciation of work as a determinant of health, which is influenced by hazardous exposure, employment structure, wages, safety protections, and workplace culture.[8,39–42] In this study, clustering of traumatic occupational injuries among immigrants in geographic areas demonstrated that immigration, place, work, and health are interrelated. The multivariable models in our study provided additional evidence to support these relationships. Furthermore, we showed a differential burden of occupational injury on communities.

Limitations

There were several limitations to our investigation. First, the data did not offer enough

TABLE 2—Three Models Evaluating Predictors of Work-Related Traumatic Injuries by Illinois Zip Codes Based on Trauma Registry Data: 2000–2009

	Model 1[a]		Model 2[b]		Model 3[c]	
Variable	b (95% CI)	*P*	b (95% CI)	*P*	b (95% CI)	*P*
Fixed effects						
Intercept	−0.67 (−1.06, −0.29)	< .001	−1.82 (−2.23, −1.41)	< .001		
Home ownership rate	−0.05 (-0.06, −0.03)	< .001	0.02 (0.00, 0.04)	.023	0.92 (0.90, 0.95)	< .001
Employed to population ratio	0.01 (0.01, 0.02)	< .001	0.00 (−0.01, 0.01)	.932	1.01 (1.01, 1.02)	< .001
Urban poverty component[d]	0.00 (−0.03, 0.02)	.764	−0.16 (−0.23, −0.10)	< .001	0.64 (0.59, 0.69)	< .001
Immigrants component[e]	0.39 (0.33, 0.44)	< .001	0.04 (−0.02, 0.11)	.198	1.66 (1.58, 1.74)	< .001
% with ≤ high school diploma	−0.01 (−0.01, 0.00)	< .001	0.02 (0.02, 0.02)	< .001	1.00 (1.00, 1.00)	.34
Zero inflated model estimates						
Intercept	−9.46 (−12.61, −6.31)	< .001	−6.46 (−7.09, −5.83)	< .001	. . .	. . .
Urban poverty component[d]	−19.85 (−27.22, −12.48)	< .001	−15.64 (−17.16, −14.13)	< .001	. . .	. . .
Immigrants component[e]	−1.13 (−1.92, −0.34)	.005	−1.24 (−1.53, −0.96)	< .001	. . .	. . .
σ^2 (random intercept for mixed model)	1.68 (1.46, 1.90)	< .001	1.44 (1.28, 1.60)	< .001	. . .	. . .
α (negative binomial)	0.07 (0.06, 0.09)	< .001	. . .		. . .	. . .

Note. CI = confidence interval. The parameter estimates have not been converted for models 1 and 2. To determine percent change in injuries per unit change in the independent variable, take the exponent of the parameter estimate. For example, for each 1-U change in home ownership rates, the count of injuries changes by a factor of 0.95 (exp-0.05).
[a]Number of work-related injuries, by zip code: zero inflated negative binomial distribution model with random effects.
[b]Rate of work-related injuries per 1000 employed, by zip code: zero inflated Poisson model with random effects.
[c]Spatial cluster data of work-related injuries per 1000 employed, by zip code: logistic regression model, fixed effects only.
[d]The urban poverty component was based on factor analysis weights, including violent crime rate, percentage vacant housing units, percentage below the poverty line, percentage African American.
[e]The immigrants component was based on factor analysis weights, including percentage foreign-born, percentage veterans in the US military (inversely correlated), and percentage Hispanic.

variables to specify the hazards, segments of the workforce, or venues for intervention. Second, we used databases that were collected for different purposes; these were not used for surveillance of adverse occupational health events. Because of the lack of specific, high quality and uniform data, injury rates were generally calculated using different surveys or censuses for the numerator and the denominator, although this was not optimal. Moreover, our denominators were crude and did not narrow down at-risk populations; this likely accounted for the weaker relationships between the factor components (independent variables) and occupational injuries. Finally, the census data we used for the denominators in rate calculations were collected every 10 years. For that reason, we used Census 2000 for the first 5 years and Census 2010 for the second 5 years of trauma data. This did not allow for an actual trend analysis. The American Community Survey now collects data annually, which would allow more accurate testing for trends in the future. It should be noted that the 283 zip codes with no injuries were predominately in areas that had limited access to hospitals with trauma units, and were composed of mainly rural, lower populated areas. Injured workers in those areas would be treated in local health care facilities and would

How to Make Sense of the Parameter Estimates in This Analysis: Illinois Trauma Registry, 2000–2009

The complex models may be confusing; therefore, examples on how to interpret the model estimates for models 1 and 2 are presented. In model 1, the parameter estimate for the employed to population ratio is 0.01. In the unmarginalized negative binomial regression estimate for a 1-U increase in employed to population ratio (increase of 1%), holding the other covariates constant, the difference in the logs of expected count of injuries would be expected to increase by 0.01 units. What does that mean? Converting the parameter estimate into an incidence rate ratio makes the data more interpretable. First, it is necessary to express the employed-to-population ratio in meaningful terms. The ratio in Illinois can vary across zip codes from less than 30% to more than 70%; therefore, it makes sense to transform the parameter estimate to express a change of 10% rather than 1% as in the previous example. Using the incidence rate ratio, a 10% increase in the employed-to-population ratio is associated with an expected increase of 11% in the number of work-related injuries over a 10-year period. In model 2, a 10% increase in employed-to-population ratio is associated with no change in the annual injury rate.

What do the zero inflated parameters mean? These estimates provide information about characteristics of the communities with zero work-related injuries. For example, in model 1, the more likely a community adheres to the immigrants component, the odds that a community would have zero work-related injuries would decrease by a factor of 0.32 (exponent of −1.13). In other words, communities with more immigrant characteristics are less likely to have zero work-related injuries. The same association is observed in model 2.

not be recorded in the ITR. Finally, our study was cross-sectional, and the associations were described rather than clarifying the cause and effect.

Conclusions

Our research demonstrates that the homes of injured workers cluster spatially and that neighborhood characteristics might be predictive of an increased burden of traumatic occupational injury. This is important for 2 reasons. First, it provides evidence of the relationships between work and health (injury), workplace injury and immigration, workplace injury and racial or urban poverty, and workplace injury and place or neighborhood. It demonstrates an inequitable burden of occupational injury on communities and highlights work as a determinant that should be included in health disparities research.

Second, the results of our investigation suggest the possibility of focusing on geographic centers for occupational health and safety interventions. Further investigation is necessary to determine the types and content of health and safety messaging and training that would be most beneficial, how that information could be delivered effectively (e.g., venues and media for communication), how to access and engage workers, and how to partner with governmental agencies, businesses, and nonprofits in this endeavor.

Finally, our study exploits both general health outcomes and population-based data sources to count occupational injuries and to describe factors that are associated with their occurrence. It demonstrates the value of using and linking existing resources to conduct occupational health surveillance. ■

About the Authors

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Contributors

L. Forst conceptualized the investigation, obtained the trauma registry data, and wrote the article. L. Friedman conducted the data analysis and co-wrote the article. B. Chin assembled the demographic data, conducted the descriptive portion of the analysis, and edited the article. Dana Madigan produced the graphics using geographic information systems and edited the article.

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Human Participant Protection

This research was approved by the institutional review board at the University of Illinois at Chicago, protocol number 2008-0060.

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