Trauma in the Neighborhood: A Geospatial Analysis and Assessment of Social Determinants of Major Injury in North America

Craig D. Newgard, MD, MPH, Robert H. Schmicker, MS, George Sopko, MD, MS, Dug Andrusiek, PhD, Walter Bialkowski, MS, Joseph P. Minei, MD, Karen Brasel, MD, MPH, Eileen Bulger, MD, Ross J. Fleischman, MD, MCR, Jeffrey D. Kerby, MD, PhD, Blair L. Bigham, MSc, ACPf, Craig R. Warden, MD, MPH, MS, and the Resuscitation Outcomes Consortium Investigators

Objectives. We sought to identify and characterize areas with high rates of major trauma events in 9 diverse cities and counties in the United States and Canada.

Methods. We analyzed a prospective, population-based cohort of injured individuals evaluated by 163 emergency medical service agencies transporting patients to 177 hospitals across the study sites between December 2005 and April 2007. Locations of injuries were geocoded, aggregated by census tract, assessed for geospatial clustering, and matched to sociodemographic measures. Negative binomial models were used to evaluate population measures.

Results. Emergency personnel evaluated 8786 major trauma patients, and data on 7326 of these patients were available for analysis. We identified 529 (13.7%) census tracts with a higher than expected incidence of major trauma events. In multivariable models, trauma events were associated with higher unemployment rates, larger percentages of non-White residents, smaller percentages of foreign-born residents, lower educational levels, smaller household sizes, younger age, and lower income levels.

Conclusions. Major trauma events tend to cluster in census tracts with distinct population characteristics, suggesting that social and contextual factors may play a role in the occurrence of significant injury events. (*Am J Public Health.* 2011;101:669–677. doi:10.2105/AJPH.2010.300063)

Injury is a major public health problem and one of the most common reasons for emergency department visits, health care expenses, morbidity, and mortality.[1–4] Although a growing body of literature has assessed individual-level injury factors and outcomes, relatively little research has evaluated how broader geographic, environmental, social, and cultural factors influence the occurrence of injury.

Better understanding such macroscopic influences may improve health policy strategies for injury prevention, including community planning to reduce violence, defining the interplay between contextual and individual-level injury factors, efficient deployment of emergency medical service (EMS) resources, and more targeted public health efforts to reduce injury-related morbidity and mortality. Geographic information systems (GIS) analysis has been suggested as a novel tool in evaluating such geospatial and contextual components of injury events,[5–7] yet the number of GIS-based injury studies remains relatively sparse.

Injury disproportionately affects individuals in certain racial, ethnic, and socioeconomic groups.[8–10] However, whether such differences function through individual-level mechanisms or are indicative of larger societal and environmental influences is unknown. Previous geospatial injury studies evaluated intentional injury (i.e., assault)[11–13] and violent crime[14] rates, falls among the elderly,[7] pedestrian injuries,[15,16] and trauma system patients.[17] These studies suggested that the locations where injuries occur are not random and that certain environmental (e.g., density of alcohol outlets), demographic, socioeconomic (e.g., poverty), and racial/ethnic factors, as well as time of day, are associated with higher injury and crime rates.

However, previous research has been limited to single geographic areas, patients with certain mechanisms of injury, and hospitalized patients.[7,11–17] It remains unclear whether similar geospatial clustering exists among patients affected by additional injury mechanisms across diverse regions and communities and whether specific environmental and sociocultural factors can reliably identify high-risk populations.

We sought to identify geospatial clusters of major trauma patients accessing 911 emergency services and to characterize socioeconomic, cultural, and demographic population measures in such locations across 9 diverse North American sites. These sites were Birmingham, Alabama; Dallas, Texas; Milwaukee, Wisconsin; Pittsburgh, Pennsylvania; Portland, Oregon; King County, Washington; Ottawa, Ontario; Toronto, Ontario; and Vancouver, British Columbia. Our overall aim was to combine both geospatial and population information to evaluate the contextual basis and broader social determinants of serious injury.

METHODS

We conducted a secondary analysis of an out-of-hospital, consecutive patient, prospective cohort registry of injured children and adults evaluated by EMS agencies and meeting field criteria for major trauma. We used an ecological study design to assess the association between rates of major injury events and population sociodemographic factors at the locations where injuries occurred.

Setting

A total of 163 primary (first-arriving) EMS agencies transporting patients to 177 acute care hospitals in 9 cities or counties across the United States and Canada gathered population-based data from December 1, 2005, through April 30, 2007. More than 200 EMS agencies participated in the field care of these patients and contributed data for our analyses. These data were collected as part of the Resuscitation Outcomes Consortium (ROC) epidemiologic out-of-hospital trauma registry (ROC Epistry-Trauma), which has been described in detail elsewhere.[18]

The 9 participating study sites vary with respect to geographic size, location, population density, geography, and EMS system structure.[19]

Selection of Participants

The primary cohort consisted of consecutive injured children and adults requiring activation of the emergency 911 system within predefined geographic regions across each site. To be included in the cohort, patients were required to have received an EMS evaluation and to have met field-based criteria for major trauma, defined by the presence of physiological compromise at any point during the out-of-hospital evaluation (systolic blood pressure level of 90 mmHg or below, respiratory rate of less than 10 or more than 29 breaths per minute, Glasgow Coma Scale score of 12 or less, field advanced airway attempt such as intubation, or traumatic death in the field). Our inclusion criteria were based on standard field trauma triage criteria that have demonstrated high specificity with respect to serious injury.[20–25]

Injury was broadly defined as any blunt, penetrating, or burn-related mechanism for which the EMS provider determined trauma to be the primary clinical insult. Injured individuals meeting our criteria were included in the study regardless of field disposition, whether or not they were transported to a hospital, the type of hospital to which they were transported (i.e., trauma center vs nontrauma center), or outcome. Injured patients who were evaluated by EMS personnel but did not survive were included whether or not resuscitative efforts were undertaken at the scene. Enrollment dates and the resulting sample size were based on a time period in which there was complete case capture and a high rate of outcome completion.

Measurement Strategy

We assessed types and mechanisms of injury on the basis of information included in EMS patient care reports. Type of injury was classified as blunt, penetrating, or burn-related. We defined 3 subgroups of patients. The first subgroup was limited to injured patients who died in the field. The second subgroup was defined as having suffered penetrating injuries (92% as a result of firearm-related incidents and stabbings). A third subgroup was classified as having suffered intentional injuries. The second and third subgroups experienced injuries frequently associated with assault, violent crime, weapon use, rape, and child battery.

For each patient, we gathered data on the location of the injury. All of the US study sites assigned a census tract location for each event, whereas Canadian sites used latitude–longitude or Universal Transverse Mercator coordinates (both projected to North American Datum 1983 geographic coordinates). In the United States, census tracts cover the entire country and include 1500 to 8000 residents per tract.[26] Although census tracts in Canada are of similar size, with 2500 to 8000 residents in each tract, they are confined to large urban cores and thus do not cover the entire country.[27] Therefore, we limited geographic regions to contiguous coverage areas (regardless of whether major trauma events occurred in those areas) to minimize bias in our analyses.

We used the point-in-polygon method to aggregate point location data to census tracts in ArcGIS 9.1 (ESRI Inc, Redlands, California).[28] The final data set consisted of all study area census tracts, with major trauma and subgroup patients aggregated by census tract.

We matched population sociodemographic measures from the US Census Bureau[29] and Statistics Canada[30] to census tracts in the study regions. Population variables included age, gender, socioeconomic status (unemployment rate, household income), non–primary language use (use of a language other than English at the US sites and use of a language other than English or French at the various Canadian sites), race/ethnicity (including foreign-born status), family composition (household size, family size), education (high school diploma or equivalent, graduate degree), and land mass. Financial measures were normalized to 2006 US currency for consistency in economic measures. Population size, number of census tracts, population measures, and the number of ROC Epistry-Trauma patients at each site are listed in Table 1.

Data Collection and Processing

The data collection and processing methods have been described in detail elsewhere.[18] Briefly, investigative teams at each ROC site identified eligible patients from participating EMS agency records. On-site EMS providers collected data on all variables. Standardized data were collected from each agency at regular intervals, processed locally, deidentified, entered into standardized data forms, and submitted to a central data coordinating center. Quality assurance processes at ROC sites included data element range and consistency checks, along with annual site visits at which randomly selected study records, data capture processes, and site-specific mechanisms for quality assurance were reviewed.

To minimize bias in our analyses and to ensure comprehensive capture of cases, we continually evaluated monthly ROC Epistry-Trauma case enrollments during data collection for each site and for individual EMS agencies. Sites or agencies that had substantially higher or lower case capture rates (relative to their average) for a given month, as determined via a Poisson distribution with a 5% cutoff, were contacted in an attempt to understand whether such fluctuations were the result of natural variation and other explainable trends as opposed to being due to biased case capture. We used these assessments to improve identification of eligible patients, minimize case ascertainment bias, and select a time period during which there was consistent case capture.

The primary study outcome was the incidence of major trauma in each census tract. Secondary outcomes included rates of traumatic deaths in the field, penetrating injuries, and intentional injuries.

Data Analysis

We analyzed the data through 2 separate approaches. First, we used a spatial scan statistic (SaTScan) to identify geospatial clustering of traumatic events at the census tract level.[31–34] We calculated an overall incidence rate across each site and generated census tract centroids (geographic weighted centers) using the tract population and number of injury events. Starting at the centroid, SaTScan generated circular windows of increasing size until a prespecified percentage of the total site population (i.e., the percentage of the population at risk) had been met. Clusters were created when points representing other census tracts fell within the

TABLE 1—Population Characteristics and Study Patients at the 9 Study Sites: Resuscitation Outcomes Consortium Epistry-Trauma Project, United States and Canada, 2005–2007

	Birmingham	Dallas	Milwaukee	Ottawa	Pittsburgh	Portland	King County	Toronto	Vancouver
Census data									
No. of census tracts	197	506	307	188	120	397	400	1307	471
Population	876 053	2 332 423	940 164	845 670	291 071	1 789 457	1 846 947	6 436 543	2 356 429
Race/ethnicity, %									
White	66.0	59.2	65.6	79.5	68.2	84.1	76.3	63.2	60.3
Black	31.5	19.7	24.6	4.6	26.2	2.8	5.2	6.0	0.9
Asian	0.9	1.3	2.6	12.9	3.0	4.8	10.5	26.3	35.7
Hispanic	1.6	8.8	8.8	0.9	1.3	7.4	5.4	1.7	1.0
Foreign born	2.1	19.4	6.7	21.3	5.2	10.8	14.7	38.7	36.4
Men, %	47.5	49.9	47.9	48.4	47.5	49.6	49.8	48.6	48.8
Age, y									
Median	36.5	31.6	33.0	39.0	37.0	35.1	36.3	38.0	38.2
<18, %	24.9	27.6	26.4	...	19.5	25.4	22.7	...	...
>65, %	12.9	7.9	12.9	12.3	15.9	10.2	10.4	12.2	13
Household composition									
Average household size	2.5	2.8	2.5	2.54	2.19	2.53	2.46	2.81	2.69
1-person households, %	27.3	27.9	33.0	...	40.4	26.7	30.1	...	...
Household income, $[a]									
Median	46 775	57 238	42 843	66 430	34 788	56 676	67 018	60 689	52 523
>100 000, %	10.1	14.5	7.0	32.5	6.7	13.1	19.3	28.0	22.3
Non–primary language use, %	0.8	10.3	3.2	10.3	1.1	3.8	3.6	21.5	23.2
Education, %									
Less than high school	21.1	26.0	23.7	11.3	20.0	12.9	9.9	17.5	15.6
Graduate degree	8.1	9.3	7.2	12.4	12.2	9.8	12.9	7.3	6
Epistry-trauma data									
Sample size	507	1116	740	910	547	449	1628	1781	650
Age, y									
Median	36	33	28	38	30	39	36	42	37
<18, %	6.3	16.7	19.7	16.1	21.1	10.5	17.2	18.2	7.1
>65, %	5.7	9.1	9.1	19.5	12.3	17.0	17.9	26.9	12.6
Rapid sequence intubation, %	0.4	0.0	0.0	0.0	4.2	15.6	17.1	0.0	0.0
Cardiopulmonary resuscitation, %	10.9	33.9	16.4	25.7	16.4	6.2	12.5	17.6	34.5
First Glasgow Coma Scale score									
<8, %	25.8	32.4	19.2	27.9	28.2	38.8	22.2	14.3	57.1
Median	11	10	14	11	14	9	13	15	6.5
First systolic blood pressure reading, mmHg									
<90, %	22.0	33.8	32.1	28.5	44.0	13.3	26.0	30.7	32.9
Median	110	110	100	115	90	129	110	90	110
First respiratory rate reading, breaths per minute									
<10 or >29, %	20.0	22.7	31.3	25.0	32.3	26.0	35.2	17.9	44.4
Median	20	18	20	18	18	18	20	18	20
Air transportation, %	12.2	2.7	3.0	2.3	16.7	3.0	4.5	1.5	9.6
Penetrating injury, %	28.5	27.9	31.1	14.7	25.3	10.6	17.6	6.6	17.4

Note. Ellipses indicate data not available.
[a]Canadian dollar values were normalized to 2006 US currency.

boundaries of a window; overlapping clusters were not allowed. Incidence rates and likelihood ratio statistics were then produced for each cluster.

Nonrandom clustering was categorized as clusters with incidence rates higher than expected according to the percentage-at-risk metric. Because SaTScan is sensitive to the percentage-at-risk parameter setting,[35] we varied this metric by 50%, 40%, 30%, 20%, 10%, and 5% to identify core clusters, which we defined as clusters of census tracts that existed in all iterations. We repeated this process separately at each of the 9 sites for all major trauma patients, traumatic deaths in the field, individuals with penetrating injuries, and individuals with intentional injuries. Additional details regarding the geospatial analysis are included in Appendix A (available as a supplement to the online version of this article at http://www.ajph.org). After identifying core clusters of major trauma patients, we used descriptive statistics to compare population measures between census tracts with and without injury clustering.

We then used multivariable negative binomial regression models to assess population and social determinants associated with injury events. For these analyses, the census tract was the unit of analysis; all tracts were included regardless of the number or rate of major trauma events. The dependent variable was the number of traumatic events in each census tract. Sites were included as fixed effects in all models to account for correlated data within sites. Because little literature existed to guide a priori selection of our population measures, we used several factors to guide variable selection for the final models.

Initially, we selected variables that we believed were of scientific importance and had plausible associations with major trauma events. We used an iterative process to remove statistically correlated (collinear) terms from the model one at a time. We then eliminated nonsignificant variables ($P > .1$) from the model in a nonautomated, backward selection process to produce a parsimonious model. We used the Hosmer–Lemeshow goodness of fit test and additional fit statistics to assess model fit. Interactions between covariates were tested with the significance level set at $P < .05$.

Because of the limited coding of race and ethnicity in the Canadian census data, we restricted all analyses involving race and ethnicity to US sites. Census measures were evaluated in both continuous and categorical formats (e.g., percentiles). We analyzed 4 models defined according to outcome: major trauma, death in the field, penetrating injury, and intentional injury.

We used SPlus 6.2 (Insightful Corp, Seattle, Washington) for database management and SaTScan 7.0 to assess geospatial clustering. Stata 8 (StataCorp LP, College Station, Texas) was used in analyses involving inferential statistics, and ArcGIS was used to create graphics.

RESULTS

EMS systems at the 9 study sites evaluated 8328 major trauma patients during the 16-month study period. After exclusion of incomplete episodes and embargoed patients enrolled in a concurrent interventional trial (n=458), events located outside of contiguous geospatial regions (n=221), and individuals with erroneous geospatial information (n=323), the primary sample available for analysis included 7326 major trauma patients. Of these patients, 1045 (14.3%) died in the field, 1376 (18.8%) had suffered penetrating injuries, and 1784 (24.4%) had suffered intentional injuries. The sample included 1137 children and adolescents (younger than 18 years), of whom 47 (4.1%) died in the field, 110 (9.7%) suffered penetrating injuries, and 183 (16.1%) suffered intentional injuries.

We identified 529 (13.7%) census tracts with higher than expected incidence rates of major trauma events (i.e., clustering). There was a nonrandom geospatial distribution of major trauma patients at each site (see Appendix B, available as a supplement to the online version of this article at http://www.ajph.org). The geospatial findings were generally consistent when the sample was restricted to traumatic deaths in the field, penetrating injuries, and intentional injuries (data not shown). Relative to census tracts without injury clustering, census tracts with clustering (for all major trauma patients as well as the 3 subgroups) tended to have slightly younger residents, higher proportions of non-White residents and unemployment, lower proportions of foreign-born residents and individuals with a high school education, and lower household incomes (Table 2).

Social determinants of major trauma, traumatic deaths in the field, penetrating injuries, and intentional injuries are shown in Table 3. The all-site model did not include covariates for race or ethnicity because of coding differences between US and Canadian census data. Higher unemployment rates were associated with increased rates of major trauma events. Higher educational levels, increased household sizes, and higher household incomes were all negatively associated with injury events. The association between non–primary language use and injury differed between the primary sample (a positive association with major trauma events) and the 3 subgroups (negative associations with field deaths and penetrating injuries).

We also found site-specific differences in rates of traumatic events. Although a number of interactions met the criteria for significance (Table 3), only the interaction between unemployment rate and household size persisted in all 4 models ($P < .05$ in the major trauma model and $P < .01$ in the other models). The interaction between median income and age was significant in both the penetrating injury model and the intentional injury model ($P < .05$).

In the model including race and ethnicity (US sites only; Table 4), the risk of major trauma increased with increasing numbers of non-White residents. The proportion of non–primary language speakers was inversely associated with major trauma events. Similar to the other models, higher rates of unemployment were associated with higher injury rates, whereas larger household size and higher family income were negatively associated with injury rates. These findings were most pronounced among the penetrating injury and intentional injury subgroups. Similar to the all-site model, we found site-specific variability in the rate of traumatic events after adjustment for other population metrics.

DISCUSSION

Our findings demonstrate that, across 9 North American sites, locations of major trauma events were not geographically random, and events disproportionately clustered in census tracts with higher rates of unemployment, lower educational levels, lower incomes, fewer families, and more non-White residents. These

TABLE 2—Comparison of Population Measures Between Geographic Areas With and Without Injury Clustering: Resuscitation Outcomes Consortium Epistry-Trauma Project, United States and Canada, 2005–2007

	Any Major Trauma		Death in Field		Penetrating Injury		Intentional Injury	
	Clustering	No Clustering	Clustering	No Clustering	Clustering	No Clustering	Clustering	No Clustering
No. of census tracts	529	3364	348	3545	335	3558	315	3578
Area-level socioeconomic indicators								
Non-White, %	38.9	32.4	39.4	32.6	49.8	31.8	48.4	32.1
Women, %	50.6	51.1	50.3	51.1	51.0	51.1	50.8	51.1
Median age, y	36.4	36.6	35.6	36.7	35.3	36.7	35.5	36.7
Median household size	2.4	2.7	2.5	2.7	2.5	2.7	2.5	2.7
Foreign born, %	24.4	24.3	19.6	24.8	22.2	24.5	22.7	24.5
Unemployment rate, %	9.3	6.1	9.8	6.2	11.1	6.1	11.6	6.1
Median income, $	42 237	55 621	44 497	54 307	35 746	55 491	35 915	55 090
Income > $100 000,[a] %	15.4	20.9	15.5	20.6	9.4	21.1	11.0	20.9
High school diploma, %	77.3	83.2	78.1	82.8	72.0	83.4	73.2	83.2

[a]Canadian dollar values were normalized to 2006 US currency.

results were most pronounced when the sample was restricted to traumatic deaths, penetrating injuries, and intentional injuries.

Previous studies have shown that individuals of certain races and certain socioeconomic classes bear a disproportionate burden of serious injury and intentional violence.[8–10,12,14] Our findings were similar, identifying high-risk, geographically based neighborhoods across many different communities in North America.

The associations between non-White race and major trauma persisted after adjustment for several other measures, including income, unemployment, education, age, household size, and primary language spoken. These findings confirm that major injury events disproportionately occur in areas with higher proportions of socially marginalized populations (i.e., populations with higher unemployment rates and lower educational levels) and racial minority communities. Because these associations were most pronounced among the field death, penetrating injury, and intentional injury subgroups, our results suggest that the setting in which intentional violence occurs has strong social determinants. The inverse relationship between household size and major trauma suggests that census tracts with higher proportions of families have a reduced incidence of major trauma and violent events or that these populations are drawn to safer neighborhoods.

Our findings have significant public health implications. Serious injuries are a large public health burden, yet relatively little research has been done on environmental and social determinants of injury. Our results suggest that injury-related morbidity and mortality (as measured through major trauma events and early traumatic death) may be related to the environment and social setting in which injury events occur. That is, the contextual setting of major trauma explains a portion of the variability in injury rates across communities. Characterizing the social and environmental aspects of such neighborhoods points to a potential relationship between the environment and the risk of major trauma.

Cusimano et al. suggested similar patterns between assaults and ambulance dispatches in Toronto that varied according to time of day; these changing patterns were explained by contextual and environmental factors in the areas studied.[13] However, their results do not allow clear distinctions to be made between individual- and community-level social factors as causal pathways explaining differing rates of trauma events across census tracts.

A notable aspect of our study is the variability in adjusted rates of major injuries between sites. This variability was evident in the multivariable regression models accounting for population-level sociodemographic factors. Although a definitive explanation for such variability is not possible from our data, potential factors include site-specific differences in patient sampling; unmeasured confounding; inherent differences between regions (e.g., US vs Canadian sites) with respect to gun control, crime and violence, mechanisms of injury (blunt vs penetrating trauma), and sociodemographic factors (e.g., poverty) that are incompletely captured by census data; and other public health, social, and health policy differences that may modify the resulting injury rates.

The differences in incidence rates and outcomes between the sites assessed in this study have been quantified and described in detail elsewhere.[36] Such differences in rates of injury events between sites do not detract from the utility of site-specific geospatial data and analyses as a public health tool, as detailed subsequently.

Our findings suggest that geospatial information can be used to target distinct high-risk populations, offering a more practical approach for implementing focused injury prevention strategies. For example, rather than implementing a broad, community-wide or regional injury prevention intervention that may be costly and difficult to assess, an alternative strategy would be to focus on distinct census tract neighborhoods. Such an approach would allow concentrated efforts targeting high-risk neighborhoods rather than diluting efforts over a broad area. Even without the benefit of policy-level interventions or an influx of public funds to clean up a given area, geographically targeted injury prevention strategies might

TABLE 3—Adjusted Population Measure Incidence Rate Ratios (IRRs) for Major Trauma Events Across the 9 Study Sites: Resuscitation Outcomes Consortium Epistry-Trauma Project, United States and Canada, 2005–2007

	Major Trauma[a] (n = 6841), IRR (95% CI)	Death in Field[b] (n = 978), IRR (95% CI)	Penetrating Injury[c] (n = 1315), IRR (95% CI)	Intentional Injury[d] (n = 1704), IRR (95% CI)
Men, %	1.0002 (1.00005, 1.0004)	1.0003 (1.00009, 1.0006)	...	...
Unemployment, %	1.06 (1.05, 1.07)	1.03 (1.01, 1.05)	1.05 (1.03, 1.06)	1.05 (1.04, 1.07)
Non–primary language use, %[e]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	0.87 (0.75, 1.00)	0.70 (0.55, 0.90)	0.86 (0.69, 1.05)	...
Quartile 3	1.02 (0.87, 1.21)	0.59 (0.44, 0.78)	0.85 (0.66, 1.09)	...
Quartile 4	1.23 (1.02, 1.49)	0.48 (0.34, 0.67)	0.65 (0.47, 0.88)	...
Median household size	0.68 (0.62, 0.75)	0.74 (0.60, 0.92)	0.73 (0.60, 0.88)	0.67 (0.57, 0.80)
Median age, y	1.03 (1.02, 1.04)	...	...	...
Adjusted median household income, $[e]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	...	0.91 (0.72, 1.15)	0.64 (0.52, 0.79)	0.68 (0.56, 0.83)
Quartile 3	...	0.69 (0.51, 0.94)	0.51 (0.39, 0.68)	0.51 (0.40, 0.66)
Quartile 4	...	0.59 (0.40, 0.88)	0.36 (0.25, 0.51)	0.44 (0.32, 0.60)
High school diploma, %	0.99 (0.98, 0.99)	0.98 (0.97, 0.99)	0.98 (0.97, 0.99)	0.98 (0.97, 0.99)
Site				
1 (Ref)	1.00	1.00	1.00	1.00
2	0.94 (0.74, 1.20)	1.18 (0.80, 1.74)	1.11 (0.81, 1.53)	1.02 (0.78, 1.33)
3	1.44 (1.14, 1.82)	1.30 (0.90, 1.88)	1.34 (1.00, 1.81)	1.32 (1.00, 1.76)
4	0.45 (0.34, 0.59)	0.83 (0.53, 1.29)	0.49 (0.33, 0.73)	0.49 (0.36, 0.68)
5	1.69 (1.25, 2.29)	1.41 (0.88, 2.27)	1.63 (1.13, 2.34)	1.57 (1.10, 2.23)
6	0.57 (0.44, 0.74)	0.35 (0.22, 0.57)	0.31 (0.21, 0.48)	0.36 (0.25, 0.51)
7	1.97 (1.54, 2.51)	1.44 (0.98, 2.14)	2.21 (1.60, 3.04)	2.42 (1.85, 3.19)
8	0.39 (0.30, 0.51)	0.47 (0.31, 0.72)	0.18 (0.12, 0.27)	0.12 (0.09, 0.17)
9	0.34 (0.25, 0.45)	1.10 (0.70, 1.71)	0.44 (0.29, 0.66)	0.36 (0.26, 0.49)

Note. CI = confidence interval. Data were based on 4129 census tracts. Estimates were obtained via multivariable negative binomial models with patient count as the outcome. The census tract was the unit of analysis. The total number of census tracts included in the regression analyses was larger than that included in the clustering analysis (4129 vs 3893) because noncontiguous census tracts were included in nongeospatial models. Main effect terms from the final models are included; however, interactions were also tested in each of these models. Ellipses indicate covariates dropped from the final model.

[a]Interactions included Site × Men, Site × High School Diploma, Household Size × Age, Non–Primary Language Use × Men, Unemployment Rate × Age, and Non–Primary Language Use × Age ($P < .001$), as well as Men × Unemployment Rate, Men × Household Size, Non–Primary Language Use × Household Size, Unemployment Rate × Household Size, and Unemployment Rate × High School Diploma ($P < .05$).

[b]Interactions included Site × Men, Site × Age, Unemployment Rate × Household Size, Median Income × Men, and Income × High School Diploma ($P < .01$).

[c]Interactions included Median Income × Non–Primary Language Use, Non–Primary Language Use × Household Size, and Unemployment Rate × Household Size ($P < .01$), as well as Median Income × Men, Median Income × Household Size, and Median Income × Age ($P < .05$).

[d]Interactions included Unemployment Rate × Household Size, Unemployment Rate × Age, Median Income × Age, and Unemployment Rate × High School Diploma ($P < .01$).

[e]Quartile 1 = 0–25th percentile; quartile 2 = 26th–50th percentile; quartile 3 = 51st–75th percentile; quartile 4 = 76th–100th percentile.

include public awareness campaigns, community policing, increased police patrols, collaborative involvement of neighborhood associations and local businesses, and other modifiable factors within specific neighborhoods.

Such interventions require an understanding of the geographic regions at highest risk, population factors that influence the occurrence of injury events, and the reasons why these factors promote injury. Our findings suggest that injury rates may be influenced by more than individual-level factors. Social, cultural, and environmental determinants may play a role in preventable injury events and represent rational targets for public health and injury prevention efforts. Deeper evaluation of causative factors associated with geographically concentrated injury events may provide creative insights into methods to reduce injuries and thereby enhance local public health efforts. Although reducing unemployment and increasing education are laudable public policy goals, such broad social change requires concerted social, policy, public health, and financial efforts.

It remains unclear whether the sociodemographic factors identified here are causally related to major trauma at the individual level (e.g., unemployed individuals are more likely to suffer major trauma) or whether such factors contribute to an environment that is conducive to injury events (e.g., regardless of individuals'

TABLE 4—Adjusted Population Measure Incidence Rate Ratios (IRRs) for Major Trauma Events Across the 6 US Sites: Resuscitation Outcomes Consortium Epistry-Trauma Project, United States, 2005–2007

	Major Trauma (n = 4666), IRR (95% CI)	Death in Field (n = 645), IRR (95% CI)	Penetrating Injury (n = 1082), IRR (95% CI)	Intentional Injury (n = 1416), IRR (95% CI)
Men, %	...	1.0003 (1.00001, 1.0005)	...	...
Unemployment, %	1.03 (1.02, 1.04)	...	1.02 (1.01, 1.03)	1.02 (1.01, 1.03)
Non-primary language use, %[a]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	0.81 (0.72, 0.93)	0.66 (0.52, 0.86)	0.80 (0.65, 0.99)	0.84 (0.69, 1.02)
Quartile 3	0.70 (0.59, 0.83)	0.47 (0.34, 0.66)	0.57 (0.44, 0.75)	0.61 (0.48, 0.78)
Quartile 4	0.62 (0.48, 0.81)	0.30 (0.18, 0.49)	0.37 (0.26, 0.55)	0.42 (0.29, 0.59)
Median household size	0.51 (0.44, 0.59)	0.56 (0.43, 0.74)	0.65 (0.53, 0.81)	0.60 (0.49, 0.73)
Median age, y	1.01 (1.00, 1.02)	...	...	...
Median household income, $[a]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	0.77 (0.66, 0.90)	0.74 (0.56, 0.98)	0.63 (0.50, 0.79)	0.65 (0.52, 0.80)
Quartile 3	0.73 (0.59, 0.90)	0.60 (0.40, 0.88)	0.45 (0.33, 0.62)	0.46 (0.34, 0.61)
Quartile 4	0.72 (0.56, 0.93)	0.42 (0.25, 0.70)	0.37 (0.24, 0.55)	0.41 (0.28, 0.60)
High school diploma, %	0.97 (0.97, 0.98)	0.98 (0.96, 0.99)	0.98 (0.97, 0.99)	0.97 (0.96, 0.98)
Non-White, %[a]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	0.99 (0.83, 1.18)	0.74 (0.51, 1.06)	1.09 (0.76, 1.56)	0.96 (0.70, 1.32)
Quartile 3	1.24 (1.03, 1.49)	0.93 (0.64, 1.34)	1.57 (1.10, 2.24)	1.47 (1.08, 2.02)
Quartile 4	1.50 (1.22, 1.85)	1.50 (1.03, 2.17)	2.87 (1.99, 4.14)	2.48 (1.78, 3.44)
Hispanic, %[a]				
Quartile 1 (Ref)	1.00	1.00	1.00	1.00
Quartile 2	...	...	...	...
Quartile 3	...	...	...	...
Quartile 4	...	...	...	...
Site				
1 (Ref)	1.00	1.00	1.00	1.00
2	1.28 (1.04, 1.57)	1.48 (1.01, 2.16)	1.33 (0.97, 1.81)	1.37 (1.03, 1.84)
3	1.63 (1.35, 1.98)	1.49 (1.07, 2.09)	1.59 (1.20, 2.12)	1.64 (1.25, 2.15)
4	1.60 (1.26, 2.04)	1.39 (0.90, 2.15)	1.81 (1.28, 2.54)	1.79 (1.29, 2.48)
5	1.00 (0.80, 1.25)	0.58 (0.36, 0.94)	0.59 (0.38, 0.89)	0.74 (0.51, 1.07)
6	3.31 (2.70, 4.06)	2.17 (1.48, 3.20)	3.29 (2.38, 4.54)	4.12 (3.05, 5.58)

Note. CI = confidence interval. Data were based on 1923 census tracts. Estimates were obtained via multivariable negative binomial models with patient count as the outcome. The census tract was the unit of analysis. The analysis was limited to US sites because race and ethnicity data were not consistently included in Canadian census data. The 6 US study sites were Birmingham, Alabama; Dallas, Texas; Milwaukee, Wisconsin; Pittsburgh, Pennsylvania; Portland, Oregon; King County, Washington; Ellipses indicate covariates dropped from the final model.
[a]Quartile 1 = 0–25th percentile; quartile 2 = 26th–50th percentile; quartile 3 = 51st–75th percentile; quartile 4 = 76th–100th percentile.

employment status, residing in an area with high unemployment rates increases their risk of major trauma). There may also be additional unmeasured factors or confounders that play a role in the causal pathway for injury events. However, improved understanding and targeted prevention efforts in the communities most affected by such events may ultimately reduce the occurrence of injury.

Limitations

This study involved several limitations that should be considered when interpreting the results. For example, the study was observational and ecological in nature, so a causal relationship between the explanatory variables (e.g., socioeconomic population measures) and major trauma events cannot be established. The relationships between sociodemographic characteristics, culture, income, poverty, race, and injury are likely multifactorial and complex (as further suggested by the number of significant interaction terms in our models). Although studies such as ours allow insights that can lead to a better understanding of these relationships, untangling all causal influences requires multiple methodologies.

Also, we described and characterized geographic areas with concentrated major trauma events rather than describing individual characteristics of major trauma patients or others directly involved in injury events (e.g., assailants). The associations demonstrated in this study apply to population characteristics of residents living in census tracts where these events occurred; they may or may not directly apply to the injured individuals themselves. Furthermore, differences exist between the United States and Canada with respect to the timing of census data collection. Although we used the most recent census data available for each country, the 2000 US census included data on population characteristics collected several years before the ROC Epistry-Trauma data collection process began. Our results may have been affected by sociodemographic shifts in the US population during this period, but we believe this is unlikely.

Our sample included injured patients meeting field criteria for major trauma as well as patients who died in the field from their injuries. However, such individuals represent only a fraction of all injured patients served by EMS systems and affected by violence. Inclusion of a broader injury population could have altered our findings. Also, specific portions of the sample (e.g., children) did not have enough patients at individual sites to conduct geospatial analyses.

Finally, as mentioned, only a sparse literature was available to guide a priori selection of covariates for our multivariable models. We based our variable selection on available research, measures commonly used to describe and characterize populations, and the presence of plausible relationships between such factors and injury. Use of different population measures or model-building strategies might have produced different results. However, the covariates retained in the final models demonstrated robust associations that persisted in multiple subgroups.

Conclusions

Our results showed that major trauma events were not geographically random and tended to cluster in census tracts with distinct population characteristics. These findings were most pronounced among injured patients who died in the field, had penetrating injuries, or had intentional injuries. Certain social and contextual factors (e.g., higher unemployment rates, lower incomes, lower educational levels) were associated with increased rates of major injury. Geospatial and population demographic information such as that gathered in this study may allow more targeted, community-based injury prevention efforts. ■

About the Authors

Craig D. Newgard, Ross J. Fleischman, and Craig R. Warden are with the Center for Policy and Research in Emergency Medicine, Department of Emergency Medicine, Oregon Health & Science University, Portland. Robert H. Schmicker is with the Department of Biostatistics, University of Washington, Seattle. George Sopko is with the National Heart, Lung and Blood Institute, National Institutes of Health, Bethesda, MD. Dug Andrusiek is with the Emergency and Health Services Commission of British Columbia, University of British Columbia, Vancouver, British Columbia, Canada. Walter Bialkowski is with the Department of Emergency Medicine, Medical College of Wisconsin, Milwaukee. Joseph P. Minei is with the Department of Surgery, University of Texas Southwestern Medical Center, Dallas. Karen Brasel is with the Department of Surgery, Medical College of Wisconsin, Milwaukee. Eileen Bulger is with the Department of Surgery, University of Washington, Seattle. Jeffrey D. Kerby is with the Department of Surgery, University of Alabama, Birmingham. Blair L. Bigham is with St. Michael's Hospital, University of Toronto, Toronto, Ontario, Canada.

Correspondence should be sent to Craig D. Newgard, MD, MPH, Department of Emergency Medicine, Center for Policy and Research in Emergency Medicine, Oregon Health & Science University, 3181 SW Sam Jackson Park Rd, Mailcode CR-114, Portland, OR 97239-3098 (e-mail: newgardc@ohsu.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints/Eprints" link.

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A total of 153 institutional review boards and research ethics boards in the United States and Canada reviewed and approved the Resuscitation Outcomes Consortium Epistry-Trauma project and waived the requirement for informed consent.

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