Published in final edited form as:

Am J Prev Med. 2016 November ; 51(5): 647–655. doi:10.1016/j.amepre.2016.08.002.

Sentinel Events Preceding Youth Firearm Violence An Investigation of Administrative Data in Delaware

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Abstract

Introduction—Accurately identifying youth at highest risk of firearm violence involvement could permit delivery of focused, comprehensive prevention services. This study explored whether readily available city and state administrative data covering life events before youth firearm violence could elucidate patterns preceding such violence.

Methods—Four hundred twenty-one individuals arrested for homicide, attempted homicide, aggravated assault, or robbery with a firearm committed in Wilmington, Delaware, from January 1, 2009 to May 21, 2014, were matched 1:3 to 1,259 Wilmington resident controls on birth year and sex. In 2015, descriptive statistics and a conditional logistic regression model using Delaware healthcare, child welfare, juvenile services, labor, and education administrative data examined associations between preceding life events and subsequent firearm violence.

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Results—In a multivariable adjusted model, experiencing a prior gunshot wound injury (AOR=11.4, 95% CI=2.7, 48.1) and being subject to community probation (AOR=13.2, 95% CI=5.7, 30.3) were associated with the highest risk of subsequent firearm violence perpetration, though multiple other sentinel events were informative. The mean number of sentinel events experienced by youth committing firearm violence was 13.0 versus 1.9 among controls (p<0.0001). Within the sample, 84.1% of youth experiencing a sentinel event in all five studied domains ultimately committed firearm violence.

Conclusions—Youth who commit firearm violence have preceding patterns of life events that markedly differ from youth not involved in firearm violence. This information is readily available from administrative data, demonstrating the potential of data sharing across city and state institutions to focus prevention strategies on those at greatest risk.

Introduction

In 2013, local and national media reported on a steady surge in firearm violence in Wilmington, Delaware.[1–3] From 2011 to 2013, the number of victims injured in shootings in the city rose more than 60%, from 95 to 154 individuals.[4] By the close of 2013, Wilmington had recorded its most violent year in memory from firearm violence. Although Wilmington is a small city of approximately 71,525 residents, when compared with all U.S. cities with more than 100,000 inhabitants, its homicide rate has been reported as high as fourth overall in recent years.[1,5]

Consequently, the Wilmington City Council passed a resolution requesting the Centers for Disease Control and Prevention (CDC) to assist in an investigation that would yield recommendations for preventive action.[3] At the invitation of the Delaware Division of Public Health, officials from CDC traveled to Wilmington in June 2014 to investigate potential solutions.

Preventing lethal violence presents a challenging task. Although violence has long been investigated by researchers from diverse domains—including public health, medicine, criminology, sociology, and psychology, among others—there exist significant barriers that cities and states face in real-world implementation of violence prevention activities. First, violence prevention activities often are implemented as domain-specific approaches (i.e., police department, child welfare) and there is a greater need for collaborative, cross-sectoral strategies.[6,7] Second, all cities may not be able to support new, expensive data collection efforts, such as occur in research studies, to investigate novel approaches or guide activities. And third, cities must often make critical decisions on how and where to focus limited resources on prevention activities. Because of these challenges, in part, there has been a growing interest across cities and states in utilizing readily available administrative data to better focus services.[8]

Municipal use of large volumes of administrative or incidental data to guide service provision is expanding, with early examples emerging in cities such as New York and Chicago in the areas of lead poisoning prevention, food safety, and unsafe housing identification, among others.[9–11] Concurrent with this work, some attempts have been made to better use administrative data to improve violence prevention activities. For example, risk stratification approaches based on administrative data have been researched in the areas of parolee recidivism, inmate misconduct, child abuse, school violence, and military suicide.[12–16] Such approaches have demonstrated considerable promise, yet have certain limitations. Often, these strategies are implemented within single departments and thus only have access to department-specific information, which can reduce performance of some risk stratification approaches and not permit service providers to have a full picture of all of an individual’s contributing risk factors.

Given broad support in Wilmington for firearm violence prevention, local partners in collaboration with CDC evaluated the feasibility of using administrative data across a wide range of state and city agencies and institutions to facilitate a better understanding of the risk of youth firearm violence perpetration, as well as promote a comprehensive, multipartner response. Administrative data were compiled on individuals’ life events from one of the most comprehensive arrays of data sources thus far used in violence prevention planning and explored for utility in gaining a more comprehensive insight into youth firearm violence perpetration.

Methods

Study Design and Setting

This study utilized a population-based, matched case-control sampling strategy to assemble a sample from which a wide variety of risk factors for firearm violence perpetration were assessed. This pilot investigation was carried out in Wilmington, Delaware, as part of a public health response performed by CDC in collaboration with local partners in June 2014.

Cases were selected from the Delaware Justice Information System (DELJIS), a statewide police database that maintains electronic records on all individuals arrested in Delaware. All Wilmington residents arrested for a violent firearm crime committed in the city of Wilmington between January 1, 2009 and May 21, 2014 were identified from DELJIS. A violent firearm crime was defined using criteria specified by Delaware law enforcement officials and included homicide, attempted homicide, aggravated assault, or robbery with a firearm. Cases were selected from DELJIS based on Delaware crime codes indicating the offense type. In addition to crime codes, arrest records also list state statute violations; all individuals charged with possession of a firearm during the commission of a felony were also included in the event that crime code information was non-specific.

Based on electronic data availability, the study focused on male cases and controls born in 1980 or after (individuals aged ≤34 years at the time of perpetration). This population represents those at highest risk of perpetration and covers 74% of interpersonal firearm violence perpetrators in Wilmington over the study time period.

A list is also maintained by DELJIS of all individuals who have received official state identification, such as a driver’s license or other identification form. This provides the most comprehensive sampling frame of the base population available. From this list, an algorithm using random numbers was used to sample Wilmington residents matched on year of birth and sex in a 3:1 ratio to cases. Statistical power to detect differences generally decreases exponentially beyond a 3:1 ratio and this number also represented the maximum number of study subjects feasible for manual review of emergency department charts.[17]

Data Sample

For case and control populations, investigators examined emergency department visit history, child welfare encounters, juvenile justice involvement, employment records, and school system events. The assessment focused on "sentinel events," defined as incidents in an individual's life that occur before the commission of a firearm crime that may be a signal or marker for increased perpetration risk.

For all cases, events that occurred before the date of the individual's first recorded violent firearm offense in Wilmington were examined. For each control matched to a case, the case's violence perpetration date was used as the same date of interest for which prior life events were examined. This allowed each matched case/control unit to have equal exposure time. Data were linked by participating agencies; available information from DELJIS for linking included name, date of birth, and Social Security number with simple deterministic matching pursued given the brief time frame for the field investigation. Linking to labor records was done by exact matching on Social Security number alone. Emergency department, juvenile justice, education, and child welfare databases were linked to using name and date of birth by exact matching; if a Social Security number was present, it was also used in the deterministic match. Unique identifiers were removed prior to analysis.

Emergency department visit details were extracted by study investigators from Christiana Care Health Care System's electronic medical records. Emergency department electronic medical records, available since 2000, were abstracted for experiences of violence victimization and any encounter involving the police (injury due to legal intervention, brought in by police, or discharged to police).

Child welfare and juvenile delinquency encounters were obtained from the Delaware Department of Services for Children, Youth and their Families with computerized records available since 1992. From the Delaware Department of Labor, unemployment information was available by quarter for the preceding 5 years (calculated from wage data); data on applications filed for unemployment benefits and the status of those applications were available since 2006.

Lastly, from the Delaware Department of Education information on school events was obtained, including: unexcused absences (available since 2009), school dropout (since 2002), receipt of social assistance such as food stamps and Medicaid (since 2009), and suspension/expulsion event data (from 2006). Finally, the Census tract of each individual's residence was determined using the U.S. Census Bureau's Geocoder. The variables that were selected for examination were those that were readily available, routinely collected, and had strong theoretic reasons for supporting a potential association with violence risk. All data were available during the entire study period, with the exception of unemployment (not available prior to July 2009).

Statistical Analysis

The distribution of sentinel events among cases and controls was first explored by plotting a timeline of each individuals' life over the study time period. Next, the prevalence of the various sentinel events among case and control populations was calculated, as well as the bivariate OR for each sentinel event. Variables were generally all coded as binary events, indicating either the presence or the absence of each sentinel event in an individual's life according to administrative records. For the unemployment variable, missing data existed prior to July 2009, and were coded as a separate category so as not to exclude these individuals from regression modeling. Census tract of residence, which is included as a control variable in multivariable modeling, was coded as a multilevel categorical variable. Census tracts with a small number of subjects were merged with nearby Census tracts to improve model stability.

For the multivariable model for firearm violence perpetration, all terms were included with the exception of variables on applications for unemployment benefits, to reduce collinearity, and variables on substantiated child maltreatment and residential detention, as they were largely nested in higher order variables.[18] ORs were calculated using conditional logistic regression with PROC LOGISTIC in SAS, version 9.3 to account for the matching in the study design.

To test differences in the mean number of sentinel events experienced by cases and controls, a permutation test was used. Lastly, the percentage of individuals within the sample who ultimately committed firearm violence and the number of major domains—health, economic, child welfare, juvenile services, and education—that they had a sentinel event in were calculated and plotted. Statistical analyses, conducted in 2015, were performed in SAS, version 9.3 and R, version 3.1.1.

Results

Four hundred twenty-one cases were identified and matched to 1,259 controls on year of birth and sex. Four individuals selected for the control population were cases. These four individuals were removed from the control list without replacement as their true classification was cases. Figure 1 displays a timeline of the life events among case and control populations prior to the violent firearm offense date for cases (or the matched date for controls). For nearly all sentinel events, cases were more likely to experience these life events than the control population.

Table 1 displays the prevalence of the various sentinel events among the case and control populations as well as the OR of the bivariable association between each sentinel event and firearm violence perpetration. Notably, 14.0% of cases experienced a gunshot wound prior to arrest for a violent firearm offense, compared with 0.8% of the control population. More than one third (34.7%) of cases had been investigated as a potential victim of maltreatment as a child, relative to 7.9% of controls. Cases had significant involvement in juvenile justice services as a youth: 63.0% had undergone community-level probation, contrasted with 7.4% of controls. Both unemployment (87.8%) and receipt of social assistance while in school

(84.5%) were present in the majority of cases with record availability, though 65.9% and 33.1% of controls, respectively, had these characteristics as well.

Table 1 also shows the results of the multivariable logistic regression model. Having been involved in the community probation system was associated with a >13-fold increase in subsequent arrest for firearm violence (AOR=13.2, 95% CI=5.7, 30.3). Additionally, experiencing a prior gunshot wound injury was associated with a >11-fold increase in subsequent arrest for a violent firearm offense (AOR=11.4, 95% CI=2.7, 48.1). Beyond involvement in prior criminal activities and firearm violence victimization, other variables were significantly associated with firearm violence arrest, including unemployment (AOR=3.0, 95% CI=1.5, 6.2) and being the recipient of social assistance programs (a proxy for poverty) while in school (AOR=2.1, 95% CI=1.0, 4.3). Multiple other studied variables —including stabbings, blunt weapon injuries, out-of-home placements for child welfare, and school dropout—demonstrated associations at the $p \leq 0.10$ level, also suggesting a potential utility for risk stratification.

Figure 2 displays the distribution of the total number of sentinel events experienced by cases and controls for sentinel events in which repeated events can be ascertained (only three variables—unemployed in preceding quarter, recipient of assistance programs ever, and ten or more unexcused absences in preceding school year are only available as single-instance variables and are thereby excluded from this plot as they do not have the structure to assess for repeat occurrences). The mean number of sentinel events experienced by youth arrested for firearm violence was 13.0 versus 1.9 among controls ($p<0.0001$). The median number of events between these two groups was 10 and 0, respectively.

Figure 3 explores the number of major domains of life that each individual experienced a sentinel event in (health, economic, child welfare, juvenile services, and educational). In the sample, 310 individuals experienced a sentinel event in no domain, 644 experienced an event in one domain, 302 in two domains, 211 in three domains, 150 in four domains, and 63 in all five domains. There is suggestion of a dose–response relationship in Figure 3 as, for example, only 7.6% of individuals who experienced a sentinel event in one domain were ultimately arrested for firearm violence compared with 84.1% of youth experiencing a sentinel event in all five domains.

Discussion

Youth arrested for firearm violence have markedly different life events than individuals not involved in firearm violence. Using data from a wide variety of domains provided unique insights into the patterns of sentinel events that could help identify youth at the highest risk of firearm violence in Wilmington. This information helps demonstrate the potential of linking and sharing data across city and state agencies to improve public health and social service assistance programs.

This investigation's assessment of administrative data confirms some important findings from recent influential studies, while contributing additional unique insights. For example, strong associations between violence victimization, youth delinquency, and subsequent crime perpetration have been reported in prior investigations.[19,20] However, this study provides assessments of multiple narrow categories of events (i.e., stabbings, blunt weapon injuries), as well as a wide array of factors that span an individual's entire life course from youth to early adulthood (i.e., child welfare placements, school-related items, and employment history). Additionally, because this investigation is able to look across the entire life history, it can assess the total burden of sentinel events and explore how impacts in multiple domains of life affect perpetration risk.

Nonetheless, the most important contribution of this study is not in assessing a diverse array of risk factors for youth firearm violence perpetration, but rather, in demonstrating the feasibility and potential of linking a diverse array of administrative data to inform real-world programmatic planning. Use of administrative data avoids the cost of survey-based data collection. Furthermore, all administrative data represent objective endpoints, thereby avoiding potential differential recall and disclosure biases associated with surveys. Data linking in the investigation was performed over an approximate 3-week period by Delaware agencies, suggesting a feasible time commitment for other locales considering such work. Lastly, use of administrative data facilitates automated risk assessment approaches, which are becoming increasingly explored for their ability to help guide limited prevention resources.[16,21,22] Statistical and computation developments have produced a range of powerful modern techniques, ranging from random forests to support vector machines, for example.[23]

Limitations

Some limitations of the current investigation should be mentioned. First, although all variables were created from administrative data, the study team manually abstracted emergency department records so as to explore additional contextual insight. Nonetheless, alterative options for automated use of hospital data exist—such as trauma registries or billing/diagnosis codes. Second, this investigation represents a pilot study based on a sample of the general population. As with all such studies, precise estimates could be affected to some degree by the sampling strategy—only those individuals present in administrative databases could be sampled as cases and controls and thus there may exist a certain degree of unmeasurable bias because of this limitation. Also, it is likely that these administrative data sources contained some degree of missing information. Missing data would be present if a professional at any of the respective agencies failed to record the presence of a sentinel event for that youth or if systematic or technical errors in agency data collection failed to capture information about young people it worked with. Unfortunately, it is impossible to quantify the degree of missing data, as a non-event and a missing data point appear in the data the same way. However, it is unlikely that missing information would have differed markedly between cases and controls. If such a differential bias did exist, theoretically, firearm violence perpetrators might have had more administrative encounters for sentinel events and thus more opportunity for missing data on these events; this would bias the study's estimates toward the null. Third, this pilot study used arrest as a proxy for perpetration; these items are not always equivalent and should be examined in future research. Furthermore, some important variables were not examined in this study, such as neighborhood-level characteristics, and should be examined in future studies. Lastly, in the study's approach, ascertaining information on an individual required matching across administrative databases. Simple deterministic matching was favored in this study, given the urgent nature of the epidemiologic response and the generally high positive predictive value of such matching; however, administrative data may contain erroneous fields that could prevent successful linkage from occurring and the development, testing, and validation of probabilistic or more-complex iterative deterministic linkage plans should be part of future work.[24]

Conclusions

Although researchers have identified important risk factors for violence perpetration, cities and states tasked with implementing real-world violence prevention initiatives often face challenges in delivery of preventive services. Many locales are limited in their ability to assess the full spectrum of risk factors individuals may face and to work across agencies to address violence. This investigation demonstrates the feasibility and potential of using linked data to more comprehensively understand youth violence perpetration risk and could be ultimately used to better focus a package of evidence-based services to the most vulnerable youth in society.[25–32] Such an approach creates potential benefit for all involved —using linked administrative data could help cities improve the cost effectiveness of service delivery, help youth at high risk for violence receive needed services, and foster safer communities for all citizens as the burden of death and injury from violence is reduced.

Acknowledgments

We thank the Delaware Division of Public Health; Delaware Department of Health and Social Services; City of Wilmington; Delaware Justice Information System; Delaware Department of Safety and Homeland Security; Delaware Department of Services for Children, Youth and their Families; Delaware Department of Education; Delaware Department of Labor; Delaware Statistical Analysis Center—Criminal Justice Council; and Christiana Care Health Care System as well as Gabrielle Ransford, Veronica Crowe, and the following Christiana Care physician residents, Emily Murphy, Brian Frank, Laura Quint, Valerie Cohen, Sarah Shafer, Erica Locke, and Emily Granitto for guidance and aid in the investigation.

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

Dr. Martin's work was supported in part by an Institutional Development Award (IDeA) from the National Institute of General Medical Sciences of NIH under grant number U54-GM104941 (Principal Investigator: Binder-Macleod). No other financial disclosures were reported by the authors of this paper.

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Figure 1.

Timeline of sentinel events preceding firearm violence perpetration for case and control populations, Wilmington, Delaware.

Note: Unemployment in quarter preceding firearm violence, receipt of social assistance, and unexcused school absences not plotted as these events are not associated with specific dates. For each case, the black dot represents the actual date of firearm violence perpetration. For the three controls that are matched to each case, the case's perpetration date is used as the date of interest to examine preceding events among controls. This permits each case-control pair to have equal exposure time.

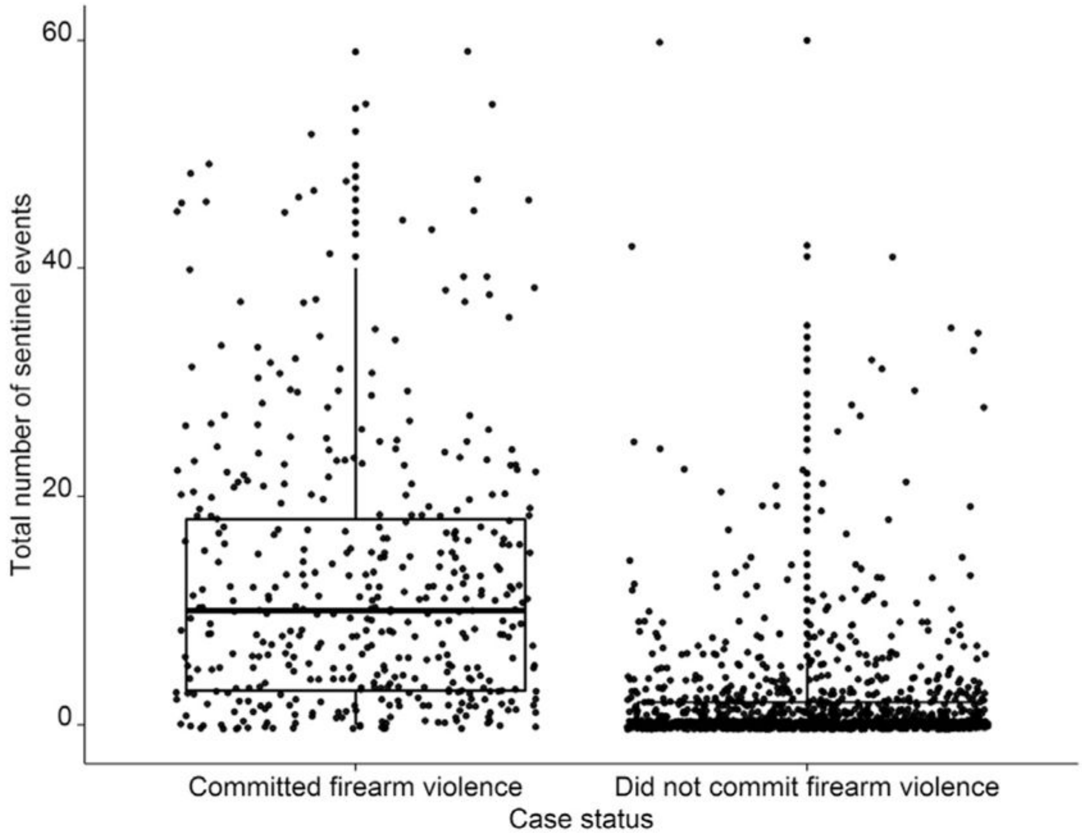

Figure 2.

Total number of sentinel events experienced by each individual and subsequent firearm violence perpetration status.

Note: Figure displays the distribution of the total number of sentinel events experienced by cases and controls. The upper boundary of each box, the line in the middle of each box, and the lower boundary of each box represents the 75th, 50th, and 25th percentile, respectively. Exact values are reported in the Results section. The whiskers extend from each box to the highest and lowest values that are within 1.5 times the interquartile range. The dots show each individual in the dataset and their corresponding number of sentinel events. Three sentinel event types (unemployed in preceding quarter, recipient of assistance programs ever, and ≥10 unexcused absences in preceding school year) are only available as single-instance variables and thereby are excluded from this plot as they do not have the structure to assess for repeat occurrences.

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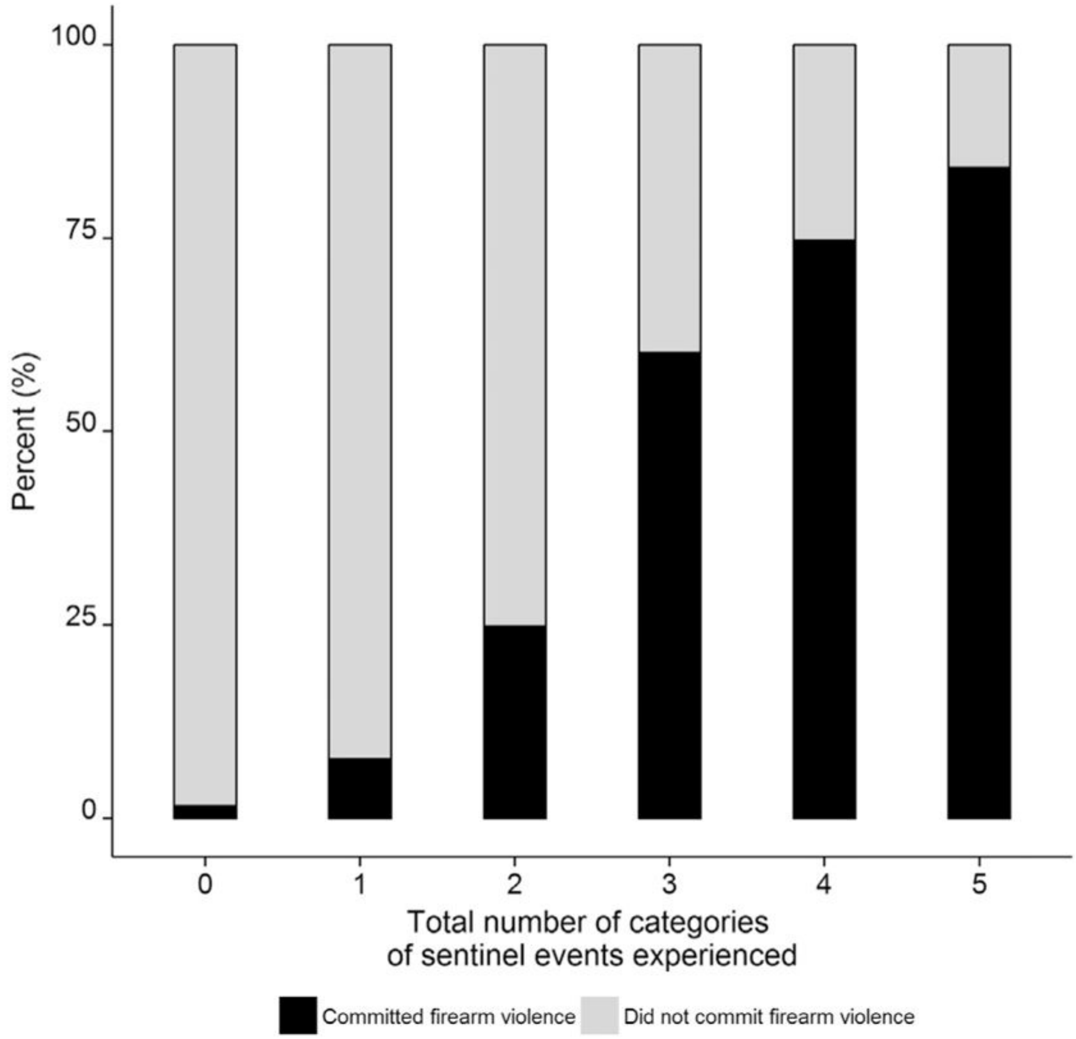

Figure 3.

Number of major categories of sentinel events experienced and subsequent firearm violence perpetration within study sample.

Note: The five potential categories of sentinel events that can be experienced are those shown in Table 1—emergency department visits, economic events, child welfare encounters, juvenile services, and educational events.

Table 1

Sentinel Events Among Case and Control Populations and Associations With Subsequent Firearm Violence Perpetration

	Prevalence among controls (*n*=1,259)		Prevalence among cases (*n*=421)		Bivariable OR			AOR[a]		
Category of sentinel event	***n***	**%**	***n***	**%**	**OR**	**95% CI**	***p*-value**	**AOR**	**95% CI**	***p*-value**
Emergency department visit history										
Gunshot wound	10	0.8	59	14.0	21.6	10.3, 45.3	**<0.0001**	11.4	2.7, 48.1	**<0.001**
Stabbing	2	0.2	19	4.5	28.5	6.6, 122.4	**<0.0001**	6.9	0.8, 56.1	0.07
Blunt weapon injury	9	0.7	20	4.8	7.3	3.2, 16.6	**<0.0001**	5.0	0.8, 31.7	0.09
Physical fight	52	4.1	75	17.8	5.1	3.5, 7.5	**<0.0001**	0.9	0.4, 2.3	0.85
Suicidal ideation/attempt, self, inflicted injury	40	3.2	29	6.9	2.3	1.4, 3.8	**<0.0001**	0.9	0.3, 2.7	0.82
Clinical encounter involves police[b]	19	1.5	86	20.4	15.7	9.2, 26.8	**<0.0001**	3.5	1.3, 9.2	**0.01**
Labor indicators										
Unemployed in quarter preceding the crime[c]	709	65.9	316	87.8	3.9	2.8, 5.5	**<0.0001**	3.0	1.5, 6.2	**<0.01**
Application filed for unemployment benefits	138	11.0	51	12.1	1.1	0.8, 1.6	0.50	—	—	—
Most recent application for unemployment benefits rejected[d]	54	39.4	22	43.1	1.4	0.4, 5.0	0.60	—	—	—
Child welfare investigation history										
Investigated as potential victim of child maltreatment	99	7.9	146	34.7	6.8	4.9, 9.4	**<0.0001**	1.0	0.5, 2.2	0.94
Child maltreatment victimization substantiated	35	2.8	66	15.7	6.6	4.2, 10.3	**<0.0001**	—	—	—
Out of home placement	12	1.0	36	8.6	10.4	5.1, 20.9	**<0.0001**	3.2	0.8, 12.5	0.10
State juvenile service participation										
Community probation	93	7.4	265	63.0	21.9	15.1, 31.9	**<0.0001**	13.2	5.7, 30.3	**<0.0001**

Category of sentinel event	Prevalence among controls (n=1,259)		Prevalence among cases (n=421)		Bivariable OR			AOR[a]		
	n	%	*n*	%	OR	95% CI	*p*-value	AOR	95% CI	*p*-value
Residential detention	35	2.8	203	48.2	46.9	26.2, 84.1	<**0.0001**	—	—	—
Behavioral health services	15	1.2	88	20.9	21.4	11.7, 39.1	<**0.0001**	2.0	0.7, 5.5	0.20
Managed care services	52	4.1	159	37.8	15.3	10.2, 22.9	<**0.0001**	2.0	0.8, 5.1	0.16
School system events[e]										
Recipient of assistance programs ever (food stamps, Medicaid, etc.)	289	33.1	311	84.5	15.9	10.7, 23.6	<**0.0001**	2.1	1.0, 4.3	**0.04**
Prior suspension/expulsion	229	26.2	181	49.2	4.7	3.4, 6.7	<**0.0001**	1.8	0.8, 4.1	0.16
Dropped out prior to high school graduation	63	7.2	100	27.2	5.8	3.9, 8.6	<**0.0001**	2.3	0.9, 5.9	0.08
≥10 unexcused absences in school year preceding crime[f]	55	24.3	56	57.7	3.9	2.3, 6.5	<**0.0001**	2.5	0.8, 8.4	0.13

Note: Boldface indicates statistical significance (p<0.05).

[a] Adjusted model also controls for census tract of residence. Variables on applications for unemployment benefits not included in multivariable model due to lack of significance at bivariable level; substantiated child maltreatment and residential detention excluded from model due to being largely nested in higher order variables.

[b] Injury from legal intervention or patient brought in/discharged to police.

[c] Percentages reported are among those with wage data available (244 individuals without wage information as data not available prior to July 2009, included in all models as separate category).

[d] Among those who have applied for benefits, one individual missing final determination.

[e] Percentages are among those for whom school enrollment was confirmed; 438 individuals are without enrollment records for a school reporting to the state. For bivariable OR calculation, those not enrolled are included as a separate category though for the adjusted model these individuals are merged with the reference category to improve model stability.

[f] 1,357 individuals not enrolled in school year preceding crime date.