



The author(s) shown below used Federal funding provided by the U.S. Department of Justice to prepare the following resource:

Document Title: Firearm Purchase Behavior and Subsequent Adverse Events

Author(s): Hannah S. Laqueur, Ph.D.

Document Number: 309601

Date Received: October 2024

Award Number: 2018-75-CX-0026

This resource has not been published by the U.S. Department of Justice. This resource is being made publicly available through the Office of Justice Programs' National Criminal Justice Reference Service.

Opinions or points of view expressed are those of the author(s) and do not necessarily reflect the official position or policies of the U.S. Department of Justice.

Summary of the project

Major goals and objectives

The primary purpose of this project was to develop and test a new large-scale approach to threat assessment that relies on objective data regarding firearm purchases. Specifically, to analyze firearm transaction records in California to better understand the firearm purchasing patterns of mass shooters and perpetrators of firearm-related crimes and to build risk prediction models to help identify individuals who might be at extreme risk for committing such crimes in the future.

The objectives of the work included:

Objective 1: To determine whether there are unusual pre-event firearm purchasing patterns among known mass shooters with a record of purchase in California (1985-2018), as compared to the general population of registered firearm purchasers in the state of California.

Objective 2. To determine whether perpetrators of homicide, robbery, or aggravated assault in California with a record of purchase (1985-2018) have distinct pre-event firearm purchasing patterns as compared to the general population of registered firearm purchasers in the state.

Objective 3: To use machine learning methods to forecast who is at an elevated risk of involvement in a mass shooting based on features generated from firearm transaction records, along with criminal history records, and other key individual and community characteristics available in the administrative data.

Objective 4: To use the same machine learning methods and predictor variables to forecast who is at elevated risk of involvement in other serious firearm violence (homicide, robbery, or aggravated assault with a firearm).

Research questions

1. Do the firearm purchasing patterns of mass shooters differ from those of ordinary California firearm purchasers who do not go on to perpetrate a shooting? Are there other notable risk factors captured in the CA DOJ transaction data?
2. Do the firearm purchasing patterns of perpetrators of firearm violence and major violent crimes differ from ordinary firearm purchasers in California?
3. What individual, handgun and purchasing characteristics are associated with California handgun purchasers who perpetrate a major violent crime or violent firearm-related crime after purchase?
4. Using firearm transaction records and other administrative data, can we predict which individual firearm purchasers will go on to perpetrate a major violent crime or firearm related crime?

Research design, methods, analytical and data analysis techniques

Description of the Sample and Measures

Mass shooter sample

We defined mass shooting and active shooting broadly, relying on several databases to identify shooters: the *Mother Jones Database on Mass Shootings* (1985–2018), which defines a mass shooting as an incident that took place in public, between strangers, and that killed four or more people (1985–2012) or three or more people (2013–present); the *Stanford Mass Shootings in America* (1985–2016), which defines a mass shooting as involving three or more victims injured or killed, and unrelated to gang, drug, or organized criminal activity; and the *Gun Violence Archive* (2013–2018), which defines a mass shooting as an attack injuring or killing four or more persons. We excluded cases where the firearm violence involved other criminal activity (e.g., gang, drug, or organized crime). We also included active

shooter incidents from the *FBI's Active Shooter Incidents (2000–2016)*, which defines an active shooting as “one or more individuals actively engaged in killing or attempting to kill people in a populated area,” irrespective of the body count.

After identifying mass and active shooters in the state, we then identified which of these individuals had a record of firearm transaction in the California DOJ’s Dealer Record of Sale (DROS) database. DROS contains archived information on all authorized handgun purchasers and their transactions in the state since 1985, with detailed transaction data beginning in 1996. We identified a total of 22 individuals who perpetrated an attack between 1996 and 2018 and had a record in DROS. We used risk-set sampling to select controls (individuals with purchasing records in DROS who did not perpetrate a mass shooting) at a ratio of 1:15, and matched cases and controls based on gender and age.

In the second analysis, the sample comprised all identified California mass and active shooters between 1985 and 2018 ($n = 55$), irrespective of whether they had a record of transaction in California's Dealer Record of Sale (DROS) database. This sample included the 22 mass and active shooters identified in the case-control analysis.

After we identified the mass and active shooters, a Crime Analyst at the California Department of Justice (CA DOJ) cross-referenced publicly available media reports and confidential criminal and transaction histories, including records in other states and information on crime weapons, to compose workups for each mass and active shooter describing their background and the attack. We then coded those workups to generate variables to be used in our analytic models. These variables included records of firearm purchase both within and outside of the state as well as illicit firearm acquisitions.

Additional variables generated from the DROS data included purchaser sex, race, and age at first and last purchase. We geocoded the purchaser addresses recorded in DROS to identify the associated census tracts and counties to obtain community characteristics. We generated and included in the models’ characteristics of the firearm acquisition including whether the handgun was acquired at a gun show and whether the transaction was a purchase (versus a denial or voluntary registration). Variables related to the firearm included: firearm category (revolver, semiautomatic pistol, or other, which included missing data), caliber (which we binned and categorized into small, medium, large), and whether the firearm was inexpensive, estimated by manufacturers selling handguns with prices in the bottom quantile of the *Blue Book of Gun Values*.

Among the full population of identified mass and active shooters (1985–2018), in addition to the variables available in DROS, we also obtained details on non-handgun acquisitions, acquisitions from

other states (coded as CA versus outside of CA), acquisitions through non-licensed dealers versus other, whether the shooter was prohibited when the attack firearms were acquired and at the time of attack, and whether firearms were regulated under California's assault weapons law and had high-capacity magazines. Descriptions of the firearm included “type” (e.g., pistol, revolver, etc.) and “category”, which characterizes the firearm's mechanism of action (e.g., semi-automatic, automatic, etc.).

Perpetrators of interpersonal violence sample and measures

We identified all persons who legally purchased a handgun in California from January 1996 to October 2021 and who, after purchase, had an arrest for a major violent crime as defined by the Uniform Crime Reporting handbook published by the Federal Bureau of Investigation or an arrest for a firearm-related violent crime. Crimes were determined to be firearm-related using offense descriptions corresponding to offense codes, dispositions present in RAPs, additional flags for firearm involvement in RAPs, and law enforcement comments in RAPs. Crimes were determined to be violent using a crosswalk of offense codes to UCR handbook categories with additional review as necessary from an RAP expert analyst. Criminal history records were obtained from the CA DOJ Automated Criminal History System (ACHS), which include all adult criminal history events in the state since 1980.

In the machine learning predictor models, these individuals and their transactions were compared to the rest of the population in DROS. In the case-control analysis, we risk-set sampled a group of controls from the DROS records.

Our key independent variables of interest related to the purchaser, their transactions, and the handgun(s) themselves. We also included purchaser criminal history (other than the post purchase outcome).

Analytic Approaches

Mass shooter analyses

A. Case-control analysis

We conducted a case-control analysis with a study population of a total of 22 individuals from California who perpetrated an attack between 1996 and 2018 and had a record of transaction in the state's DOJ Dealer Record of Sale database. We used risk-set sampling to select controls (individuals with purchasing records in DROS who did not perpetrate a mass shooting) at a ratio of 1:15, and matched cases and controls based on gender and age. We compared purchasing behaviors and other relevant risk factors using conditional logistic regression.

B. Mixed Model examining legal and illegal transactions

In the second analysis of mass shooters, the sample comprised all identified California mass and active shooters between 1985 and 2018 ($n = 55$), irrespective of whether they had a record of transaction in California's Dealer Record of Sale (DROS) database. We implemented a mixed model to evaluate factors associated with firearms acquired in close temporal proximity to the attack, including firearms acquired through unauthorized means. Unauthorized acquisitions included theft, acquisition through an unlicensed dealer, home manufacture, and straw purchasing.

Perpetrators of other firearm-related crime and major violent crime

A. Machine Learning Analysis

Criminal history information, legal handgun purchasing trends, and purchaser demographics were used as input features to predict time to arrest. Features in the model were included as one of four types: constant, the time since an event, characteristics of the most recent purchase or arrest, and lifetime purchase and arrest characteristics. The latter three types are all time dependent. Time since last purchase or arrest was operationalized in models through an inverse transformation,

$$f(\text{yearsSinceEvent}) = 1 - \frac{1}{1 + \text{yearsSinceEvent}}$$

This transform was used to scale variables to be between 0, for an event occurring at that moment, and 1, which we defined as having never occurred. "Years since event" was included as a continuous variable.

Criminal history features included the cumulative number of times a purchaser had been arrested at a given date for felonies and for misdemeanors, the years since the purchaser was last arrested; using 58 categories of crime defined by the California department of justice, which category of crime did the most recent arrest corresponds to; and indicators denoting if a purchaser has ever been arrested for each of the 58 crime categories. All criminal history features were time dependent.

Handgun purchasing trends were captured with features including the total number of handguns purchased at a given date, years since last legal handgun purchase, and characteristics of the last legal handgun purchase such as the type of handgun (single shot, semi-automatic, revolver, derringer or other); caliber, categorized into small, medium, and large; median cost of a handgun from a manufacturer, categorized into two groups; the type of retailer (licensed dealer, private party, pawn shop, or other; and if the handgun was purchased at a gun show. Finally, demographic features included the purchasers age, race, and gender.

We use a gradient boosting machine (GBM) with a Cox proportional hazards loss function to predict risk of arrest for violent crime. This ensemble method iteratively fits simple learners, tree models with a small subset of all the included features, that improve with each iteration to minimize a loss function.

We used a tree depth of 3, and the number of trees is chosen to maximize the time-dependent C-Index. We used an early stopping approach that ends when there is less than 5% improvement to the C-Index. We split the data into a training set, containing 70% of purchasers and a test set containing 30% of purchasers. The training set was under-sampled to obtain a 1:10 ratio of purchasers with an outcome arrest to purchasers without an outcome arrest. Importantly, all model evaluation was performed on the fully imbalanced test set data.

We obtained risk scores for each purchaser based on the predicted hazard function values from the trained model. We evaluated the model using the time-dependent C-Index as well as ROC curves for predicting arrest based on risk score after a given duration of time, with varying durations. We compared the distributions of risk scores between purchasers with an outcome arrest and purchasers with no outcome arrest using standard descriptive statistics and graphics. Of particular interest were extreme risk scores. We identified purchasers that surpassed risk scores greater than the 99.9% percentile of purchaser median risk score.

Finally, we conducted a variable importance analysis to identify the most important features for predicting the outcome arrest. Importance is determined using the relative importance measure. We also examine partial dependence plots to estimate the duration risk persists following a handgun purchases and arrests.

B. Case-control Analysis

For the case-control analyses, individuals entered the cohort at the time of their first purchase and are considered at risk until December 31, 2021, their death from any cause, or if they could no longer be identified as a resident of California. To ensure that we had complete legal handgun purchasing records for individuals from the age at which they were legally eligible to purchase (age 21), we enrolled individuals based on age, over a twenty-four year period (1996-2020): those with a record of purchase who were age 21 in 1996, individuals aged 21-22 in 1997, individuals aged 21-23 in 1997, and so on, up to individuals aged 21-45 in 2020. Though this approach sacrifices the study of older purchasers, given our study focus on interpersonal violence and the well-established finding that criminal risk peaks in the early to mid-twenties and declines significantly with age,¹² are primary interest

was in younger individuals. Importantly, we did not enroll or match on age at time of entry into the study population. That is, an individual who was 21 in 1996 could have, for example, purchased their first handgun in 2010 and entered the cohort at age 35. For this individual, we would have eleven years of follow-up from first purchase.

We used incidence density sampling to select 10 controls from DROS who were still at-risk at the time of the case's arrest. Under this sampling approach, controls may be randomly selected as controls more than once, and a person selected as control may later become a case. The odds ratio provides an estimate of the rate ratio for the full cohort. Cases and controls were matched on gender for statistical efficiency.

Our primary interest was in the handgun purchase most proximal to the criminal event, thus, if a purchaser had multiple purchases during the exposure period, we focused on the characteristics of the transaction and handgun pertaining to the purchase closest in time to the arrest (the "index" purchase). However, we were also interested in capturing prior transaction patterns and thus we also included a continuous variable for the total number of purchases per person and a categorical variable indicating time between the index purchase and the prior purchase (coded as only 1 purchase, 1 to 2 years since the prior purchase, 2 to 4 years since the prior purchase, or 5 or more years since the prior purchase). We created a 3-level variable to capture whether the index purchase differed from any prior purchases for a given characteristic: 1) the purchaser had only 1 purchase; 2) the purchaser had more than 1 purchase and the index purchase did not differ from any prior; and 3) the purchaser had more than 1 purchase and the index purchase differed from any prior.

Transaction characteristics included those used in the machine learning models. These included whether the handgun was purchased at a retail store as compared to a gun show; whether the transaction record was a retail sale, pawn, voluntary registration or collector's report; and the distance between the purchaser's home address and the location of dealer. Handgun characteristics included handgun category (revolver, semiautomatic pistol or other), caliber (categorized in small, e.g., .22, .25, .32; medium, e.g., .38, .3, 9 mm; and large, e.g., .40, .44, .45); and an indicator for whether the gun was "inexpensive," proxied by the manufacture and the bottom quantile of prices listed in the *Blue Book of Gun Values*.

We included criminal history arrest data. These variables included arrests for a violent crime involving a firearm (pre-purchase), violent crime not involving a firearm, non-violent misuse of a firearm, property crime, drug or alcohol related crime, and other crime.

We analyzed the data using conditional logistic regression. This is mathematically identical to a stratified Cox model. Cases and controls are time-matched and compared within risk sets at the time of the case's arrest. Thus, controls are censored at the time of the case's arrests and, if there are any subsequent purchases or arrests, these are not included in analyses of that risk set).

We report adjusted odds ratios (aOR) and 95% confidence intervals (CI) for the independent variables described above. In the main models, we specified the referent group for categorical variables as the group for which we were most interested in a comparison.

Expected applicability of the research

Our study of mass and active shooters is the first to examine their legal firearm acquisition patterns compared to a control group of authorized purchasers. Our findings speak to our understanding of pre-attack acquisition behaviors and suggest purchasing histories that may be deserving of further scrutiny.

The machine learning analyses provides research that speaks to the potential for firearm transaction records to help enable evidence-based determinations of individual risk of extreme firearm violence. A risk prediction tool could be used in conjunction with other sources of information and data that law enforcement currently relies on to assess the validity of a threat to which they've been alerted, such as records of previous home visits or restraining orders. The case-control analysis helps to identify important risk factors and the interaction between criminal history and purchasing behavior.

Participants and other collaborating organizations

University of California Firearm Violence Research Center. California Department of Justice.

Changes in approach from original design and reason for change, if applicable

For the study of mass shooters, we did not have sufficient sample size to implement a machine learning approach or a multivariate model. Instead, we compared mass shooters to non-mass shooter purchasers using univariate analyses. We used incidence density sampling to match mass and active shooters to other purchasers and compared the two groups using conditional logistic regressions.

Second, we supplemented this work with a characterization of the firearm transaction patterns of 55 mass and active shooters who perpetrated attacks between 1985 and 2018, irrespective of whether they had a record of transaction in DROS. We implemented a mixed model to identify factors associated with firearms acquired in close temporal proximity to the attack.

We are also pursuing a secondary analysis of the mass shooters in California that we identified that further examines, through qualitative analysis, potential flags that could have led to treatment and the points of intervention or potential intervention.

For the machine learning study of perpetrators of firearm violence and major violent crime, we decided to implement a survival analysis machine learning approach rather than simple classification of a zero/one outcome. Survival analysis is a statistical method that aims to predict the time to an event. It can accommodate censored data and time varying covariates. Unlike a Cox proportional hazards model, we implement a machine learning approach that is better equipped to handle high-dimensional data and is designed for the task of prediction as compared to interpretation. Additionally, we decided to model the outcome in two ways: (1) arrests for major violent crime, and (2) arrests for firearm-related violent crime.

For the case-control, we used a rolling cohort. Because data is only available beginning in 1996, and we wanted to capture individuals full potential purchasing trajectories, we constrained those who could enroll based on age and time, as described in the methods.

Outcomes

Activities/accomplishments

To date, we have published a manuscript on mass shooter purchasing patterns. The second manuscript, using machine learning to predict major violent crime and firearm-related violence, is under development with all statistical analyses have been completed and portions drafted. This research is being presented at the National Research Conference for the Prevention of Firearm-Related Harms on November 1, 2023. We expect the manuscript to be complete before the end of the year. The third paper, which uses a case-control approach to analyze associations between purchasing patterns, prior criminal history and subsequent violence, is currently under peer review. Finally, a fourth manuscript is under development that will further analyze the mass shooter case studies.

Results and Findings

Mass shooter analyses

We found that mass and active shooters purchased more handguns overall and more semi-automatic pistols in the year prior to the attack relative to controls, potentially indicating preparation for the mass or active shooting. Results demonstrate shorter purchase trajectories among mass and active shooters relative to controls; mass and active shooters started purchasing at an older age and reached the attack date at a younger age. A history of purchase denials was associated with 23.4 times the odds of being a mass or active shooter, suggesting that mass and active shooters have higher rates of prohibitions, and/or attempts to bypass background checks.

In the analysis of all identified mass and active shooters in California, mixed model results indicated that firearms obtained closer to the time of attack were more likely to be long guns than pistols, acquired out-of-state, obtained by unauthorized methods rather than through a licensed dealer, and discharged during the attack.

Interpersonal firearm violence case-control analysis

The cohort included 1,212,144 individuals, of whom 6,153 were arrested for firearm-related violent crime (0.5%). Cases were matched to 61,530 controls to form the study sample. The largest risk factor was a prior criminal history: purchasers had close to six times the risk of firearm-related violent crime arrest if they had a prior arrest within three years of the index purchase. Several transaction and firearm characteristics were also associated with FRV. For example, risk increased an estimated 37% if the firearm was redeemed at a pawn shop and decreased an estimated 17% if the transaction was a registered private party transfer (vs. retail purchase) and 37% if the firearm was a bolt action firearm (vs. semi-automatic). In the interaction models, most of the purchase and firearm features only remained significant among those with no criminal history. Among those with no purchase history, the magnitude of the associations generally increased. For example, purchasing a low-cost handgun increased risk an estimated 49%.

Consistent with previous research, criminal history was the most important risk factor for firearm-related violent crime among legal firearm purchasers, with risk particularly high among those whose prior arrest is in close temporal proximity. Several transaction and firearm characteristics were associated with firearm-related violent crime, but these features provide little evidence of additional risk for those with a prior criminal record.

Interpersonal violence machine learning analysis

[Study results are preliminary and subject to change.]

Our data consisted of a total of 2,984,719 handgun purchasers, among whom 1.9% had at least one arrest for a major violent crime; approximately 0.8% were arrested for perpetrating violence with a firearm (.8%).

Looking at the distribution of risk scores from the model, approximately 20% of the major violent crime perpetrations after purchaser are among those individuals identified to be among the riskiest top 5%. Focusing on the riskiest 1%, close to 10% had the outcome, and among the riskiest .01%, 13% went on to perpetrate homicide, robbery, aggravated assault, or rape within five years.

The variable importance measures related to the individual's purchasing history show time since last handgun purchase was by far the most important risk predictor, followed by the number of handguns purchased, time since a denial, and the number of previous denials. Individuals were at highest risk shortly after purchase, suggested some legal purchasing with criminal intent. Denials are a well-known risk factor for subsequent criminal behavior.

The most important criminal history predictor was time since last arrest. This is well-established in the criminology literature: risk declines over time. The next most important predictor was the number of misdemeanor arrests followed by the number of felony arrests and if the individual had ever been arrested for a violent crime. California prohibits purchase among those with violent misdemeanor convictions, but only for a period of 10 years. Further, our predictors were arrest rather than conviction.

Limitations

Limitations of the mass shooter study included ambiguity regarding definitions of what constitutes mass violence, which may limit cross-study comparisons of findings, and a smaller proportion of shooters with a history of authorized purchase, relative to national data, potentially due to California's relatively stringent firearm policies, which may limit generalizability.

The sample size of mass and active shooters in the case-control analysis was small, limiting our ability to conduct multivariate analysis. We were missing active shooter incidents occurring between

1996 and 1999, and 2017 to 2018. Our detailed DROS transaction data began in 1996, excluding a case-control analysis of shooters who perpetrated an attack prior to 1996.

Another limitation, relevant to both the mass shooter studies and the studies of perpetrators of firearm violence more generally is that, although California implemented a comprehensive background check policy in 1991, which requires almost all sales to be conducted through a licensed firearm retailer, firearm transaction records may nonetheless be incomplete and subject to measurement error. In addition, data are not representative of long gun sales (which were only recorded beginning in 2014) or illegal acquisitions. California has comparatively stringent restrictions on firearm purchase and possession, and results from the current study may not generalize to other states.

The analyses examining criminal histories and purchasing patterns of individuals who perpetrated a major violent crime and a firearm related crime necessarily relied on criminal history arrest records. Arrests are an imperfect proxy for criminal behavior. We were not able to identify when individuals left the state.

Finally, though the predictive models suggests there are clear risk factors, and we are able to identify extremely risky individuals, the risk prediction remains proof of concept as opposed to an assessment upon which direct action could be taken.

Artifacts

List of Products (to date)

1. Firearm Purchase Behavior and Subsequent Adverse Events. Talk presented at the American Society of Criminology Annual Meeting, San Francisco, CA. 2019.
2. Analyzing Firearm Transaction Records to Identify High Risk Purchasers. Talk presented at the National Institute of Justice Topical Meeting on Rare Incidents Data Collection Models to Advance Research on Mass Violence, San Antonio, TX. 2019.
3. Purchasing Patterns and Mass Shootings. Cassandra Fecho, Masters Practicum, Public Health Sciences, UC Davis. 2019-2020.
4. Laqueur, H., Wintemute, G. Identifying High Risk Firearm Owners to Prevent Mass Violence. *Criminology & Public Policy*. 2020
5. Presentation to the American Society of Criminology Annual Conference, Atlanta, Georgia. November 2022.

6. Predicting violent crime among handgun purchasers in California using handgun purchase trends and criminal histories. Poster presented at the National Research Conference for the Prevention of Firearm-Related Harms. November 2022.
7. Firearm purchasing characteristics associated with perpetration of violent crimes. Presentation accepted to the Society for Advancement of Violence and Injury Research. (SAVIR). Denver, Co. (unable to attend because conference date coincided with being 38 weeks pregnant).
8. Tomsich EA, Crawford A, McCort CD, Wintemute GJ, Laqueur HS. Firearm acquisition patterns and characteristics of California mass and active shooters. *Journal of Criminal Justice*. May 2023.
9. Predicting violent crime among handgun purchasers in California using handgun purchase trends and criminal histories. Poster presented at the Society for Epidemiologic Research Annual Meeting, June 2023.
10. Predicting Violent Crime Among Handgun Purchasers in California Using Handgun Purchase Trends and Criminal Histories. Presentation to the National Research Conference for the Prevention of Firearm-Related Harms. Chicago, IL. November 2023.

Data sets generated

We generated several analytic datasets. We are not, however, permitted to share the data given our data use agreements with CA DOJ.

Dissemination activities

Dissemination activities thus far have included presentations at conferences (listed previously) and publication in a peer-reviewed journal. Further dissemination activities will include the publication of the remaining findings in peer-reviewed journals. These publications will be accompanied by press releases, and we will notify the national media of our findings. Finally, we will arrange meetings with the California Department of Justice to discuss our findings and their implications.