Andrew Tamez, Ace Padilla,
Jason Stisser, Erin O'Neil

Qualified Immunity: An Analysis of Effect on Police Shooting Deaths

Background

Qualified immunity is a precedent established by the U.S. Supreme Court, which protects a police officer from civil litigation for violation of a person's constitutional rights. Qualified immunity can only be invoked if a clearly established law was not in place to indicate the officer's actions were illegal during the time the violation occurred. This precedent is an important policy issue that impacts day-to-day encounters between the various police forces and the civil populace.

Objectives

Our research aims to determine whether qualified immunity influences the number of police shooting deaths. We identified three states, Connecticut, Colorado, and New Mexico, who eliminated qualified immunity for police officers in 2021 for state constitution violations. In this project, we are interested in whether these states have shown a statistically significant change in shooting deaths since dissolving qualified immunity. We also look to identify if there is a significant difference in the number of police shooting deaths per capita of 100,000 people between states who revoked qualified immunity and those that have not.

Data Curation

The states we chose to analyze were the three states that eliminated qualified immunity in 2021: Connecticut, Colorado, and New Mexico. We then chose three red states, Florida, Texas, and Mississippi, and three blue states, New York, California, and Illinois. Each of the latter two has two of higher population and one of lower population. We pulled nine spreadsheets from the washingtonpost.com GitHub one for each of our nine states of interest. For each state, the comma-separated value (CSV) files contained officially released data on police shooting deaths that occurred between 2015 to present day. For our purposes, we were only interested in the year, the state of occurrence, and the number of shooting deaths that occurred. We pulled the data into a pandas dataframe. We then cleaned the data and removed all the columns that contained unnecessary information.

The other two CSV files were pulled from the census.gov website and contained the census data for all the states for our years of interest between 2015 – 2023. To clean this data, we removed all columns with unnecessary information. We also changed the names of the states to their respective abbreviations to make merging easier. We further filtered the data to only include the states of interest.

Upon completion of the cleaning of the input data, we merged the data together into one pandas dataframe to add a new column and perform our calculations for the per capita shooting deaths per state. We used suffixes to make reading the column names easier and formatted year_pop, to represent the state population for the respective year, year_shootings, to represent the number of shooting deaths for a given year, and year_percapita.

We also used Seaborn and Plotly.express/Choropleth to create our line plots, heatmaps, and state-colored heatmaps to graphically visualize our calculated results. Once this analysis was complete, we took our per capita averages and developed a proportion hypothesis test to mathematically determine whether the difference in averages between the states was statistically significant enough to conclude the effect qualified immunity had on the number of police shootings or if any changes seen were by chance.

Due to the change in assignment submission, the code was adjusted for those without the CSV data files so those without the data could run the code. These changes actually allowed for easier use of CoLab by all participants after the completion of the final project. This was a monumental lesson learned as the barrier for MAC versus Windows operating system was no longer a hinderance.

Hypothesis Testing

We divided the states into two groups to compare their respective shooting deaths rate per capita. Group I consisted of states that retained qualified immunity (CA, FL, IL, MS, NY, TX), while Group II included the states that eliminated it (CO, CT, NM). Our initial assumption (null hypothesis) was that there was no difference in the average shooting death rates between the two groups. Conversely, our alternative hypothesis suggested that Group II would have a lower shooting death rate per capita than Group I. We chose our alternative hypothesis to force a direction, so the burden of proof lay in qualified immunity having an impact on police shooting deaths. To test the hypothesis, we used R to calculate the average shooting death rate for each group then calculated the test statistic (z-value) for hypothesis testing.

One of the original challenges in this project was finding a way for our team to collectively work on a coding project at the same time. We attempted to use the Google Colab platform to simultaneously work on the code at the same time, however due to technical issues between group members using different operating systems, Mac versus Windows, we had difficulties working around Google Colab. These difficulties resulted in us sharing an .ipynb file back and forth. This did not, however, hinder our ability to conduct our work. We were able to split the project into pieces where one team member was able to clean and merge all the CSV documents, another team member took the document and conducted the mathematical computations and graphics, and then the output of that analysis was handed over to the other two team members for use in hypothesis testing and analysis in R.

Results

Our calculated test statistic was –0.2911, which we then tested using the student t-distribution function in R to calculate a p-value of 0.395. Given this p-value, our test did not provide sufficient evidence to reject the null hypothesis. This result indicates there was not sufficient evidence to indicate that the removal of qualified immunity resulted in a statistically significant difference in the shooting deaths per capita rates.

Conclusions

We conclude, based on the current data, that removing qualified immunity does not have an impact on the number of deaths by police shootings. The proportion of police shooting deaths per 100,000 people in states with qualified immunity is the same as the proportion of shootings for states without. This result is interesting, but less so than some of the insights realized as we worked through this project. We attempted to control the litany of factors by selecting states on opposite ends of the political spectrum to account for differences in laws which may have contributed to the number of police shooting deaths. We initially assumed only qualified immunity would have affected the number of deaths, but this assumption may have proven false. We also segregated the time periods to assess a period in which all states had immunity and a period where three did not. Our group maintained a consistent dialogue, in our various classes together and on Microsoft Teams, as we tried to wrap our collective heads around the problem. Significant challenges included collaborating on code across two languages, Python and R, while we updated our assumptions and considered the questions which arose as we considered the data sets from different angles. Our conclusion was apparent early, and a sizable portion of our time was spent making sure we were answering the right question, in the right way, and then filtering and visualizing the data in a way which allowed us to tell the story.

Finally, we learned more from the process than from the results. Among the lessons learned were insights on problem framing, technical collaboration, version control and quality assurance/quality control. Our deliberate preparation, including rehearsals and in-person collaboration sessions, helped us present our results, and we completed our project with notes on how to improve our visual products to help the audience understand the information better. This project concluded as a great learning experience which will help each of us as we look forward to our thesis research and future roles as analyst.