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Police Union Membership and Lethal Use of Force

Scott Barger

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USF Graduate Thesis 2021

Abstract: I examine the Fraternal Order of Police union presence in cities as an explanation for lethal use of violence. Using a novel dataset of FOP union presence, I utilize a simple log log OLS linear model to explore the relationships between FOP unions and lethal use of force. I find robust evidence that FOP unions have higher incidences of death at the hands of police, compared to cities without a FOP union. Exposure to FOP leads to an increase in baseline risk of death by police by 17%. This effect increases for larger cities.

Police lethal use of force is a common occurrence in the United States. Academics and researchers who are tracking these numbers show 1021 people were killed by police in 2020, and 321 people have been killed in 2021. The United States stands out among developed nations as a country that is prone to police violence. One area of interest in the literature is police unions and their effects on police officers and police lethal use of force (Dharmapala et al. 2019). There has been groundbreaking work on how police unions use their state sanctioned violence to influence collective bargaining processes with the state (Ichniowski, 1989). However, there is a lack in the literature on specific unions within policing and unionization as a determinant for police lethal use of force. The specific focus of this paper is on the Fraternal Order of Police (herein FOP). The FOP union is the largest de facto police officer’s union in the united states, with over 300,000 members and 2,100 lodges operating in all 50 states. This
union particularly stands out, not only because of the size, but because of their specific union contracts and promises to those who join. They tout a strong team of lawyers who are ready to defend officers in abuse complaints from citizens and civil lawsuits. They have also not been critically studied to my knowledge, and I believed it was important to provide some quantitative research on the Fraternal Order of Police. Therefore, I directly estimate the impact a FOP lodge has on police lethal use of force. I find that being in a city where a FOP lodge is located increases police lethal use of force by about 17%, a significant and large magnitude affect. I also find that while population scales with police lethal use of force, the effect of being in a FOP city is nearly half of population size.

It is important to note the decision to unionize is complex and endogenous with a variety of issues. Police precincts might operate in a particular crime ridden city and want a strong union to help them in legislative fights. It is also possible that FOP lodges appear due to the size of a city. As a city grows in population, police officers might gravitate towards an already established and large police union for collective bargaining fights. Whatever the mechanism is, there is an endogenous process with FOP cities and police lethal use of force. This paper does not aim to provide a causal statement. Due to the limited dataset, I am unable to create exogenous variation with respect to FOP exposure. However, I do believe the strong and significant association is a worthwhile contribution to the literature and signal to researchers working on police violence. State after state, my results hold and are significant, exposure to FOP lodges increases police lethal use of force. I also look at potential covariates such as total homicides in a city, demographics, and historical processes of segregation (redlining) and find they do not affect the significance of my results. It is possible that FOP lodges can have reverse effects on crime and increase crime in a city, due to harsher treatment of civilians, more frequent stops, and more harassment. For this reason, I do not include total crime of a city, instead I choose homicides. Homicides are a physical act and can not be forged or forgotten and have high potential to increase police lethal use of force in a city.

1. Literature Review
What theoretical model can help us understand FOP violence? What are the broader determinants of violence within police precincts and how have policing norms shaped and protected “bad apple” police officers? From the very beginning of human civilization, since the creation of nation-states, there has been a police force (military) designed to maintain law and order within a state. This can be modeled as a stationary bandit and roving bandit from Andrew Young (2016) research on Visigoths. In this model the stationary bandit provides public goods in the form of law and order by monopolizing violence. Rather than your town being attacked at random by roving bandits, you sanction a specific type of bandit “stationary bandit” to monopolize violence. This is essentially the formation of a state in its simplest form. A desire for protections against roving bandits, by legitimizing a single bandit to uphold agreed upon laws and public goods. Understanding the beginning formations of a policing institution can help us understand how policing norms can evolve.

The police were created from a desire to form nation-states and a vital necessity in a nation’s foundation (Weber, 2009). Police are created from a need to protect laws; a nation-state needs to have a legitimate use of violence and monopolize it. If the police do not have a monopoly on violence, we would consider that state a failed state (Acemoglu Robinson & Santos 2013) akin to a Hobbesian natural state. This creates an in-grouping mechanism, are you apart of the state or not, and are you protected by the police force or not. In-grouping is a foundational aspect of nation states and nationalism; being a part of a nation is a valued aspect of society. There is evidence of this in context after context, in schools’ American children are required to stand and give the pledge of allegiance. The state then holds violent power over the population vis-à-vis policing and military. By violence, I do not just mean random beatings of citizens, I am referring to the power to jail someone, the power to take property etc. We accept this because policing is a vital aspect of law and order, we need police to enforce laws and ensure roving bandits do not come and steal all of my belongings. Essentially, the state becomes the monopolist on banditry and has exclusive rights over violence (Young 2016). Framing a state’s creation in this manner allows us to consider the exact role a policing institution should have and understand how evolution of norms around policing can lead to
undesirable albeit stable outcomes. A police force may be necessary for a functioning state, but evolutionary norms around policing can lead to bad outcomes where police are unnecessarily violent, particularly towards specific out-groups such as the African American community.

Evolutionary stability and dynamics have increasingly been used in the economics literature to explain how norms propagate within a society. Elinor Ostrom used evolutionary stability to explain how collective action and social norms can come to fruition (Ostrom 2000). In most of the literature, evolutionary stability is focusing on norms around cooperation and altruism that explain why seemingly rational agents might break from rationality (Bendor & Swistak 1997). However, norms can also collapse and diverge to bad outcomes. In the case of police officers, norms around group loyalty (do not inform internal affairs about your partners police brutality etc.) and brotherhood have potentially collapsed into bad outcomes. There is a noticeable us vs them dynamic in the news and media around police officers. The code of silence, as laid out in Skolnicks (2008) paper, shows how obligations to fellow police officers can protect those who violate criminal law. There are well documented cases of judicial obstruction by police officers refusing to give testimony against fellow police officers accused of ethical violations (Mollen Commission in New York City). The rise in social movements such as Black Lives Matter and anti-police rhetoric have only increased this us vs them and I believe this has led to increases in the brotherhood mentality within police unions. The norms around what it means to be a police officer are being reinforced by the us vs them dynamics. This has led to an increase in group loyalty and brotherhood, which potentially has huge negative consequences for police accountability.

There is potential for huge abuse as norms around state sanctioned violence evolve. If someone has a legitimate use of violence, at the margin this can create a more hostile work environment. Agents might be just a little rougher, use a little more force than necessary etc. This is edge theory articulated in Paoline’s paper (Paoline 2003). Edge theory states police officers who face dangerous situations must always be in control of the situation. This itself is an evolutionary norm stemming from police officers facing dangerous situations. To minimize
the harm against them, they must “maintain the edge” (Brown 1988) (Manning 2003) (Paoline 2003) or be in control of the situation at all times. This can potentially lead to situations where simple missteps by citizens can lead to extremely violent outcomes, sometimes fatal. Maintaining the edge can help explain why police lethal use of force has increased in recent decades. Couple this with evolutionary norms around policing such as group loyalty and you have a recipe for a violent institution that is quiet about their abuses.

Another potential string in the theoretical web that can explain police lethal use of force within FOP unions is moral hazard and adverse selection (Arrow 1968) (Akerlof 1978) (Pauly 1968) (Stiglitz 1983). The protections provided by FOP unions via the legal team and organizational structure have allowed union members to engage in riskier behavior. Because the FOP provides such a safety net to their members, police officers find it easier to “maintain the edge” via violent intimidation. They are protected on the backend by the FOP union, and therefore have the ability to engage in riskier behavior knowing they will be protected by the FOP union (at least somewhat protected). When you then consider the potential for evolving norms around us vs them dynamics, you once again have a recipe for a failed institution. You have a state sanctioned institution with a monopoly on violence, who are extremely loyal to their group, and now are faced with quasi-immunity if they become too violent.

Lastly, a theoretical explanation for FOP’s lethal use of force could be an adverse selection information asymmetry problem. Adverse selection is usually applied to failed markets where one party has more information (Akerlof 1978) and is able to extract extra rents from the market. This same theoretical concept can be applied to a police job market. A union does not have complete information over who is joining their union, only the agent does. It is possible that “bad apple” police officers are self-selecting into FOP unions due to endogenous processes linked to FOP protections and their legal defense team. This creates a market failure where FOP unions have “bad apples” self-selecting into their unions unbeknownst to the union at large. This also leads into problems of sorting for police officers. FOP unions are primarily located in big cities, so there could be a desire for “bad apple” police officers to sort into these cities to
clean up the streets (Chan 1996). Areas and cities that tend to have more crime might influence the evolution of policing norms in that area. These areas require different norms than a rural homogeneous community. This could directly explain why the Oakland Police Department looks drastically different than the Sonoma Police Department. A rural city does not need the strong policing norms a bigger city like Oakland does.

As we push this system through time, we get an outcome where police officers in Oakland are potentially more violent than police officers in rural communities. Couple this with some FOP moral hazard, and you once again have high potential for a failed institution that is too violent and exerts too much force on their citizens. This institution is then reinforced via evolutionary stable norms around group loyalty and persists due to monopolistic powers over violence within a state. This theoretical layout is the basis for my thesis, and I will contribute directly to the literature by highlighting the stark differences between cities with a FOP union presence and those without.

2. Data

The data collection method for this paper required extensive web scraping. The national FOP, based in Tennessee, does not list any local lodges by state. Therefore, I was required to scrape via google every state FOP location. To do this, I utilized the beautiful soup and selenium python packages. Because of the limited novel dataset, I was only able to verify if a FOP was present in a city based on the union’s own records. Therefore, it is possible my dataset is not exhaustive, and there are more FOP lodges I cannot account for because they are not listed anywhere on the internet. If I found a city with a FOP union, that entire city is coded as being exposed to a FOP union. There are potential future areas of research in geo-spatial data that could further showcase the effects of FOP exposure. For example, plotting the FOP address on a map and then using GIS to plot the lethal use of force dataset could give us interesting results about distance to FOP offices and violent outcomes. This would also measure the heterogeneities from distance from a FOP lodge. Another limitation to this dataset is there is no
time variable for when a FOP was created. A time variable would allow for much more robust inferences, as a variety of statistical approaches would become available (diff-in diff).

The next section of the dataset is granular police lethal use of force data from 2010-2020 from the activists at mapping police violence and campaign zero (Mckkesson & Sinyangwe). This dataset granular and detailed, with zip codes and specific addresses of where the lethal use of force occurred. I combined this dataset with census data and collapsed the dataset down by county. Therefore, I have every county and their total police lethal use of force instances from a 10-year period. I lost some police lethal use of force data due to fuzzy matches (string to string matching) but am left with 4809 police lethal use of force incidences. This only includes those states which I have FOP data for (24 states) and is not representative of the entire United States. Finally, I combined all 3 datasets together, giving me a binary FOP exposure indicator along with population size and lethal use of force data (cross tab dataset). For example, there are roughly 120 police lethal use of force incidents in Los Angeles from 2010-2020 and Los Angeles is home to a FOP lodge. At the county level, this number increases to 300 police lethal use of force incidences for Los Angeles County. There are possibilities for heterogenous effects of FOP lodges, but for the purposes of this paper I am unable to identify these effects. Pooling at the county level allows access to unique datasets that are not collected at the city level. For instance, redlining data from mapping inequality (Nelson & Madron) is collected at the county level. Similarly, homicide data (not police lethal use of force data, but total homicides) is collected at the county level as well as basic demographic information. Therefore, there are some counties with multiple FOP lodges. For the purposes of this paper, I am only interested in FOP exposure and create a binary for FOP exposure regardless of number of FOP lodges per county.

3. Methodology

The main econometric method for this paper is a log log OLS linear model. We know from the city scaling literature (Bettencourt 2013) (Ortman et al. 2016) that crime and economic outputs scale with city size and population. As you increase city size and population density
grows, crime grows with it nonlinearly. Therefore, I include log population as a control and as a strong covariate to FOP exposure. As you increase in city size, police lethal use of force will increase. It is important to look at the interaction effects between population size and FOP exposure because I believe they covary together strongly. A potential statistical approach could be to use an ANCOVA model to understand how population and FOP covary with respect to police lethal use of force. For the purposes of this associational paper, I chose a simple OLS linear model. I run the model at the city level and the county level. The base econometric model for this paper is as follows:

\[
\ln(LethalForce) = \alpha + \theta \ln(Population)_j + \gamma FOP_j + \psi x_j + \rho FE + \epsilon_j
\]

Where Police Lethal Use of Force is my interested dependent variable, FOP is an indicator variable for FOP exposure for county/city i, log(population) for county/city i, and \( \rho FE \) is a state level fixed effect. The i represents both models, at the county level, and the city level. The standard errors are clustered at the state level. This specification captures the overall effect of a FOP lodge on Police Lethal Use of Force, ignoring any potential scaling structures. For example, this econometric specification does not consider the effects of population size on FOP lodge presence and the \( \gamma \) coefficient represents the Local Average Treatment Effect across all counties/cities. In order to further understand this relationship, I also run a OLS linear model but allow FOP exposure and population to move together by interacting them. The equation is as follows:

\[
\ln(LethalForce) = \alpha + \theta \ln(Population)_j + \gamma FOP_j + \beta \ln(Population)_j \times FOP + \psi x_j + \rho FE + \epsilon_j
\]
This is the foundational regression for this paper and captures the association of FOP exposure to lethal use of force while allowing for different county sizes to impact Police Lethal Use of Force. The state fixed effects absorb any variation between states, and the interaction coefficient $\beta$ represents FOP exposure with county size. Now, the $\gamma$ coefficient for FOP is interpreted as the intercept for Police lethal use of force, with population zero for a county. Therefore, this coefficient will turn negative and the $\beta$ coefficient will be interpreted as the elasticity of police lethal use of force as a city/county with a FOP lodge increases in size.

4. Results

Figures (1) and (2) show a baseline fit of the data in log. There is a clear increase in police lethal use of force in FOP cities. Figures (1) and (2) show the upper end of the distribution, from city size (log) 10 and higher. This is where the FOP cities have the largest increase in police lethal use of force. However, these figures do not reflect the nonlinear scaling aspect of city sizes and police lethal use of force. I use a nonparametric model to show the nonlinear increases in lethal use of force. I then separate out FOP cities and counties from non FOP. Figures (3) and (4) show the results at the county and city level. The fit is noisier, however there is a clear increase in police lethal use of force in FOP cities and counties.
Figure 1

All 24 States

Log Police Homicides, 2010-2020

City Population (log), FOP Cities in Red

Figure 2

All 24 States

Log Police Homicides, 2010-2020

County Population (log) (log), FOP Counties in Red
Figure (3)

Figure (4)
The results from the equation (1) and (2) are in table (1). Column (1) is at the county level and does not include the interaction term. FOP lodge presence in a county increases police lethal use of force by 17.1%. This is a local average effect irrespective of population sizes. Population also increases lethal use of force by 57.2%. This fits economic theoretical scaling models. As you increase population, crime increases, therefore a police response will also increase. Column (2) estimates the effect with FOP lodge and population interacted, as in equation (2).

Critically, the scaling effect of population and FOP lodge is significant and large in magnitude. We interpret this interaction coefficient as the elasticity of FOP lodge presence and population size. A 10% increase in population increases police lethal use of force by 4.7%. If that county has a FOP lodge, the effect grows by 3%. A county with a FOP lodge has an increase (increasing population by 10%) in police lethal use of force by 7.73%. Columns (3) and (4) report at the city level and report similar magnitudes and significance. In Columns (2) and (4) the FOP lodge coefficient turns negative, because it measures FOP lodge presence without a population, and becomes the intercept for a city or county with population zero.

**TABLE 1**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Log Police Homicides</th>
<th>(2) Log Police Homicides</th>
<th>(3) Log Police Homicides</th>
<th>(4) Log Police Homicides</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOP Lodge</td>
<td>0.171***</td>
<td>-3.289***</td>
<td>0.189***</td>
<td>-2.653***</td>
</tr>
<tr>
<td></td>
<td>(0.0756)</td>
<td>(0.564)</td>
<td>(0.0137)</td>
<td>(0.153)</td>
</tr>
<tr>
<td>Population(Log)</td>
<td>0.572***</td>
<td>0.473***</td>
<td>0.189***</td>
<td>0.167***</td>
</tr>
<tr>
<td></td>
<td>(0.0356)</td>
<td>(0.0416)</td>
<td>(0.00574)</td>
<td>(0.00451)</td>
</tr>
<tr>
<td>FOP*Population(Log)</td>
<td>0.300***</td>
<td></td>
<td>0.260***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0490)</td>
<td></td>
<td>(0.0140)</td>
<td></td>
</tr>
</tbody>
</table>

No: No interaction, Yes: Interaction, Observations: 893, 893, 1,876, 1,876, R-squared: 0.682, 0.708, 0.436, 0.470.
5. Robustness Check

I check these results against potential confounders, such as homicides within the county, the demographics of the county, and historical processes of segregation. I use redlining data from *Mapping Inequality* to proxy for overall historical segregation. This is only one form of segregation and racial oppression in the United States, but it will provide key insights into understanding where FOP lodges are located. If FOP lodges are just located in historically redlined cities, this model will capture the relationship. Table (3) reports the results of these checks.

As expected, in column (1) I lose some significance and magnitude on the FOP coefficient. African American population is noisy and not a great predictor of police lethal use of force. However, redlined cities show a 66% increase in police lethal use of force. Column (2) includes the interaction term for FOP lodges and population, as well as a redlining interaction term with population. Both interaction terms are significant and positive. This means that while redlined districts see increases in police lethal use of force, they do not explain FOP lodge increases in police lethal use of force. Column (3) includes the last robustness check I use, log homicides by county. As expected, this coefficient is large in magnitude and significant. However, it does not explain the variation in FOP lodge increases in police lethal use of force. My initial results are robust to these covariate checks.
As another robustness check, I cut off the top 5% most and least populated cities. This will control for any strong outliers that could be biasing my results upwards. I run the exact same specification as my initial results, but with fewer observations. The results are reported in table (4). I lose significance on my average treatment across the sample. Cutting off the top end of the distribution creates noise in the coefficient, and I am unable to find significance. However, when I include the interaction term with population, I see significance and similar magnitude. The coefficient on the interaction term is robust within the middle of the

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Log Police Homicides</th>
<th>(2) Log Police Homicides</th>
<th>(3) Log Police Homicides</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOP Lodge</td>
<td>0.114*</td>
<td>-2.018***</td>
<td>-1.178**</td>
</tr>
<tr>
<td></td>
<td>(0.0648)</td>
<td>(0.552)</td>
<td>(0.518)</td>
</tr>
<tr>
<td>Population (Log)</td>
<td>0.532***</td>
<td>0.444***</td>
<td>0.352***</td>
</tr>
<tr>
<td></td>
<td>(0.0350)</td>
<td>(0.0465)</td>
<td>(0.0525)</td>
</tr>
<tr>
<td>FOP*Population(Log)</td>
<td>0.186***</td>
<td>0.107**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0474)</td>
<td>(0.0441)</td>
<td></td>
</tr>
<tr>
<td>Redline</td>
<td>0.666***</td>
<td>-2.819**</td>
<td>0.226**</td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td>(1.226)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Redline*Population(Log)</td>
<td></td>
<td>0.262**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0994)</td>
<td></td>
</tr>
<tr>
<td>Population African American</td>
<td>-0.0234</td>
<td>-0.0105</td>
<td>-0.0676***</td>
</tr>
<tr>
<td>(Log)</td>
<td>(0.0222)</td>
<td>(0.0218)</td>
<td>(0.0191)</td>
</tr>
<tr>
<td>Homicides(Log)</td>
<td></td>
<td></td>
<td>0.385***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0515)</td>
</tr>
<tr>
<td>Observations</td>
<td>893</td>
<td>893</td>
<td>644</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.709</td>
<td>0.730</td>
<td>0.741</td>
</tr>
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distribution. FOP lodges still increase police lethal use of force, despite removing the largest counties in the dataset.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Tails off log Regressions</th>
<th>(1)</th>
<th>(2)</th>
</tr>
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<tr>
<td>Population(Log)</td>
<td>0.509***</td>
<td>0.459***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0336)</td>
<td>(0.0376)</td>
<td></td>
</tr>
<tr>
<td>FOP Lodge</td>
<td>0.113</td>
<td>-2.090***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0671)</td>
<td>(0.629)</td>
<td></td>
</tr>
<tr>
<td>FOP*Population(Log)</td>
<td>0.194***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0556)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations 832 832
R-squared 0.581 0.592

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

These results fit within the theoretical models on scaling effects from cities. The larger the city, the more lethal use of force that city will see. However, my paper provides a unique contribution that has not been considered by academics. I have discovered a strong association between lethal use of force and a specific police union within the United States. The FOP union is strongly associated with increases in lethal use of violence, that are not explained by variations between counties and states. Being in a FOP lodge city increases your baseline risk of police lethal use of force by 17%. This effect grows significantly larger in magnitude as you increase city size. This is a public health concern, as the current era becomes more and more aware of policing problems within black and brown communities, I believe my findings are timely and important. When making decisions about public funding for police precincts, or the new defund the police movement, activists can look to my results. I believe there is a moral hazard in joining a FOP union creating a system where police officers can enforce their will, sometimes leading to the death of civilians.
Future research should further clarify the determinants of why FOP unions are particularly costly to the public health. Another pathway my findings open is a geospatial analysis. Analyzing the distance from FOP lodge locations and lethal use of force could provide an accurate causal story that shows close proximity to FOP lodges increases lethal use of force. Researchers could potentially uncover establishment dates for FOP unions, which would allow for a variety of exogenous variation in timing. A diff-in-diff analysis that compares pre FOP treatment to post FOP treatment would still have issues with non-random treatment, but the results would be closer to causality and could potentially solve some of the non-random problems inherent to this system. Regardless, this association deserves a careful examination, and potentially, a complete overhaul of the FOP organization.

References

Pauly, Mark V. "The economics of moral hazard: comment." The american economic review 58.3 (1968): 531-537.


