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Police, Public and Community Violence:  
Exploring the Relationships Between Use of Deadly Force, Law  
Enforcement Killed, and Homicide Rates in the United States

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ABSTRACT AND ARTICLE INFORMATION

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This research utilizes a structural vector-autoregression that analyzes the intertemporal relationship between the number of use of deadly force incidents, number of law enforcement officers killed, and the national homicide rate in the United States. The analysis finds support for two hypotheses: (1) Unexpected increases in law enforcement killed are associated with increases in homicide rates in future months; and (2) Unexpected increases in homicide rates are associated with increases in the number of law enforcement officers killed in future months. Unexpected spikes in law enforcement killed may signal a general weakening of the police as a formal mechanism of social control, leading to increased rates of fatal violence. On the other hand, a shock to the homicide rate associated with an increase in the number of law enforcement officers killed might be explained by a shift in national-level structural factors that increase the likelihood of fatal violence, which eventually includes the murder of officers.

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The 2014 killing of Michael Brown by Officer Darren Wilson in Ferguson, MO, has become a focal point for police reform efforts in the 21st Century. Not only did this unfortunate event intensify the #BlackLivesMatter movement (which started with the 2012 shooting of Trayvon Martin by Neighborhood Watch member George Zimmerman), but it also drew increased attention to controversial police shootings in other cities that might have otherwise failed to make national news. Ferguson and high-profile police killings in other cities that year (including Eric Garner in New York, Tamir Rice in Cleveland, and others) led to President Obama's formation of a Task Force on 21st Century Policing charged with identifying best practices and making recommendations to the President on how policing practices can promote effective crime reduction while building public trust. During the deliberations of the President's Task Force in early 2015, there were additional high-profile cases such as the death of Freddie Grey while in custody of Baltimore police and the shooting of Walter Scott in South Carolina. Most recently, the May 2020 murder of George Floyd in Minneapolis, Minnesota has led to a new wave of protests demanding police reform.

In the wake of these horrible events, there have also been concerns about the police-public violence relationship (particularly in the context of both the image and reality of increasing militarization of police in the United States; for example, see Balko 2013), the phenomenon of de-policing (or the so-called "Ferguson Effect"; see MacDonald, 2015), and a general erosion of trust and confidence in the police. Similarly, law enforcement officers have expressed concerns about a "war on cops" that directly connects violence against law enforcement into these broader national discussions about police-public violence (see, e.g., MacDonald, 2017; Moule, 2020; Nix et al., 2018).

In addition, and as part of the fact-finding of the President's Task Force, national attention was drawn to the fact that the United States at present does not maintain comprehensive national statistics on police shootings, much less the broader category of police use of force. That is, when asked the basic question, "how often does this happen?" no one could provide an answer with a reasonable degree of precision or certainty. Journalists tended to seize on this issue as if it were a new discovery (e.g., Lowery, 2014), and a variety of elected and appointed officials, including the FBI Director, expressed astonishment at the fact that the United States does not collect comprehensive data on police shootings (McCarthy, 2015). But this is not a new problem by any means (e.g., see White, 2016). It is a long standing and well-known problem among policing scholars, who have

been discussing it for years, though largely in the dusty annals of academic proceedings and scholarly journals (perhaps that is part of the problem).

Data concerns aside, there is a relative dearth of research on the incidence of police use of deadly force, particularly with regard to its link to other fatal violence. In brief, the available literature consistently points to a correlation between homicide in general and homicide by police. One of the few examples of research examining the impact of citizens killed by police and the homicide rate on the number of law enforcement officers killed in the line of duty demonstrated a significant relationship between police killings on homicides of police (Kent, 2010). However, what is missing is a clear understanding of the intertemporal relationship between the two, as well as an elaborated understanding of the specific relationship between homicides of law enforcement officers and homicides by law enforcement officers. In this study, we seek to address this issue by examining the relationship between law enforcement killings (using the data from the Supplemental Homicide Reports) and fatal violence, specifically the murder of law enforcement officers (using data from the National Law Enforcement Officer Memorial Fund, 2016) and homicide rates, while utilizing an econometric model known as Vector Autoregression (VAR). We believe the application of this methodology represents a novel contribution to the literature on this topic. In the next section, we review the literature examining the relationship between violence and killings by police.

## Literature Review

About 30 years ago, Robert Langworthy (1986) opened his article exploring the temporal relationship between police shootings and criminal homicide with the following statement: "The most consistent finding appearing in the empirical literature on police use of deadly force is the very strong correlation between the incidence of police use of deadly force and the incidence of criminal homicide" (p. 377). This rather bold assessment was based upon just four U.S. studies and one Australian study. These five studies included three state-level analyses (Hawkins & Ward, 1970; Jacobs & Britt, 1979; Kania & Mackey, 1977), one city-level study (Sherman & Langworthy, 1979), and one study focused on within city variation in a single agency (Fyfe, 1980). Each of these studies had their unique sets of limitations, but all of them were cross-sectional in nature, and while all were informative and made important contributions, none could be regarded as particularly conclusive. Yet, the limited evidence was sufficiently interesting that Langworthy (1986) argued that the best next step was to try and disentangle temporal order.

While there have been several studies of police use of force generally during the past 30 years, there have been far fewer focused on the use of deadly force. In fact, we can add only about 16 additional studies that have investigated the relationship between police shootings and levels of violence (see Table 1). On balance, these studies as a whole are not particularly rigorous from a methodological point of view; they all have design limitations that restrict the extent to which we can draw meaningful conclusions about the relationship between community violence and police shootings. To be fair, a common problem is the well-known lack of adequate data about police shootings, which we discuss in detail later.

These studies can be categorized within three general levels of analysis. Five studies are at the micro-level, focused on within city variation in police shootings in New York, Miami, Philadelphia, and St. Louis (Alpert, 1989; Fyfe, 1980; Klinger et al., 2016; Langworthy, 1986; White, 2003). Seven studies can be described as meso-level, focused on variation in police shootings across samples of large cities (Fyfe, 1982; Jacobs & O'Brien, 1998; Liska & Yu, 1992; Matulia, 1985; Sherman & Langworthy, 1979; Smith, 2003, 2004; Sorenson et al., 1993). Finally, four studies are macro-level. Three are focused on state-level variation in police shootings (Hawkins & Ward, 1970; Jacobs & Britt, 1979; Kania & Mackey, 1977), the first being Australian and the two more recent ones being U.S. studies. The fourth is a national level time-series analysis of policing killings and predatory homicide (MacDonald et al., 2001).

The earlier literature (pre-1986) is all cross-sectional in design and tended to employ bivariate analytic methods (with the exception of Jacobs & Britt, 1979), whereas most of the post-1986 literature uses multivariate methods. While all of the studies report data for an extended time period (typically five to ten years), due to the relative infrequency of police shootings, the majority of studies use aggregated counts or rates as the dependent variable. There are three longitudinal studies, two of which are micro-level, including Langworthy's (1986) time-series analysis of Fyfe's (1980) NYPD shooting data, and White's (2003) time-series analysis of police shootings in Philadelphia (however, White, 2003, did not assess the relationship between homicide and police shootings as part of the time-series analysis).

The data sources employed in these studies include Vital Statistics (Jacobs & Britt 1979; Kania & Mackey 1977; Liska & Yu, 1992; Sherman & Langworthy, 1979), Supplemental Homicide Reports (SHR; Jacobs & O'Brien, 1998; MacDonald et al., 2001, Smith, 2003, 2004; Sorenson et al., 1993), and agency data (Alpert, 1989; Fyfe, 1980, 1982; Klinger et al., 2016; Langworthy, 1986; Matulia, 1985; White,

2003), as well as some alternative sources such as newspaper articles to fill in gaps (White, 2003).

Also of interest are the varying theoretical frameworks. Most of the studies focus on conflict theory or racial threat, and/or community violence, as an explanation for police shootings (Fyfe, 1980; Jacobs & Britt, 1979; Jacobs & O'Brien 1998; Klinger et al., 2016; Langworthy, 1986; Liska & Yu, 1992; MacDonald et al., 2001; Smith 2003, 2004; Sorenson et al., 1993), while others simply focus on structural correlates or methodological concerns without an explicit theoretical focus (Kania & Mackey, 1977; Matulia, 1985; Sherman & Langworthy, 1979), or they are focused on organizational correlates, agency policy, and limits on police discretion (Alpert, 1989; Fyfe, 1982; Smith, 2003, 2004; White, 2003).

As previously noted, based upon the accumulating evidence of a correlation between homicide and police shootings, Langworthy (1986) sought to tease out temporal order using Fyfe's (1980) shooting data from the NYPD. He framed this as a test of three competing hypotheses: (1) the "brutalization" hypothesis, which suggests that exposure to state violence in the form of executions and homicides by the police will lead to less restrained use of violence by both the public and police against each other; (2) the "perception-of-danger" hypothesis, which suggests that police exposure to violence or the perception of violence in their immediate work environment leads to increased police violence; or (3) that the observed relationship between general homicide and police homicide is spurious in that some extraneous variable is a cause of both general homicide and police homicide. Langworthy examined monthly counts of criminal homicides and police shootings in New York City during the five-year period 1971-1975, the same data used by Fyfe (1980) in his cross-sectional analysis of police shootings across NYPD police zones. In the course of fitting ARIMA models to the data, Langworthy found that police shootings exhibited autocorrelation while criminal homicides did not. After controlling for the autocorrelation (with a differenced moving-average model), Langworthy examined the lagged effects of the two series and found no evidence of a temporal relationship between criminal homicide and police shootings. He concluded that this supported the hypothesis of a spurious relationship in the reported cross-sectional studies.

An additional longitudinal analysis by MacDonald and colleagues (2001) is one of the more pertinent pieces of research to the current study. Through the framework of danger-perception theory, the monthly frequency of justifiable police homicides was examined as a function of the number of predatory

**Table 1. Literature examining the relationship between violence and police shootings**

Authors	Units of analysis	Data	Time period	Dependent Variable	Design	Methods	Focus	Key findings for violence and police killings
Hawkins & Ward (1970)	Six Australian States	Agency data	1948-1968	Aggregate rate	Cross-sectional	Bivariate	Armed vs. disarmed policy	General homicide rate correlated with police homicide rate
Kania & Mackey (1977)	U.S. States	Vital Statistics	1961-1970	Aggregate rate	Cross-sectional	Bivariate	Structural correlates	Homicide rate correlated with police homicide rate
Jacobs & Britt (1979)	U.S. States	Vital Statistics	1961-1970	Aggregate rate	Cross-sectional	Multivariate	Conflict theory	Violence index (violent crimes and riots) related to police homicide rate
Sherman & Langworthy (1979)	36 cities with populations > 250,000	Vital Statistics and alternate data	1967-1976	Aggregate rate	Cross-sectional	Bivariate	Methodological focus, community characteristics, agency structure, agency policies	Violent crime and homicide rates correlated with police killings
Fyfe (1980)	NYPD's 20 police zones (3 to 5 precincts each)	Agency data	1971-1975	Aggregate rate	Cross-sectional	Bivariate	Community violence	Homicide rates positively related to police shooting rates
Fyfe (1982)	Memphis and NYPD	Agency data	1971-1975 (NYPD); 1969-1976, but not 1972 (Memphis)	Aggregate rate	Cross-sectional	Bivariate	Intradepartmental variation in elective vs. nonelective shootings; racial disproportionality	Levels of community violence positively related to police shootings
Matulia (1985)	57 largest U.S. Cities	Agency data	1970-1979	Five-year average frequency	Cross-sectional	Bivariate	Police exposure to violence, agency policies	Levels of community violence (including general homicide and homicide of police) positively related to police shootings
Langworthy (1986)	NYPD shooting incidents in Fyfe (1980)	Agency data	1971-1975	Time series created from Fyfe's (1980) data	Longitudinal	Bivariate ARIMA	Community violence	Concludes that Fyfe's results are spurious since a time-series could not be constructed
Alpert (1989)	Miami	Agency data	1980-1986		Cross-sectional	Multivariate		Levels of community violence positively related to police shootings
Liska & Yu (1992)	45 large cities (based on Matulia survey data)	Vital Statistics	1970-1979	Aggregate rate	Cross-sectional	Multivariate	Conflict/threat, community violence	Violent crime related to police killings
Sorenson et al. (1993)	Cities with populations > 100,000	SHR	1980-1984	Aggregate rate	Cross-sectional	Multivariate	Conflict, community violence	Violent crime rate positively related to police killings, less so in largest cities; may be intervening variable
Jacobs & O'Brien (1998)	Cities with populations > 100,000	SHR	1980-1986	Aggregate rate	Cross-sectional	Multivariate	Conflict/threat, reactive violence	Higher murder rates related to higher rates of police killings
White (2003)	Philadelphia	Agency data and newspaper accounts	1970-1992	Monthly frequency	Longitudinal	Bivariate ARIMA	External discretion control, impact of 4 controls on discretion	Exposure to violence in the late 1980's possibly related to increase in police shootings
Smith (2003, 2004)	Cities with 100,000 or more persons and responding to LEMAS ( $n=179$ )	SHR	1994-1998	Aggregate counts	Cross-sectional	Multivariate	Conflict/threat, community violence, organizational correlates (professionalism and bureaucratic control)	Violent crime rate positively related to police killings

homicides, measured as the robbery-homicide count. Both variables were collected from SHR data. At the national level, the results of the study identified a significant relationship between predatory homicide and police homicide. However, it is important to note that the time-series analysis used to model the relationship implicitly assumes that there is no feedback between the two variables. Specifically, it models police shootings as a function of predatory homicides and does not take into account the fact that police homicides can, in turn, impact the levels of predatory homicide. This is an inherent problem with time-series analyses and in most instances represents a misspecification of the model (Sims, 1980).

Setting aside the data limitations of Vital Statistics, SHR, and agency data, we can conclude that across time, location, levels of analysis, data sources, analytic methods, and theoretical frameworks, all 16 studies, with the exception of Langworthy (1986), confirm a relationship between violence and police killings. Langworthy's (1986) piece is, of course, the most critical thus far toward establishing the true nature of the relationship between violence and police shootings but was limited to a five-year period in one city, and that is why additional studies of the temporal relationship is probably most important. What is missing from the literature is a longitudinal study above the micro-level of analysis that accounts for the cyclical relationship between the variables under study.

Another important aspect to discuss is the relationship between community violence and law enforcement officers killed in the line of duty. Although relatively few studies have examined this topic, it is important to briefly discuss those that are applicable to the current research. Examining macro-level characteristics of 165 cities in the United States over a 10 year period, Jacobs and Carmichael (2002) found that cities in which economic inequality was greatest between White and Black citizens also had the highest levels of police homicides, although this relationship was tempered in cities with African-American mayors. Research has also found that county-level demographics, economies, law enforcement agency type, urbanization, and geographic location are all associated with officers killed in the line of duty. Specifically, Kaminski (2008) showed that officer homicides increased in counties that were economically struggling, had larger relative numbers of African-Americans, more people within the age range of 25-34, and counties with larger relative numbers of non-sheriff department agencies. Officer homicides actually decreased in areas with higher levels of urbanicity and counties in the Northeast region of the United States. Importantly, this research controlled for the number of sworn officers in

each county. Kent's research (2010) supported some of the aforementioned results, finding increased homicide risk for officers in cities with high income inequality based on race as well as those with proportionately more African-Americans, while African-American leadership in cities decreased the risk. In an examination of the cyclical relationship of officers killed in the line of duty, the public killed during use of force incidents, and social media, Bejan and colleagues (2018) found that increased social media activity of the Black Lives Matter movement increased the homicide risk to both law enforcement officers and minority citizens. Finally, combining both homicide and assault data, Fridell and colleagues (2009) found that agencies with higher use of body armor were more likely to have violence targeting their officers, although the authors believe that this is an artifact of their cross-sectional design, where departments with more acts of violence against their officers are more likely to encourage the use of body armor. In addition, the research also provides evidence that departments who less aggressively engaged in use of force also decreased the likelihood that their officers would be assaulted or killed. Finally, directly related to community-level correlates connected to violence against officers, the authors of the study found that communities with higher crime rates also had more incidents of violence targeting their law enforcement officers.

In the sections that follow, we describe the current study, which seeks to address this issue, our methods, analysis, and conclusions.

## Method

### The Current Study

The purpose of this current study is to examine the relationship between fatal violence and law enforcement killings (Use of Deadly Force) in the United States between 1976 and 2014. Fatal violence is operationalized using two variables: the number of law enforcement officers murdered in the line of duty (Law Enforcement Killed) and the national homicide rate (Homicide Rate). Use of deadly force is operationalized as the number of felons killed by law enforcement officers. The recursive temporal relationships between these variables are analyzed by aggregating count and rate data to monthly observations. Based on this research focus, we present two research questions that are broken into six testable hypotheses.

H<sub>1</sub>: The number of law enforcement officers killed will be associated with the number of use of deadly force incidents in the future.

H<sub>2</sub>: The number of use of deadly force incidents will be associated with the number of law enforcement officers killed in the future.

H<sub>3</sub>: The number of use of deadly force incidents will be associated with the national homicide rate in the future.

H<sub>4</sub>: Changes in the national homicide rate will be associated with the number of use of deadly force incidents in the future.

H<sub>5</sub>: Changes in the national homicide rates will be associated with the number of law enforcement officers killed in the future.

H<sub>6</sub>: The number of law enforcement officers killed will be associated with the national homicide rate in the future.

## Measures

To test our hypotheses, this study examines the relationship between three variables: (1) the monthly number of incidents in which law enforcement officers were murdered while on duty (Law Enforcement Killed), (2) the monthly number of incidents in which felons were killed by law enforcement officers (Use of Deadly Force), and (3) the monthly national homicide rate (Homicide Rate). Temporally, we focus on the time period between January 1, 1976 and December 31, 2014 and the geographic region of the United States that includes the 50 states and the District of Columbia. To maximize our statistical power when examining the relationship between law enforcement, citizen, and community violence, the years 1976 through 2014 were chosen based on our access to the Supplementary Homicide Report data, which was only available for these years in monthly counts when the analysis was conducted.

The data for the analysis originate from multiple sources. Cases of law enforcement killed were collected from the National Law Enforcement Officers Memorial Fund (NLEOMF; 2016). The website archives and makes publicly available the names, as well as other information, of law enforcement officers who died while on duty. According to Kaminski and Marvell (2002), the NLEOMF uses multiple sources to identify officers who died in the line of duty, including “state and local police memorials, newspaper accounts, officers’ relatives, historians and reports of the Public Safety Officers’ Benefit Program” (p. 188). Although

NLEOMF has information on officers who died in the line of duty as far back as 1791 (a sheriff murdered while serving a writ of ejectment in Columbia County, New York), this analysis only includes officers who were killed while on duty between 1976 and 2014 in the United States. In addition, for our analysis, the officer must have been killed based on any of the following causes – beatings, bombings, gunfire, poisoning, stabbings, strangulations, or terrorism. Officers included in NLEOMF who were killed in United States territories or from other causes, such as vehicular accidents, were not included. Using the department and date variables, the individual level data were aggregated to the incident level to be consistent with the data on use of deadly force incidents and to limit any outsized influence of outlier events, such as the Oklahoma City Bombing or the 9/11 Terrorist Attacks, on the analysis. These incident counts were then aggregated to a monthly count of incidents that occurred within the period under study.

The NLEOMF is not without its limitations, however, and it is important to discuss those as they also have the potential to limit our findings. As one reviewer pointed out, the Law Enforcement Officers Killed and Assaulted (LEOKA) data, which are collected under the Federal Bureau of Investigation’s Uniform Crime Reporting program, also tracks law enforcement officers killed in the line of duty. For LEOKA data, the Department of Justice does also contact departments if they find out that an officer was killed through other means, but how reliable this methodology is in identifying non-reported cases, especially the further back in time we go, is unknown. Related to this, there have been estimates that only 87% of agencies have reported to LEOKA (Uchida & King, 2002). Also, NLEOMF data can be continuously updated, so missing cases can be added years after an event, increasing the validity of the dataset. Unfortunately, there is no mechanism for LEOKA data to be updated once it is officially published by the government. Given that both datasets appear to be both reliable and valid in capturing data on law enforcements officers killed in the line of duty (Kaminski & Marvell, 2002), we decided to use the NLEOMF data because we could not find LEOKA monthly data available prior to 1987 at the time of our original analysis. As we conducted a time series analysis, it was important that our N was as large as possible, while still being theoretically justifiable. Because of this, we chose to use the NLEOMF data as it afforded us an additional 11 years of analysis. In addition, NLEOMF has also been used in prior research using similar methodologies (see, e.g., Bejan et al., 2018).

Similar to other studies on the topic (e.g., MacDonald et al., 2001), the frequency of use of

deadly force incidents and the monthly homicide incident count were taken from the Federal Bureau of Investigation's Uniform Crime Report Supplementary Homicide Report (SHR) data. These data were accessed through the Inter-university Consortium for Political and Social Research's National Archive of Criminal Justice Data. The SHR contains information that is reported by law enforcement officers on non-negligent and justifiable killings in their jurisdictions. Although the SHR is currently one of the only decades-long data collection efforts for homicides committed by law enforcement in the United States, there is still much research that critiques the data. For this research, the most pertinent critique is that of data missing from jurisdictions that do not report. As reporting homicide data through the UCR program is voluntary, there can be months and even years where jurisdictions, and in several extreme examples even states, have not reported or their reports did not satisfy FBI data quality criteria. Over the years, researchers have attempted to validate the SHR by comparing it to other sources and have identified systematic differences between data sources that are supposedly measuring the same phenomenon (Braga et al., 1999; Loftin et al., 2008). Although some argue that this is a problem, especially when conducting county-level analyses (Pridemore, 2005), Fox (2004) argues that the missing cases in the SHR should be considered missing at random because attributes of the homicides do not impact the likelihood of the incident missing from the SHR, as reporting patterns are determined at the department level, not the incident level. For example, if a felon is killed by a law enforcement officer in a jurisdiction, it would be expected that the incident is reported to the SHR based on whether or not the jurisdiction itself reports all homicides, not based on the specifics of the case. However, research has shown that felons killed by law enforcement officers, which are coded as justifiable homicides in the SHR, are systematically underreported, so the missing at random argument may not hold true for subcategories of homicide (Loftin et al., 2003). In addition, researchers focusing specifically on SHR in relation to use of deadly force incidents also have called into question the validity and reliability of the data (Klinger, 2012; Williams et al., 2016). Currently, there are open-source data collection efforts that capture much higher levels of individuals killed by law enforcement (see, e.g., *The Washington Post*, <https://www.washingtonpost.com/graphics/investigations/police-shootings-database/>), and the Department of Justice is also engaged in revamping their data collection efforts (see <https://www.fbi.gov/services/cjis/ucr/use-of-force>). To reiterate, however, even with its severe limitations, the SHR is the only dataset available to conduct

longitudinal research on this topic that seeks to understand the relationship between police, citizen, and community violence prior to the last decade.

On the face of it, it is difficult to argue that jurisdictions are not systematically underreporting incidents where use of deadly force occurs, while still reporting other types of homicides. For this research, however, as we are using the SHR data to calculate national-level estimates of the number of use of deadly force incidents and the national monthly homicide rates, we argue that missing cases are not as large of a concern. As the analytical technique being utilized is concerned with changes over time, any reliability issues with the SHR that create a systematic undercount should be more or less constant during the time period under study. That is to say, that variation observed over time is most likely not the result of changes in the levels of underreporting of homicides but instead are caused by variables exogenous to the data collection. Also, fluctuations in the reporting patterns of individual jurisdictions should have a minimal impact on the overall count at the national level.

Eleven separate SHR datasets were combined into one to estimate the count of use of deadly force incidents between 1976 and 2014. Fox's (2007) victim level data identified cases between 1976 and 2004, and for the years 2005 through 2014, ten datasets compiled from the SHR were downloaded. These files were aggregated to the incident level and combined to obtain information for two variables. First, all of the homicide incidents that had their circumstance coded as a felon killed by police were used to calculate a monthly count of use of deadly force incidents. Second, a monthly count of all homicide incidents reported through the SHR was calculated. Finally, the monthly homicide incident counts were combined with monthly national population estimates to calculate the monthly homicide rate per 100,000 persons during the time period under study (United States Bureau of Census, 2016). Although in some types of analyses using count and rates data could be inappropriate, this is not true with VAR. Many examples of research utilizing this methodology can be found in the VAR literature. For one example, see the seminal work of Christiano and colleagues (1999), who use variables in multiple units of analysis in the same VAR model (e.g., real consumption, gross domestic product deflator, real gross domestic product, and the growth rate of money supply). What is important is that the VAR variables are stationary, thus some variables require a transformation, which also changes the variable's original unit of analysis. For another example of research with multiple units of analysis using VAR, see Kilian (2009), which estimates a tri-variate VAR using percent change in

the global crude oil production, real economic activity index, and an inflation adjusted price of oil.

## Procedure

We have chosen to employ a structural vector autoregression (VAR) model to examine the relationship between the variables under study. VAR models were first introduced in the economic literature by Sims (1980), which was an alternative to the large scale simultaneous equations models popular at that time (Kilian, 2013): “Sims’ research program stressed the need to dispense with ad hoc dynamic exclusion restrictions in regression models and to discard empirically implausible exogeneity assumptions. He also stressed the need to model all endogenous variables jointly rather than one equation at a time. All of these points have stood the test of time” (Kilian, 2013, p. 515). In other words, VAR analyses model the dynamic relationships between the variables under study and how they impact each other over time. This type of analysis acknowledges that all variables being examined have the possibility of affecting each other and that modeling the feedback loop between variables is more appropriate, and less restrictive (assumption-wise), than an analysis that assumes only independent variables can impact the dependent variable, and not vice versa. Another advantage of a VAR model is to model hypothetical scenarios about what would happen if there is a sudden and unexpected change in one of the endogenous system variables also known as a structural shock. A VAR model is able to trace the effects of a one-time structural shock on other endogenous variables. For these reasons, we determined that the best way to model the relationship between law enforcement killed, use of deadly force, and the homicide rate, is through a structural VAR model.

## Results

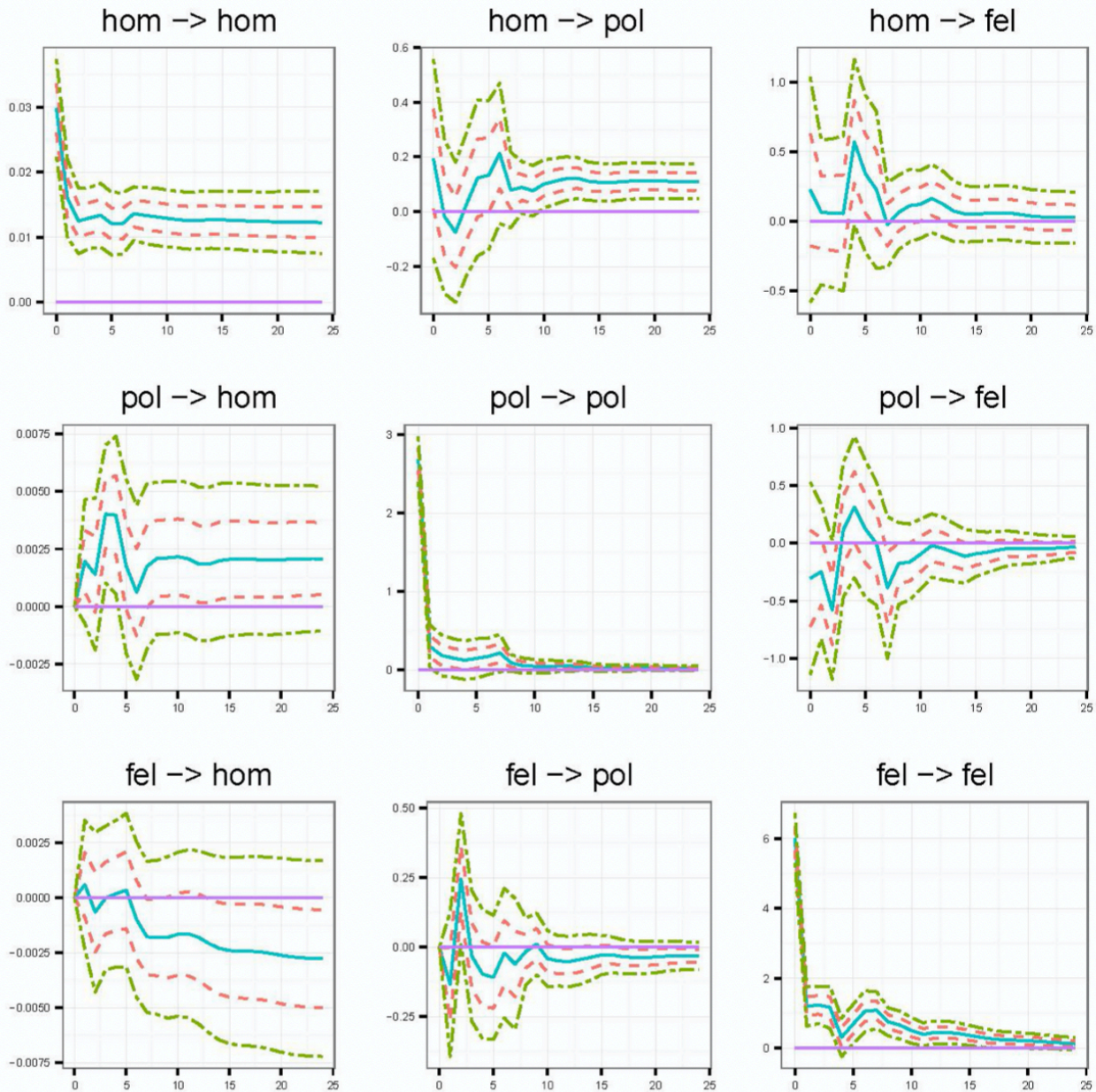
Descriptive information about the three variables is presented in Table 2. The mean monthly homicide rate per 100,000 people is equal to 0.54, the median is 0.56, with a range of 0.75. The lowest monthly homicide rate occurred in February 2011, and the month with the highest homicide rate was August 1980. It is worth noting that the rate peaked again in December 1992, before starting its historic decline. The mean monthly count of incidents where in which law enforcement was killed was 5.95 with a median of 6. The range was 16, with a minimum of one incident where in which law enforcement was killed and a maximum of 17. For the monthly incident count where in which use of deadly force occurred, there was a

mean of 31.36 incidents per month and a median of 31. The lowest number of incidents per month observed was 14, and the maximum was 54.

**Table 2. Univariate descriptive statistics for untransformed data**

	Monthly homicide rate per 100,000 population	Monthly incident count law enforcement killed	Monthly incident count use of deadly force
Mean	0.54	5.95	31.36
Median	0.56	6.00	31.00
Standard Deviation	0.16	3.09	6.97
Minimum	0.25	1.00	14.00
Maximum	1.00	17.00	54.00

The results of impulse response analysis are presented in Figure 1.<sup>1</sup> These plot the impulse response functions (IRF) of all variables to one standard deviation shock of the endogenous variables in the system.<sup>2</sup> For this model, we present nine plots, each showing the impact of a one standard deviation shock of one of the three variables against either itself, or the other two variables.<sup>3</sup> In addition, variable names have been shortened as follows to fit on each plot: number of incidents per month in which a police officer was killed (pol); number of incidents per month in which use of deadly force occurred against felons (fel); and the monthly homicide rate per 100,000 population (hom). From our model, there are two significant results supporting two of our hypotheses: Changes in the national homicide rates will be associated with the number of law enforcement officers killed in the future, and the number of law enforcement officers killed will be associated with the national homicide rate in the future. Returning to Figure 1, the plot located in the first row and the second column (hom → pol) represents a one standard deviation shock to the homicide rate on the monthly number of police officers killed in the line of duty. The solid line is the median impulse response, while the dash lines and the dot-dashed lines represent 68% and 95% confidence bands, respectively. For there to be a statistically significant effect of a shock, all lines must be either above or below zero. In this case, for the first nine months after the shock, there is no association between the homicide rate and the number of police officers killed. The story changes 10 months after the shocks. Since the 95% confidence bands do not include zero for months 10 through 24, we can claim that there is a statistically significant association

**Figure 1. Impulse response function (IRF) plots**

between the homicide rate shock on the number of police officers killed, and it occurs 10 months after the shock occurs. To reiterate, 10 months after an unexpected increase in the homicide rate, there is an increase in the number of law enforcement officers killed in the line of duty. When examining the second row of plots, first column, an unexpected increase in the number of law enforcement officers killed is associated with an increase in the homicide rate 3-4 months after the shock (pol  $\rightarrow$  hom). A shock to law

enforcement killed has a short-term effect on the number of police officers killed, and this shock becomes insignificant after the first 2 months when the lower 95% confidence band drops below zero. This tells us that an unexpected spike in violence against law enforcement has a short-lived association with the homicide rate, meaning that, accounting for all the variables in the system, this type of shock is not persistent. The same shock has no effect on the number of use of deadly force incidents (pol  $\rightarrow$  fel), which

suggests that use of deadly force incidents are not retaliatory during the time period under study.

### Discussion

Two of the six posited hypotheses were supported by the analysis. In both of the models, a one standard deviation shock to the number of law enforcement officers killed was associated with an increase in the homicide rate approximately three to four months after the shock. In one of the models, a one standard deviation shock to the national homicide rate was associated with a persistent increase in the number of law enforcement officers killed, starting at approximately nine months after the shock. Also, although not necessarily surprising, both models showed a significant relationship between the variable number of law enforcement officers killed and itself. This means that fatal violence against law enforcement leads to more fatal violence against law enforcement.

There was no support found for the other four hypotheses. Specifically, there was no evidence that a relationship exists, in either direction, between the number of law enforcement officers killed and the use of deadly force. To state it another way, we found no evidence that police being killed in the line of duty results in the public being killed by police, or vice versa. This is counter to the “war on cops” narrative discussed in the introduction to the paper and adds to a small body of literature that casts empirical doubt on the idea that there is an increase in violence against law enforcement officers after the deaths of citizens when deadly force is used (Bejan et al., 2018; Maguire et al., 2017). Similarly, there is no evidence that a relationship exists between the number of use of deadly force incidents and the national homicide rate, which is in contradiction to prior research findings. It is important to reiterate that the SHR data on the number of use of deadly force incidents have been critiqued as invalid and unreliable. Perhaps the issues with these data impacted the results of the analysis and contributed to the insignificant findings.

To begin to contextualize the results we ask, what are we to make of the finding that the number of law enforcement officers killed is a possible 3- to 4-month leading indicator for increases in the general homicide rate? One possible explanation is that an increase in the frequency of law enforcement killed may signal a general weakening of the police as a formal mechanism of social control, leading to increased rates of violence. In this light, the murder of police officers may disinhibit or embolden offenders to commit violence. This is somewhat consistent with Turk’s (1969) conflict theory, insofar as an increasing frequency of law enforcement killed may be perceived

by subjects as undermining the authorities’ (i.e., police) degree of organization and overall authority and legitimacy in society, and perhaps even increasing the subjects’ perceived degree of organization, leading to a net increased likelihood of conflict. Lanza-Kaduce and Greenleaf (1994) derived several testable hypotheses about police-public interactions from Turk’s theory, which might be broadened into general violence, not just violence in interactions with police. They note that conflict is maximized when a congruent and unsophisticated authority interacts with congruent, organized, and unsophisticated subjects. However, Lanza-Kaduce and Greenleaf (1994) presume that the police are organized by definition. Here, we suggest that killings of law enforcement may tend to undermine the perceived organization of police, and this may explain why resulting fatal violence would broaden beyond that directed toward law enforcement into general violence, holding level of sophistication and the congruence of cultural and behavioral norms constant. Another hypothesis for this relationship, posited by one of our insightful reviewers, is that law enforcement deaths could lead to de-policing in the community, which could, in turn, lead to higher homicide rates. It is conceivable that this de-policing could be dependent on low levels of political and community support for a department after one of their officers is killed, therefore demotivating officers to engage in proactive policing.

On the other hand, the results demonstrated that a shock to the homicide rate, our measure for general fatal violence, was associated with an increase in the number of monthly incidents of specific fatal violence against law enforcement approximately nine months later, a pattern that persisted for the rest of the four-year time frame. To put it another way, increased homicide rates appear to be a 9-month leading indicator for increased law enforcement deaths. Theoretically, the relationship between the two could possibly be explained as a shift in national-level structural factors that increase the likelihood of fatal violence, which eventually will include the murder of police officers. Could it be that increases in homicides in general must first occur, signaling a shift in the nation’s aptitude for violence and creating an atmosphere that is more supportive of homicide, before the specific threat to law enforcement officers also increases? Interestingly, both significant findings tell a story of increasing levels of cyclical fatal violence, from increased homicide rates, to increased incidents of police murders, back to increased homicide rates.

Additionally, although we did not initially hypothesize about this relationship, we also saw that the killings of law enforcement officers is actually associated with acts of fatal violence against officers

in the future. This pattern was also demonstrated in terms of use of deadly force incidents. One might speculate that these acts might create a national atmosphere and attitude where such violence is normalized, and it leads to future acts of the same type of violence. Such an explanation would be consistent with the conflict perspective discussed above, as it may signal growing social support (i.e., increased complexity of social organization), which would be expected to increase the probability of conflict with police (Lanza-Kaduce & Greenleaf, 1994).

It is also important to discuss the lack of evidence supporting our other hypotheses, specifically those examining the relationship between law enforcement killed and the use of deadly force. The analysis found no significant relationship between the use of deadly force and the number of law enforcement officers killed, regardless of the temporal ordering. This goes against current, anecdotal explanations by both supporters of the Black Lives Matters movement and advocates for law enforcement officers, who argue that each side is putting the other at greater risk for violent victimization and that with each homicide event, the risk of retaliatory killings increases. The media, in turn, increases public awareness of events where officers kill or are killed, shaping the public perception that these types of homicide are increasing in frequency and seriousness. Whether or not these incidents are currently increasing in prevalence, or whether it is only the media attention that has increased, is outside the limits of the data used for this research. However, what we can state, based on 39 years of monthly data, is that when controlling for the temporal and cyclical relationships between incidents where law enforcement are killed and use of deadly force incidents, neither is significantly associated with the other.

The policy implications of this research show how national level trends can have important impacts at the local level. Most importantly, from a law enforcement agency perspective, is the finding that increases in general fatal violence (homicide rates) are a possible nine-month leading indicator for the frequency of law enforcement killed. It is necessary to clarify that we are not stating that spikes in homicide rates in an agency's community are indicative of future acts of violence in that community but that trends at the national level can increase the risk to all law enforcement officers in the United States. This information can lead to actionable precautions for officers when increases in homicide rates are observed.

Unfortunately, there currently is no real-time crime data dissemination effort at the national level that would be able to provide departments with homicide rates with a turnaround time of less than nine

months. A national effort that focused on collecting and disseminating leading indicators of violence against law enforcement officers and other potential victims so that they were useful in violence prevention would be an important program to consider. In addition, another implication of this research is that limiting the number of incidents where law enforcement are killed through better training, better use of technology, and better policy, could actually limit future increases in the general homicide rate and even future killings of law enforcement. Conversely, as was already discussed, limiting the increases in the general homicide rate will subsequently limit future acts of violence against law enforcement officers. Understanding this, and breaking the cycle of violence between these types of fatal violence, could lead to an overall decrease in fatal violence in the United States and a safer working environment for law enforcement.

### Limitations

Clearly, there are limitations to this research. First, the analysis does not account for the spatial distribution of murders of law enforcement officers nor of the use of deadly force. As this is a national-level study, we do not model the potential variation in the impact of these incidents across potentially meaningful spatial units. One might hypothesize that regions within the United States that have higher homicide rates and more police murders might exhibit even stronger relationships between the variables examined. On the other hand, regions with low homicide rates and few incidents of law enforcement killed might reveal no relationship between these variables.

Second, the data used in this study are not without limitations. Our measure of general violence, the monthly homicide rate, is based on the number of cases submitted to the SHR, which research has shown to be an undercount. A researcher's belief in whether these incidents are missing at random, or systematically missing, will drive their level of concern about the extent to which the undercount limits the utility of SHR data and subsequently the results of the study. Also specific to the SHR is the fact that it does not include, or at least does not present a way for researchers to systematically identify, use of deadly force incidents. Instead, it relegates officer involved killings to only those that are committed against felons, that is, homicides by law enforcement officers that can easily be labeled justifiable. There is no incentive for agencies to submit data on officers who are involved in killings where their actions are labeled manslaughter or murder.

Finally, with the NLEOMF data, we must acknowledge that the number of incidents in which

officers were murdered in the line of duty is also most likely an undercount. As the public interface of the NLEOMF website does not offer a way to search for officers who are feloniously killed, we focused our data collection effort on specific causes of death (e.g., gunfire, stabbings, beatings). This systematically excludes some types of incidents, for example, if an officer is run over by a car driven by a fleeing felon.

Future research on the relationship between law enforcement killed, use of deadly force, and homicide rates should account for the spatial distribution of these variables. It is possible that a panel vector-autoregression analysis could tease out regional differences in these relationships. In addition, although VAR was specifically developed to move past cross-sectional analyses (when researchers aggregate time series data and perform cross sectional analysis, thus ignoring the dynamic relationship between endogenous variables in the model) that utilize independent variables to explain variance and control for exogenous variables, in order to test criminological and sociological theories that might help explain the observed relationships, the available literature suggests that variables associated with operationalizations of conflict and/or racial threat perspectives should be considered. Finally, there is not only a general and important need to improve national level data collection related to police use of deadly force, as most recently argued by Williams and colleagues (2016), but also to make data on the killings of police easily accessible for researchers to analyze.

### Conclusion

This research explored the intertemporal relationships between the monthly counts of law enforcement killed, police use of deadly force, and the national homicide rate. VAR analysis supported the hypothesis that increases in the homicide rate cause increases in the number of incidents in which law enforcement are killed, as well as the fact that increases in the incidents resulting in law enforcement killed cause increases in homicide rates. The findings of the study have the potential to inform policy and practice not only for law enforcement officers, but for institutions tasked with national level crime data collection. Additionally, as violence between law enforcement officers and the public has taken center stage in the current discussion on policing in the United States, the findings also demonstrate that there is no evidence to support the hypothesis that at the national level, the murders of law enforcement officers leads to an escalation in fatal violence against criminal offenders, or vice versa.

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## Endnotes

<sup>1</sup> Please see the Methodological Appendix for the full description of the analysis.

<sup>2</sup> Inference is carried out using the recursive design wild bootstrap by Gonçalves and Kilian (2004) with 1,000 replications. If one carries out a standard residual-based bootstrap procedure for dynamic models, this may lead to biased results and flawed conclusions if reduced form model residuals have serial correlation and/or heteroskedasticity, which is our case (Kilian & Goncalves, 2004). This methodology specifically addresses concerns related to our model assumptions as the sample path generated by this method reflects the same properties of the data used to generate said path. Thus, we do not impose any specific assumptions on the distributions when generating our confidence intervals.

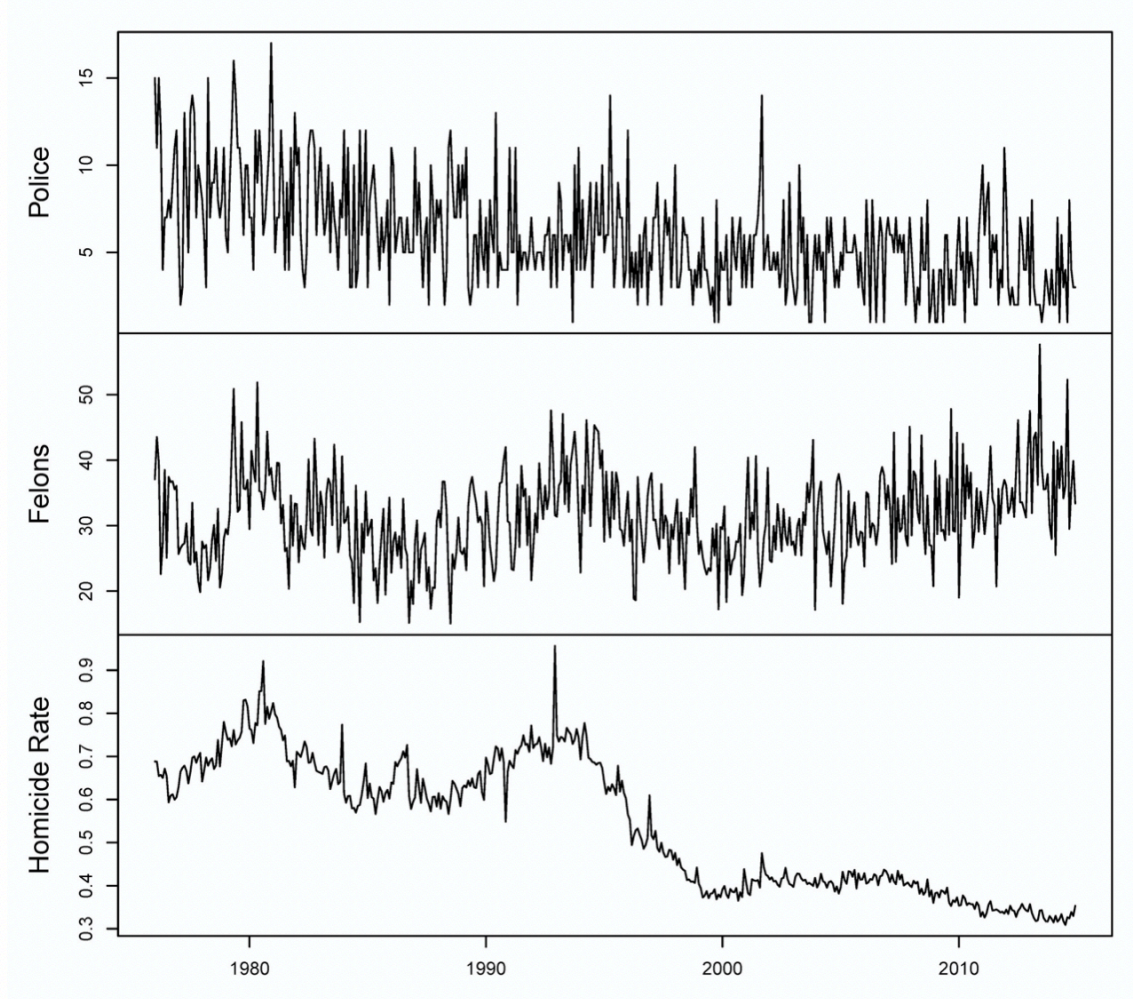
<sup>3</sup> Typically, it is not common to discuss the diagonal plots of the IRF analysis because it is expected that the structural shocks of a particular variable will have statistically significant effect on the variables. For example, as the homicide rate unexpectedly increases, it leads a higher number of homicides thus increasing the homicide rate.

<sup>4</sup> Since we are examining the relationship between the variables over the span of 39 years, we deseasonalize the data using the X-13ARIMA-SEATS seasonal adjustment program developed by the Census Bureau (Monsel, 2007; Sax, 2015).

Methodological Appendix

Examining the trends of the data, we find that the homicide rate variable exhibits clear patterns of seasonality.<sup>4</sup> Figure 2 plots the seasonally adjusted series used in the analysis. Tables 3 and 4 present the Pearson’s correlation coefficients between the variables for the untransformed data and when the variables are log-differenced. In their original units of measurement, we see that the relationship between the monthly number of law enforcement officers killed incidents, and the homicide rate is of moderate strength. However, all other correlations for both the untransformed data and the log-differenced data are extremely weak, denoting no significant correlation between those variables at the bivariate level.

**Figure 2. Monthly observations of variables in original unit of measurement with seasonal adjustment**



**Table 3. Pearson’s correlation coefficients for the untransformed data**

	Homicide rate	Law enforcement killed	Use of deadly force
Homicide rate	1		
Law enforcement killed	0.455	1	
Use of deadly force	0.032	-0.026	1

**Table 4. Pearson's correlation coefficients for the log-differenced data**

	Homicide rate	Law enforcement killed	Use of deadly force
Homicide rate	1		
Law enforcement killed	-0.016	1	
Use of deadly force	0.046	0.007	1

Table 5 shows the results of the unit root tests. It is customary to run Augmented Dickey-Fuller (ADF) tests against three data generating processes: random walk (none), random walk with drift (drift), and random walk with drift and time trend (trend). In the social sciences, most data do not follow a deterministic time trend (Clark, 1987; Nelson & Plosser, 1982; Watson, 1986); therefore, it is difficult to argue that the variables used in our analysis follow a deterministic time trend since myriad factors could be influencing them. Test results suggest that both law enforcement killed and use of deadly force incidents can be treated as stationary variables if tested against the random walk with drift model. However, the same variables could be deemed non-stationary if tested against the random walk model. The homicide rate variable was found to be non-stationary based on all three sets of ADF tests. A closer look at the homicide rate variable reveals that it is theoretically bounded by 0 and 100,000, although practically, it is bounded by 0 and 1 as no monthly homicide rate exceeded 1 homicide for every 100,000 persons. In this case, it is plausible to assume that the underlying data generation process is actually stationary despite the results of the ADF tests.

To further investigate the stationarity of the data, we run Phillips-Perron (PP) test (Phillips & Perron, 1988). Unlike the ADF test, the results of this test are robust to the presence of serial correlation and heteroscedasticity. Table 6 lists the test results for each series and shows that each series is stationary. Taken together, both tests allow us to claim that all 3 sets of data are stationary.

**Table 5. Unit root tests: Augmented Dickey-Fuller unit roots test**

Variable	Levels			First Difference		
	None	Drift	Trend	None	Drift	Trend
Homicide rate	-0.98	-0.79	-2.94	-17.60	-17.62	-17.61
Law enforcement killed	-1.39	-3.51	-14.21	-15.10	-15.08	-15.07
Use of deadly force	-0.45	-7.61	-7.84	-17.60	-17.62	-17.61

Note: The optimal lag length was determined using Bayesian Information Criteria (BIC). The 5% critical values used: *none* = -1.95; *drift* = -2.87 and *trend* = 3.42.

**Table 6. Unit root tests: Phillips-Perron (PP) test**

Variable	$Z_{\alpha}$	$Z_{t_{\alpha}}$
Homicide rate	-26.24 [0.0181]	-3.8239 [0.0179]
Law enforcement killed	-428.38 [0.01*]	-19.963 [0.01*]
Use of deadly force	-372.24 [0.01*]	-16.098 [0.01*]

\* the printed value is smaller than the printed value reported here.

Even though there are many VAR related resources, the reader is referred to Lütkepohl (2005) for a complete treatment of VAR models and its derivatives. A good overview of structural VAR models is presented in Kilian (2013). We denote the homicide rate, the number of law enforcement officers killed, and the number of use of deadly force incidents in month  $t$  by  $h_t$ ,  $p_t$  and  $f_t$  respectively. The reduced form VAR model can be written as

$$\begin{aligned} h_t &= \alpha_0 + \sum_{i=1}^p \alpha_{1i} h_{t-i} + \sum_{i=1}^p \alpha_{2i} p_{t-i} + \sum_{i=1}^p \alpha_{3i} f_{t-i} + e_{ht} \\ p_t &= \beta_0 + \sum_{i=1}^p \beta_{1i} h_{t-i} + \sum_{i=1}^p \beta_{2i} p_{t-i} + \sum_{i=1}^p \beta_{3i} f_{t-i} + e_{pt} \\ f_t &= \gamma_0 + \sum_{i=1}^p \gamma_{1i} h_{t-i} + \sum_{i=1}^p \gamma_{2i} p_{t-i} + \sum_{i=1}^p \gamma_{3i} f_{t-i} + e_{ft} \end{aligned} \tag{1}$$

Rewrite (1) in a matrix form:

$$X_t = \alpha + \sum_{i=1}^p A_i X_{t-i} + e_t \tag{2}$$

where  $X_t = (h_t, p_t, f_t)'$ ,  $e_t = (e_{ht}, e_{pt}, e_{ft})'$  and  $p$  is a non-negative integer whose value is determined by the Akaike Information Criterion (AIC). The reduced form residuals,  $e_t$ , are uncorrelated with variables in period  $t - 1$  and earlier, but are correlated with other variables at time  $t$ . We assume that  $e_t$  is related to the structural shocks according to  $e_t = A_0^{-1} \varepsilon_t$ , where  $A_0$  is a matrix of contemporaneous effect. We can rewrite (2) in terms of the structural shocks by pre-multiplying by  $A_0$ .

$$A_0 X_t = \delta + \sum_{i=1}^p B_i X_{t-i} + \varepsilon_t \tag{3}$$

where  $\delta = (A_0) \alpha$ ,  $B_i = (A_0) A_i \ \forall i = 1, \dots, p$ . Equation 2 is a reduced form VAR where the off-diagonal elements of the covariance matrix are non-zero thus implying the correlation between the reduced form residuals and other endogenous variables at time  $t$ , while equation 3 is a structural VAR model with the covariance matrix being an identity matrix [ $\varepsilon_t \sim (0, \Sigma_\varepsilon = I_3)$ ] by design, which implies that the residual are structural (orthogonal) shocks with mean 0 and standard deviation of 1. By construction,  $e_t = A_0^{-1} \varepsilon_t$  which implies

$$\Sigma_e = E(e_t e_t') = E(A_0^{-1} \varepsilon_t (A_0^{-1} \varepsilon_t)') = E(A_0^{-1} \varepsilon_t \varepsilon_t' (A_0^{-1})') = E(A_0^{-1} \Sigma_\varepsilon A_0^{-1}) = A_0^{-1} (A_0^{-1})' \tag{4}$$

where we used the fact that  $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon_t') = I_3$ . The reduced form covariance matrix  $\Sigma_e$  has 6 unique elements, while by construction  $A_0^{-1}$  has potentially 9 unique elements; thus, it is impossible to recover structural parameters from the reduced form estimates without additional restrictions. To uniquely identify  $A_0^{-1}$  we need to impose  $K(K - 1) / 2 = 3(3 - 1) / 2 = 3$  unique restrictions, where  $K$  is the number of endogenous variables in a VAR model, in our case we have 3 endogenous variables. The most common approach is to impose zero restrictions on the selected elements of  $A_0^{-1}$ , also called exclusion restrictions. In addition, the most common approach to disentangle structural shocks from the reduced form innovations using exclusion restrictions is to use the Choleski decomposition, which decomposes a square matrix into a product of a lower diagonal matrix and its transpose. Applying the Choleski decomposition to (3) results in a recursively identified structural VAR model:

$$e_t = \begin{bmatrix} e_{ht} \\ e_{pt} \\ e_{ft} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{ht} \\ \varepsilon_{pt} \\ \varepsilon_{ft} \end{bmatrix} \tag{5}$$

We call the structural shock  $\varepsilon_{ht}$ , the homicide rate shock,  $\varepsilon_{pt}$ , the law enforcement killed shock, and  $\varepsilon_{ft}$ , the use of deadly force shock. The identifying assumptions underlying (5) imply that (i) the homicide rate is not

affected by unexpected changes in either law enforcement killed and use of force incidents, contemporaneously. What we are saying is that the overall level of fatal violence in the United States is determined by factors other than the number of law enforcement officers killed and use of deadly force incidents, and it takes at least one month for changes in the other variable to have an impact on the homicide rate. *(ii)* We allow for the possibility that the number of law enforcement officers killed will change in the same month following the shock to the homicide rate, but it will take one month for the law enforcement killed to react if there is an unexpected spike in the number of use of deadly force incidents, and *(iii)* homicide rate changes and number of law enforcement officers killed will affect the number of use of force incidents contemporaneously.