Is the recent increase in national homicide abnormal? Testing the application of fan charts in monitoring national homicide trends over time

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Structured Abstract

Purpose: The goal of this study is to compare the increase in the 2015 national homicide rate to the historical data series and other violent crime rate changes.

Methods: We use ARIMA models and a one-step ahead forecasting technique to predict national homicide, rape, robbery, and aggravated assault rates in the United States. Annual Uniform Crime Report data published by the Federal Bureau of Investigation are used in our analysis.

Results: The 2015 homicide rate increased above the 90% prediction interval for our model, but not more conservative intervals. Predictions intervals for other national level crime rates consistently produced correct coverage using our forecasting approach.

Conclusions: Our findings provide weak evidence that the national homicide rate spiked in 2015, though data for 2016 – 2018 do not show a continued anomalous increase in the U.S. homicide rate.

Keywords: Homicide-rates, time-series, outliers, forecasting, data-visualization

Data and code to replicate the findings can be downloaded from

https://www.dropbox.com/sh/3086vt0qly5qho6/AABq_weh2LTmtBp426vhZ0EHa?dl=0

Introduction

Recent increases in homicides continually receive attention from media outlets, and have been a focus of a growing body of research (Davey & Smith, 2015; McDowall, 2019; Rosenfeld & Fox, 2019; Rosenfeld, Spivak, & Muhlhausen, 2017; Wheeler & Kovandzic, 2018). The New York Times sparked a debate on recent changes in crime when they reported that, in a sample consisting of 10 big cities, including Philadelphia, New York, Milwaukee, and St. Louis, homicides increased by 32.8 percent on average from 2014 to 2015. In a report on homicide trends commissioned by the National Institute of Justice, Rosenfeld and colleagues (2017) argued that national homicide rates in 2015 increased by a substantial amount, and such an uptick necessitates more attention. James Comey, the Federal Bureau of Investigations (FBI) director during the period, acknowledged the recent increases in violent crimes in major U.S. cities and suggested that the increase could be attributed to police officer's reluctance to engage in law enforcement activities (Schmidt & Apuzzo, 2015). There presumption is that police officers desire to avoid controversy over their use of force against minorities and other members of society, thus reducing their enforcement of the law and allowing more violent individuals to remain unrestrained – and then commit future violent crime. Others have proposed that civilian perceptions of police legitimacy have decreased as a result of high profile incidents of police brutality, thus leading to individuals acting brazenly with disregard for the law. Research on these two takes on the “Ferguson Effect” attempts to tease out any negative consequences stemming from de-policing (reductions in police presence, traffic stops, stop and frisks) on violent crime. Both scholars and practitioners assumed the recent change in crime statistics was substantial and warranted more scrutiny for public safety.

The upward spike in homicides provides the backdrop to this paper's research question: do increases in homicide in recent years show abnormal patterns when compared to historical crime trends? Despite high levels of attention from members of the media, public, and scholarly society, academic

research has just begun to examine the change in recent homicide trends (Lauritsen & Lentz, 2019; McDowall, 2019; Pyrooz, Decker, Wolfe, & Shjarback, 2016; Rosenfeld & Fox, 2019; Wheeler & Kovandzic, 2018). Such questions are not new, and past increases in homicides prompted similar questions of whether crime was waving (Barnett, Kleitman, & Larson, 1975).

One of the issues in monitoring crime trends is the use of appropriate methods to identify abnormal patterns in changes over time. Prior studies examining temporal crime patterns relied on two methods: descriptive analysis of percent changes over time, or a structural break test, also known as trend analysis (Cook & Cook, 2011; McDowall, 2014; McDowall & Loftin, 2005; Pyrooz et al., 2016; Rosenfeld, 2016; Rosenfeld, 2018; Rosenfeld et al., 2017). Although each technique has their own utility, they have a limited ability to identify outliers in recent crime patterns due to potential bias embedded in percent change or a lack of post-observations required for the trend analysis. The limitations of these two conventional methods prompted the motivation for this work, to develop more rigorous methods to examine the abnormality of crime rates over time.

Recent studies offered an alternative approach for monitoring crime trends; the use of forecasts and fan charts (Wheeler, 2016; Wheeler & Kovandzic, 2018). The procedure to identify outlying patterns in crime trends can be described as follows: (a) specify the statistical model reflecting the series of crime data, (b) use a forecasting method to estimate prediction intervals around crime during the period of time of interest, (c) determine whether observations of interest fall inside or outside the forecasted prediction intervals. Some researchers have employed this method and showed its utility in identifying abnormality in recent changes in crime patterns (Wheeler, 2016; Wheeler & Kovandzic, 2018). These studies focused on temporal crime patterns at the city level, with little attention paid to national crime patterns. Given the fact that researchers and law enforcement agencies found homicide

increases across the United States (Davey & Smith, 2015; Pyrooz et al., 2016; Rosenfeld et al., 2017), examination of the potential abnormality in recent national homicide patterns is needed.

The present study can contribute to the literature on temporal patterns in homicide in two ways. First, this study employs a forecasting method and uses fan charts to graph national level homicide data to examine whether recent homicide increases are significant compared to prediction intervals generated from historical homicide patterns. By considering national level accounts, it is possible to better understand whether the recent increase in homicide is abnormal or a result of random fluctuation. Second, we will compare the recent change in homicide with those for robbery, rape, and aggravated assault. This allows us to assess the potential for abnormality in recent increase in homicide by assessing whether the change is pronounced only in the homicide series or if a significant change occurs across the other UCR part 1 violent crimes.

Literature Review

Three unique data analytic techniques have been used to examine crime trends: percent change, trend analysis, and fan chart prediction modeling. The first approach, percent change, is simple and easy to interpret, perhaps one reason why its use has continued in the presence of more advanced methods. Trend analysis requires a series of data with a sufficient number of observations before and after a believed breakpoint. This is useful in retrospective studies of crime, but has little potential for analyzing current and timely changes in national-level data that are updated annually. The third approach incorporates plotting a series of data and various prediction intervals together and seeing if the observed data values fall within predicted boundaries.

Percent Change

Percent change has been a widely used technique for primary and supplementary analyses of crime patterns. Basically, this method can be done by subtracting the value of interest from a reference value and then dividing the resulting difference by the reference value. For example, if a crime rate went from 10 (the pre period), to 11 (the post period), the percentage change would be $(11-10)/10$, an increase of 10%.

Easy calculation and interpretation facilitate the widespread use of the method by media outlets, academics, and practitioners. For example, Rosenfeld and colleagues (2017) calculated a yearly percent change for homicides from 1961 to 2015 and found the homicide rate to increase by 11.4 percent from 2014 to 2015, the largest percent rise between years since 1968. The percent change approach has also been applied to incarceration and crime rates (Aebi, Linde, & Delgrande, 2015; Piquero, 2005) and is commonly used in reports issued by the Bureau of Justice Statistics. Such reports cover descriptive statistics for crime victimizations (Morgan & Truman, 2018), pre-trial detention rates (Cohen, 2013), federal prosecutions (Motivans & Snyder, 2018), and correctional facilities (Kaeble & Cowhig, 2018; Zeng, 2019). Percent change calculations were frequently used to refer to the growth or decay in crime counts or populations on a year to year basis in those reports – documents produced to inform federal policymakers.

There are three disadvantages that come from using the percent change method. First, the variance of the statistic is not defined (Wheeler, 2016). This makes it difficult to identify actual outlying values (Wheeler & Kovandzic, 2018). So one cannot simply look at a percentage change of 20% and say it is an anomalous increase. It depends on the historical data series whether such an increase is larger or typical.

Further, there is no consensus on the standards for the selection of the value in historical data as a reference. While McDowall (2002) examined the percent change over a 7-year period, Rosenfeld (2017) calculated yearly percent change over historical data for the significance of percent change, and Piquero (2005) used four years before and after an intervention to examine the change in Florida's index crime rate. The lack of selection rules produces the additional difficulty to set a threshold to identify actual outliers, and can result in cherry picking baseline years to reinforce ones preference, whether those preferences be to say crime is going up or within the status quo.

Second, low baseline values tend to result in high variance. Since the numerator in the percent change is the historical crime rate, crimes with lower rates will more easily have larger percent changes (Wheeler, 2016). Rotolo and Tittle (2006) argue against using percent change in their examination of the effect of city population on crime rates, especially for measuring homicide, and opt for using absolute changes to avoid the distortion accompanying modest absolute increases in cities with low crime rates. Either approach requires a researcher to use their discretion and defend the chosen metric.

Third, percent change increases are biased to be larger in magnitude than percent change decreases. By nature, percent change calculations are not symmetric. For example, when a homicide rate of 5 increases to 6, the result is a 20 percent increase, where $Post_{hr}$ and Pre_{hr} are the post and pre homicide rates respectively:

$$\frac{Post_{hr} - Pre_{hr}}{Pre_{hr}} = \frac{6 - 5}{5} = 0.2 \quad (1)$$

When a homicide rate of 6 falls to 5, it can be interpreted as a 17 percent decrease.

$$\frac{Post_{hr} - Pre_{hr}}{Pre_{hr}} = \frac{5 - 6}{6} \approx -0.17 \quad (2)$$

Additional decreases of the same absolute value will result in larger percent change decreases over a period of time. In other words, fluctuations in the homicide rate can produce non-symmetric percent change calculations and bias one's interpretation of crime trends. Positive percent changes will tend to be larger in magnitude than negative percent changes.

Given the declining pattern of crime during the 1990s and 2000s, the homicide rate in 2014 was low. The low homicide rate is likely to result in high variance, leading one to erroneously identify the change from 2014 to 2015 as significant. It is possible that positive bias may lead people to interpret the recent increases as significant and in need of a policy response (Wheeler & Kovandzic, 2018).

Trend Analysis

The second statistical approach for monitoring crime trends is trend analysis, commonly referred to as interrupted time series analysis or a structural break test. The test assumes nonlinear dynamics of change in crime. It is postulated that the crime generating process fundamentally changes and the data follow a second model after the fundamental change when compared to before (McDowall, 2014). This shift is assumed to be attributed to an abrupt external shock or lasting effect from an intervention. The analysis further assesses significant differences in parameters between the models. For example, McDowall and Loftin (2005) used the Chow test (a conventional break test), SupF statistic, and double maximum tests (advanced statistical techniques) to test for possible structural breaks in annual crime data from 1993 to 2001 and the homicide series from 1925 to 2000. Other research has utilized the trend analysis/interrupted time series approach to estimate the effectiveness of police practices (Krimmel & Mele, 1998; Stolzenberg, 2019) and legislation (Kovandzic, Sloan, & Vieraitis, 2004; Reynolds, Seydlitz, & Jenkins, 2000; Stolzenberg & D'Alessio, 1997). Results of these studies have practical implications for policy initiatives, ranging from sentencing practices to body worn cameras. Again, this

paper does not suggest trend analysis is a poor technique; just the utility is limited to examining historical changes.

An extension of this method looks for two structural changes in trends. Cook and Cook (2010) examined features of crime data from 1960 to 2007 using the minimum Lagrange Multiplier (LM) unit root test which incorporates two potential points of structural change; avoiding the reliance on methods that only test for one breakpoint. Restricting models to just one breakpoint could produce an incorrect dating of a structural point in temporal crime patterns which may actually be more dynamic. Although break tests have their utility in identifying the nonlinear dynamics in crime trends, the approach is not useful to identify potential abnormalities in recent changes in crime. One of the requirements for structural break tests is the use of a trimming fraction. Division of the data into different segments with a substantial number of observations allows for stable estimates of the distinct crime models for different periods (Parker, Mancik, & Stansfield, 2017; Piehl, Cooper, Braga, & Kennedy, 2003). Structural break tests require each separate segment drawn from the original data to contain enough data points to produce stable estimates. Since the focus of this paper is on the homicide rate, which has seen changes since 2014, the structural break test is not an appropriate method to examine the significance of the change in crime during the recent period.

Fan Charts

Recent research on temporal crime trends suggests an alternative approach: a forecasting method and a fan chart technique in response to the lack of statistical techniques that can be used to analyze year by year changes in crime rates (Wheeler, 2016; Wheeler & Kovandzic, 2018). Wheeler and Kovandzic (2018) used random effects binomial regression models to generate prediction intervals and examined the significance of change in homicide rates in U.S. cities by assessing whether or not observed values

fell within prediction intervals. Using homicide rates per 100,000 in cities with populations over 100,000, the results indicated that the majority of cities are within predicted intervals and thereby city level changes in homicides from 2014 to 2015 were not abnormal. This approach has some advantages over conventional methods. First, the technique has little dependence on the baseline average in crime series (Wheeler, 2016). Because of this, it can produce a consistent threshold used to identify the significance of a change relative to historical patterns. Second, the method has a symmetric nature of increases and decreases (Wheeler, 2016). This feature can minimize the positive bias associated with the percent change method, reduce the tendency to consider increases as significant more often than reductions, and thereby lead to more accurate estimates of the statistics. Third, the method can provide relative levels of evidence for *how* anomalous is a particular pattern. So one cannot only say whether it is a high outlier but also say how exactly high it is, such as saying an occurrence may be a 1 in 20, 1 in 100, or 1 in 1,000 chance occurrence.

Outside of criminology and criminal justice, fan charts have been used in forecasting inflation (Álvarez & Sánchez, 2019; Wallis, 1999), projecting GDP (Cronin & Dowd, 2013; Demetrescu & Wang, 2014) and public debt (Fukač & Kirkby, 2017; Paret, 2017), analyzing stock prices (Clements, Izan, & Lan, 2013), and identifying potential banking crises (Lang & Schmidt, 2016). All are problems that have to be addressed by public policy in a timely manner. Reliance on percent change or trend analysis to develop economic policy would restrict economists' ability to react to changes in the economy, so they use a different method. The use of fan charts in criminology and criminal justice has been limited, but increased use could provide practitioners and researchers an effective tool for monitoring policy – especially since it allows for estimates and predictions. Substituting or supplementing percent change calculations and trend analysis with prediction modeling and fan charts can allow more timely reactions to changes in the criminal justice field; including police practices,

sentencing laws, and other pieces of legislation. Or the obverse, they can help identify when recent fluctuations are within typical historical changes, and subsequently do not appear to be excessively influenced by recent exogenous shocks.

Causes of Violent Crime Increase

Several studies on the increase in homicide and other violent crimes have attempted to identify causal mechanisms that could be responsible for increased violence in the country. Many focus on the effect of de-policing and decreased perceptions of police legitimacy throughout the nation as a result of high profile incidents of police fatally shooting civilians (e.g., Michael Brown, Freddie Gray). Rosenfeld (2016) helps begin the discussion on issues with confidence in the police and detrimental effects reduced legitimacy can have, but the main analyses suggested increased drug market involvement by individuals as part of the opioid epidemic and prison releases outpacing prison intake to be to potential causes of increased violence. These, along with actual changes in police practices, could influence crime rates.

Police departments in the state of Missouri changed their strategy following the incident in Ferguson. Shjarback et al. (2017) studied police activity in counties throughout Missouri for 2014 and 2015. They failed to find a statistically significant decrease in the number of police stops (though there was a decrease in volume) but did find a statistically significant increase in the “hit rate” which suggests police officers in Missouri made better quality stops. Making better stops could lead to increases in police legitimacy and reduce the number of instances that result in people feeling harassed by or frustrated with police.

With a detailed look at the effect of police shootings and de-policing in Baltimore, Morgan and Pally (2016) found shootings and homicides in Baltimore to increase during the two months after Freddie Gray was killed. Arrests declined during the same time period, suggesting an effect partially

related to de-policing. Later in 2015, they note the installment of a new police commissioner coincided with an increase in arrests and decreases in violent incidents (Morgan & Pally, 2016). The 2016 homicide spike in Chicago was another case study for researchers. Cassell and Fowles (2018) suggest the increase in shootings and homicides was related to a drastic drop in stop and frisks.

Three nationwide studies of changes in police practices and perceptions of officers and violent crime provide mixed support for the presence of a Ferguson effect. Cities with higher concerns about police violence were associated with higher levels of violent crime and larger increases in violence (Gross & Mann, 2017). Similarly, police violence was related to higher levels of violence in U.S. counties (Gaston, Cunningham, & Gilezeau, 2019). Rosenfeld and Wallman (2019) did not find evidence for the de-policing explanation of the rise in homicide in 53 large cities when considering arrest rates for violent, property, drug, weapons, and minor crimes.

While this study does not itself examine different structural causes of homicide increases or decreases, the findings are still relevant. To the extent that researchers observe an increase, a natural response is to attempt to explain what is causing those ups-and-downs (Rosenfeld, 2018). However, such random fluctuations may be typical given historical patterns of national level homicide trends (McDowall, 2002). As such, any interpretation that an increase in some structural factor *also* increased homicide may be flawed because the initial evidence for the anomalous increase in the underlying rate over time may be quite weak.

Current Study

The existing studies suggested the utility in the use of the alternative method in identifying the abnormality in recent crime change compared to historical homicide rates. However, the prior studies only focus on the examination of the abnormality in crime in a city or crime type across U.S. cities

(Wheeler, 2016; Wheeler & Kovandzic, 2018). To fill this gap, this study examines the application of the suggested statistical method to national-level homicide rates in two ways.

First, this study explores whether the recent change in homicide is abnormal compared to historical homicide rates with the forecast and fan chart methods. One needs a model to demonstrate what would be expected for the given period of time to identify whether homicide rates are substantially increasing (Wheeler & Kovandzic, 2018). This method allows one to recognize whether the homicide increases are significant by assessing whether homicide rates fall into the predicted intervals or out of the boundaries (Wheeler, 2016).

Second, we assess whether the spike in homicide is uniquely abnormal by comparing the recent patterns in homicides to those for other types of violent crimes. Some studies argued that the increases in homicides may be driven by the overall growth in violence and violent crime incidents (Lauritsen & Lentz, 2019). Although each individual violent crime type exhibits increases and decreases in their rates over time, overall patterns over time across violent crimes are relatively consistent (Cook & Cook, 2011; McDowall & Loftin, 2005). If recent homicide rates shows a significant change that is not present for other types of crime, this may lend support for the idea that homicide abnormally increased in 2015. Therefore, the uniqueness in temporal patterns in one type of crime compared to those for other crime types offers a way to examine the importance of an atypical variation.

Data

The data for this study were drawn from official Uniform Crime Report (UCR) statistics published by the Federal Bureau of Investigation from 1960 to 2018¹. While the main analysis is

¹ The crime data for each offense type from 1960 to 1998 comes from Uniform Crime Reporting Statistics Data Tool, <https://www.ucrdatatool.gov/Search/Crime/State/TrendsInOneVar.cfm> (To create the homicide data using the tool, we selected “United States – Total” for option a, “murder rate” for b, and enter the range from 1960 to 1998 for option c, then

focused on national level homicide rates, we also replicate the analysis using other national level UCR violent crime rate estimates for aggravated assaults, robberies, and rapes. The motivation to examine additional crime series is in part to identify if the coverage rates for the procedure suggested for homicides are also accurate for other crime series. The second is to also identify if the other series have anomalous recent increases as well, since UCR crime rates tend to be highly correlated with one another.

We take several steps for consistent analysis with official crime reporting statistics. First, we use the old definition of rape for consistency in our analysis. In 2011, FBI broadened the scope of rape to include different types of sexual assault which had been excluded by prior definition. Although the use of the new definition captures a more comprehensive version of rape, data have only been collected under the new definition since 2013, which does not allow us to compare the entire historical trend of rape to homicide – even if the old and new definitions follow similar patterns (Bierie & Davis-Siegel, 2015). Second, this study uses standardized measures for all four violent crime types. The use of a count variable without any further process can cause bias because the results can be driven by a different population size over time. Therefore, this study uses rates of each crime type standardized with the U.S. population estimates as annual rates per 100,000.²

Methods

Analytic Plan

This study proceeds by employing the alternative monitoring method for homicides over time. We will show two steps to determine whether the recent homicide increase is substantially significant in

click “get table.”. The same procedure was done for the other types of crime.) The source of 1999-2018 offense data is 2018 Crime in the United States, covering 1999 to 2018 (See Table 1: Crime in the United States by Volume and Rate per 100,000 Inhabitants, 1999–2018, FBI: Unif. Crime Reporting, <https://ucr.fbi.gov/crime-in-the-u.s/2018/crime-in-the-u.s.-2018/topic-pages/tables/table-1>)

² We calculate the rates ourselves using the final counts and population estimates from the UCR reports. We do not rely on the less accurate rates that are rounded in the reports.

relation to the historical patterns of homicides. The first step is to select a proper time series model fit for the homicide series. After the model is chosen, we will produce prediction intervals with the one-step ahead forecasting technique. We will then apply the same method to the other violent crimes to compare the 2014 to 2015 change to see if the homicide rate increase happened alone or along with rape, robbery, and aggravated assault. Next, prediction regions for each individual crime type will be constructed to see if their values in 2015 fall within or outside of the forecasted regions. Then, this study will compare rape, robbery, and aggravated assault trends with that for homicide to evaluate whether the temporal change is pronounced in homicides compared to other violent crimes.

Selecting a National Homicide Model

The first step of the identifying process is to construct a suitable baseline model for national homicide rates. While several ways are available, we employ an Autoregressive Integrated Moving Average (ARIMA) model, one of the conventional approaches of time-series analysis. The primary advantage of this approach is its performance in terms of forecasting. Forecasted values of ARIMA models have better coverage of observed time series than those by any other traditional econometric forecasting models, especially for short-term forecasts (Gujarati, 2010). Another benefit of using this approach is found in its ability to fit temporal crime patterns at the national level (McDowall, 2002; McDowall and Loftin, 2005). Most of the one-step-ahead forecasts from ARIMA model for homicides from 1926 to 1998 are consistent with actual observations in homicide series (McDowall, 2002). This study will create the model for the national homicide rate based on an ARIMA approach, selecting an appropriate ARIMA model using homicide data from 1960 –1990. We automate this selection by using the the Hyndman-Khandakar algorithm, implemented in R in the forecast package (Hyndman et al., 2019; Hyndman and Khandakar, 2008) using the *auto.arima* function. After that ARIMA model is estimated, we then generate one-year-ahead prediction intervals (e.g. use the 1960 to 1990 data to

generate a prediction interval for 1991). To do this same process for 1992, we still choose the same order ARIMA model, but re-estimate the coefficients using the full 1960 to 1991 data. We then repeat that process of estimating one year ahead prediction intervals until evaluating the 2018 UCR data. Consistent with Wheeler and Kovandzic's (2018) approach, we generated 50% and 80% prediction intervals. Further, this study produced 90% and 98% intervals for the conservative statistically significant test for identifying outliers. For the comparison, prediction interval and corresponding actual values are displayed in a graph, sometimes referred to as a fan chart (Spiegelhalter, Pearson, & Short, 2011).

We then illustrate the same analysis for other national level UCR violent crime rates; aggravated assaults, robberies, and (legacy) rape. This provides additional evidence that the procedure can generate approximate coverage across many different crime types, and the results are not idiosyncratic to only US homicide rates. Additionally, since setting the training/test data split year to 1990 is arbitrary, we conduct additional analysis varying this cut-point in which we estimate the ARIMA model and generate future predictions, varying the split year from 1980 through 2000.

Results

Homicide Rate Prediction and Outlier Identification

Based on the auto.arima algorithm, a ARIMA(1,1,0) model was selected for the 1960 to 1990 national level homicide rates. The equation for the homicide series can be written as:

$$Y_t = Y_{t-1} + \theta(Y_{t-1} - Y_{t-2}) + \epsilon_t \quad (3)$$

The model represents a first-order autoregressive model without the intercept. The model does not include an intercept since the intercept is not significant, meaning the series does not have any trend

and follows a random walk pattern. The Y_{t-1} term is the first lag, or the immediately prior values in time series. θ illustrates the coefficient of the differences between the first and second lag of an observation, and ε_t is the value of random shock at time t . It is interpreted that national homicide rates is a function of the value of its immediate previous observations, the impact of the differences between the prior two years homicide rates, and unexplained factors.

The residual statistics supported the adequacy of the selected model. The autocorrelation function (ACF) plot shown in Figure 1 indicates that none of the lagged observations are out of the threshold marked by horizontal blue dashed lines. Also, the p-value of Chi-square analysis for the residuals of the ARIMA (1, 1, 0) in Table 1 is higher than 0.05, meaning we fail to reject the null hypothesis that there is no autocorrelation between the errors. These results indicate that the chosen model reasonably accounts for autocorrelation and can be used as an adequate model for homicides over time.

[Insert Figure 1 Here]

The model comparison also suggests that our model is the best fit for the homicide data compared to varying types of time series models. Table 1 shows the model fit statistics for our baseline model and different types of models around the selected one. As discussed before, the residual analysis for ARIMA (1, 1, 0) found the current model has no autocorrelation that should be accounted for. Further, the value of the corrected AIC of the first-order autoregressive model is lower than those for the other potential models. All of these figures suggested that the ARIMA (1,1,0) can provide the better fitted model which has no autocorrelation and the better model fit statistics compared with other potential models while accounting for the possible impact of error terms, the different order of autoregressive term, or the combinations of autoregressive and error terms.

[Insert Table 1 Here]

The current study evaluates the overall performance of the prediction intervals obtained from the baseline model on 1991 to 2018 homicides. The assumption of the prediction interval is that it should cover a certain percentage of the actual observations it was designed to predict. For example, if there is a 90% prediction interval generated based on the model, the interval should cover 90% of the future observations. Table 2 shows the coverages for each prediction interval for homicide from 1991 to 2018. Although the coverage rate is not perfect, generally the model is close to the expected range.

[Insert Table 2 Here]

Regarding the accuracy of the 50% prediction interval, the lower bound should have 25% of the observations below the intervals. Lower values than predicted occurred 43% of the time in the sample. The results suggest that the lower interval moderately overestimated actual homicide rates for 1991 to 2018. The 50% prediction band covers 43% of actual observations. The prediction interval is substantially close to its expected coverage of 50%. Fourteen percent of the observations were higher than the upper bound of the 50% prediction interval. It means that the upper interval under predicts homicide rates for those forecasted year. What we can see is that the homicide rate was overpredicted by the 50% interval, likely a result of the steady decline in the homicide rate that began in the 1990s.

The coverage rates for the 80% and 90% bands were close to their expected range. While some aspects of each band relatively did not perform well (i.e., slight underprediction in the upper bound of 80%), the overall performance for the intervals are close to the nominal coverage shown in Table 2. 98% intervals also demonstrated a relatively acceptable coverage performance similar to the other bands. In sum, the results of the performance evaluation indicated that prediction bands for the predicted

percentage are sufficient to be used to identify abnormal homicide pattern compared to the historical trend in homicides.

Figure 2 displays each prediction interval compared to the corresponding observations for homicides from 1991 and 2018. The model has stable prediction intervals across the sample because of the static one step ahead forecast method. Examining the recent homicide series, the homicide rate for 2015 was above the upper limit of the 90% prediction band, but not the upper end of the 98% prediction interval. The national level homicide rate in 2015 rounded to three decimals was 4.950, and the 99th percentile of the forecast was 4.955.

This result is consistent with the outcome of city-level homicide analysis (Wheeler & Kovandzic, 2018), even though the forecast intervals are much smaller at the national level than when forecasting any individual city. Subsequent years after 2015 are more within the typical range of the prediction intervals, all being covered by the 90% prediction interval.

[Insert Figure 2 Here]

As such the results can be interpreted as offering some evidence for an anomalous increase in the national level homicide rate in 2015. By our model, it was approximately a 1 out of 100 chance the homicide rate would be that high, given historical patterns. But more clearly 2015's increase is a short-term aberration in the long-term crime drop (Rosenfeld & Fox, 2019).

Comparing Homicide to Other Violent Crime

We applied the same method to data for the other Part 1 violent crimes: aggravated assault, robbery, and rape. The time series model used for these crime types were the ARIMA model because prior studies showed that the ARIMA model accounted for a substantial portion of the variation for UCR

Part 1 index crimes, including aggravated assault, robbery, and burglary (McDowall & Loftin, 2005).

We estimated the models for each crime type on observations from 1960-1990. The results of automatic procedures for the selection of ARIMA models indicated that series of data for three different types of crime fitted into different subsets of ARIMA model. The model for rape was the same as that for homicides, a first-order autoregressive model without an intercept. The results indicated that a first-order moving average with drift was the best fit for the robbery series. The estimated time series model for aggravated assault was a first-order ARIMA model with drift.

[INSERT FIGURES 3-5 Around Here]

The results of residual diagnosis indicate that none of the models for the crimes examined have a significant amount of residual temporal autocorrelation. While the prediction interval coverage rate for aggravated assault is relatively not good compared other crime types, the overall performance for all three crime types was close to expectations in terms of the coverage rate. Observations in 2015 for all rape, robbery, and aggravated assault showed an increase but values remained under the upper limit of the 50% prediction interval for each series. Consistent with the results on homicides, trends in each violent crime type from 2016 to 2018 changed within the predicted range; however, while aggravated assault and robbery matched the movement in homicide, rape rates have continued to increase since 2013.

Varying the Testing/Training Data Years

One final analysis that we present is whether the coverage results are sensitive to picking the test/train split at 1990. To do this supplemental analysis, we conducted the same procedure, choosing the ARIMA model on the train set, and then generate one year head prediction intervals and check the coverage. We do this varying the training/test year split, from 1980 through 2000. For simplicity we

only report the overall coverage rate for all four crime types combined, and those coverage rates are shown in Table 3.

[INSERT TABLE 3 around here]

This subsequently varies the total number of testing years. So for example, when the training is limited to 1960-1990 (the main results presented in the prior section), with four crimes there are 28 test observations, for a total of 128 data points. If setting the training data to earlier years, there will be more points. This is reflected in the Total N column of Table 3.

Table 3 shows that for each of the different prediction intervals, coverage rates are generally worse when using fewer years to select the order of the ARIMA model. Coverage rates are lower than one would expect, until selecting training years in the mid 90's. After that coverage rates appear to be slightly larger than one would expect.

There are multiple potential reasons for the results. One is that with fewer years to select the ARIMA model, there are more errors, and this subsequently causes worse future forecasts. Another potential explanation though is that there was more volatility in crime rates in the early 90's (before the crime drop), and those years are to blame for the poorer overall coverage rates. However these results suggest that the main analyses presented, using the training data set from 1960 to 1990 does not bias the results to have better coverage. Using a longer training dataset results in better coverage rates across the four crime types examined here.

Conclusion

Media outlets reported the seemingly abrupt increase in homicide in big cities in the United States and scholars examining homicide trends also argued the change in homicide was substantial enough to demand scrutiny and attention in the interest of public safety (Rosenfeld et al., 2017).

Although a growing number of studies have explored the significance of the 2015 increase in homicide, their findings are limited by a reliance on percent change or trend analysis, which have limitations in finding the abnormal patterns in recent changes over time (Wheeler, 2016; Wheeler & Kovandzic, 2018). This study builds upon the prior literature by using a forecasting method with an accompanying fan chart to examine whether the 2015 homicide rate increase is significant or just a result of random fluctuations. Past research using percent change techniques has suggested the 2015 increase in the national homicide rate was significant. In conjunction with their findings, we offer a similar interpretation of the homicide increase in 2015, although having arrived at the conclusion through the use of ARIMA prediction models and fan charts – strengthening the overall conclusion that the national homicide rate significantly increased in 2015. Our model estimates that the 2015 increase was near a 1 in 100 chance occurrence given the historical data, which we believe is sufficient to suggest that 2015 was an anomalous increase. Although such a bright line is ultimately arguable, individuals can set such a threshold themselves to determine if such a chance occurrence is worth further investigation or any subsequent responses.

Our comparative analysis indicates that the change in 2015 is pronounced only in homicides and not in other violent crime. The analysis above for homicides finds that the 90% prediction intervals failed to cover the 2015 homicide rise while observed annual rates for the other three crime types are covered by the prediction bands. The overall temporal patterns for robbery, a crime that trends closely with homicide, are similar to those of homicide during the predicted period; marked by a sudden decline in the 1990s, slight fluctuations in the 2000s, and decreasing and seemingly spiking patterns in the 2010s. Despite the relative similarity in the patterns between homicide and robbery, the homicide rise in 2015 was significant while the increase in robbery was not. In short, comparative analysis found that the rising pattern is only significant in homicides, implying the rise in the 2015 homicide rate was abnormal

compared to other violent crimes. It is important to note here that while homicide, robbery, and aggravated assault rates increased from 2014 to 2016 and decreased from 2016 to 2018, the rape rate failed to decline and increased from 2013 to 2018. It is beyond the scope of our work here to explain the reason the rape rate did not decrease after 2016 as the other violent crime rates did, but future research can work to uncover potential causal factors.

Even though our results align with prior studies, our paper contributes to the literature on temporal crime patterns by suggesting and demonstrating an alternative way to monitor crime trends and annual fluctuations in crime statistics. Federal government employees have mainly used percent change calculations in their official reports, which can result in chasing the noise and inefficient uses of resources. As a result, policy implemented in response to such analysis may not be as effective or could result in unintended consequences; however, the primary concern here is that percent change calculations cause one to draw the conclusion that a policy response is necessary when it may not be needed. For example, the government responded to the Police Executive Research Forum (PERF) request for financial support in response to crime increases from 2004 to 2006 by funding them to hire more police officers, increase training and provide technical assistance. However, Rosenfeld and Oliver (2008) later found the crime increase was not substantial and just the result of external variables rather than a lack of law enforcement officers. Similar inferences may be made based on more recent trends, where short term fluctuations should not be viewed as so anomalous that they demand immediate attention and investment. If practitioners or policymakers employ the suggested method in the policy-making process, it may lead to timelier and more effective policy responses. Lawmakers and police departments can use the forecasting method with daily, weekly, monthly, or yearly data to estimate the number of police officers they will need to respond to a certain number of crime incidents. Academics can do the same to produce new knowledge of crime trends without relying on a method that is biased

and volatile (percent change) or having to wait to complete a retrospective study of longer term trends (via structural breaks).

The methods used in this study can be also be directly applied by criminal justice practitioners. Specifically, the one-step ahead forecasting technique can be applied as part of the problem-oriented policing approach to law enforcement crime prevention strategies. State and federal prison bureaus can use this to estimate future prison populations and ensure they have the appropriate capacity each year. Prosecutors, defense attorneys, and courts at any level can do the same to adequately provide counsel and other court functions for cases in their jurisdiction. Utilizing ARIMA models instead of percent change or trend analysis may be able to functionally improve budget and personnel appropriations.

A current limitation of applying such advice is that the FBI is often a year behind in reporting national level homicide estimates. Thus such forecasts are too old to be effectively used for allocation decisions, at least at the federal level. However, the utility of such forecasts to assist in anomaly detection are still relevant. It would be easily possible for the FBI to not only release direct estimates of homicides, but also provide such error intervals to better contextualize such ups and downs. This would preempt overinterpreting minor fluctuations, whether it be by the media, politicians, or criminal justice researchers.

We do not suppose prediction modelling to serve as the only method for exploring recent changes in criminal justice related issues, for in our own work we recognize there are limitations involving data and analysis. One of the limitations of this study is our reliance upon official UCR data. While homicide is likely to be detected or reported, the other violent crimes could be underreported and introduce bias into our estimates. Also, the use of national estimates of crime may cause some errors. The national estimates of crime rates are the result of the imputation process for incomplete information

on reported crime or missing cases. The analysis results may be less valid due to the use of data different from true figures. Such errors can lead one to misinterpret the result that homicide increase is abnormal. Still, the forecasting and fan chart approach offers a viable alternative method, as shown by the coverage of the prediction intervals for not only homicides but other national level violence crime estimates here. But its application will always have limitations. The prediction intervals are only as good as the specified model and the data it is supplied.

Another limitation is that we rely on statistical methods in which the underlying data have no errors themselves. The same idea of a fan chart could in principle be applied to the National Crime Victimization Survey (Rennison, 2000), although they have estimates of the prevalence of particular acts, not an official number. Future research may attempt to build models that not only take into account forecast error in identifying significant shifts in crime, but also sampling error as well.

Another limitation of the work is that while we can identify if an increase is abnormal or within the prior historical changes, we cannot directly identify a cause of those changes. So while we identify that the 2015 homicide rate has some evidence it is anomalous compared to historical patterns, we cannot attribute it to any particular cause, such as de-policing. We do not include any structural level variables like past work (Gaston et al., 2019; Gross & Mann, 2017; Rosenfeld, 2016; Rosenfeld & Wallman, 2019) that tries to tease out the effect of changing drug markets, civilian concerns of police violence, or de-policing strategies. While incorporating different covariates may help identify different factors that contribute to macro level homicide trends, including covariates rarely increases forecasting accuracy (Hyndman & Athanasopoulos, 2018). Since those variables often themselves have uncertainty, they will not necessarily improve forecasts of future crime trends. Still, this technique can be used as a first stage test as to whether some recent shock is causing homicides to increase. If recent changes fall within historical prediction bands, it does not offer evidence that anything abnormal is currently

occurring. One should not use minor fluctuations in homicide rates (or any crimes) to ex ante attribute those short term fluctuations to any particular exogenous shock.

Finally, we are unable to determine if the observed abnormality in the 2015 homicide rate is a singular outlier, or part of a structural change in the homicide trend. For several possibilities, recent increases in macro level crime trends have not been uniform, so it is not clear if the long term crime drop beginning in the 1990's has plateaued, or if overall crime is starting to slowly increase in an entire reversal from the prior crime decline. Another is that different factors over time, such as the lethality of violence (Berg, 2019), may be causing longer term trends, but are too small to be effectively detected by this technique. It is also the case that singular cities can disproportionately contribute to national level homicide increases (Rosenfeld, 2016).

Even if identifying an anomalous national level change, it would not directly say whether such a shock is relevant for the entire U.S., or just a few select jurisdictions. It is the case though that similar analysis can be conducted at the city level to identify anomalous changes (Wheeler & Kovandzic, 2018). But city level analyses will have more error in the forecasts than national level estimates, due to the fact that homicide is a quite rare event. Still, we believe national level analysis are still relevant, especially given they are often used to justify particular policy responses. Given that many cities often follow national level trends (McDowall & Loftin, 2009), it may be better to start with national level analysis from a monitoring perspective, and when an anomaly is detected to drill further into the data to attempt to uncover if particular cities are driving that change.

Researchers, practitioners, media outlets, and politicians should continue to monitor violent crime rates, comparing them to one another and within the data series before making a definitive statement on the "trend" of any type of violence. Crime analysts employed by larger police departments

have direct access to calls for service, incident, and arrest data for their city. It is becoming more common for police departments in big cities to make their crime data publicly available (e.g., opendata.gov) and to update an online database each week or month, facilitating timely access by researchers independent of the police department. Such data availability allows studies of local crime rates, though aggregated national studies will still lag behind actual crime occurrences due to the length of time (up to 18 months) it takes for official UCR data to be published. Given we find evidence that homicide trends follow a random walk pattern, as do other researchers (McDowall, 2002; McDowall & Loftin, 2005), it would suggest the overall rate may meander up-and-down for in the short run for any particular period, and so two or three year increases are not guaranteed proof that the crime declines observed in the prior 25 years are reversing. The fan charts we illustrate here can help identify short run aberrations, and thus give more immediate feedback to policy makers on crime trends, without needing to wait for years to identify long term trends.

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Table 1: Comparison of different ARIMA models

Model	Residual analysis	AICc*
ARIMA (1,1,0):	$X^2=3.97$, $p = 0.55$	-93.11
ARIMA (0,1,0):	$X^2=14.37$, $p = 0.03$	-79.56
ARIMA (0,1,1):	$X^2= 5.01$, $p = 0.41$	-88.16
ARIMA (1,1,1):	$X^2= 3.44$, $p = 0.49$	-90.86
ARIMA (2,1,0):	$X^2=3.19$, $p = 0.53$	-91.00
ARIMA (2,1,1):	$X^2= 2.90$, $p = 0.41$	-88.56

*Corrected AIC

Table 2: Coverage Rates for the 50%, 80%, 90%, and 98% prediction intervals

Out of Sample, 1991 - 2018								
	Homicide		Aggravated Assault		Robbery		Rape	
	N	%	N	%	N	%	N	%
<i>Coverage of 50% Intervals</i>								
Low(25th)	12	43	23	82	17	61	17	61
Covered	12	43	4	14	11	39	11	39
High(75th)	4	14	1	4	0	0	0	0
<i>Coverage of 80% Intervals</i>								
Low(10th)	3	11	14	50	5	18	5	18
Covered	24	86	14	50	23	82	23	82
High(90th)	1	4	0	0	0	0	0	0
<i>Coverage of 90% Intervals</i>								
Low(5th)	2	7	9	32	3	11	3	11
Covered	25	89	19	68	25	89	25	89
High(95th)	1	4	0	0	0	0	0	0
<i>Coverage of 98% Intervals</i>								
Low(1th)	0	0	3	11	0	0	0	0
Covered	27	96	25	89	28	100	28	100
High(99th)	1	4	0	0	0	0	0	0
Total	28		28		28		28	

Table 3: Coverage Rates When Varying the Training Data Cut Point (from 1980 through 2000)

Year Split	Cover 50%	Cover 80%	Cover 90%	Cover 98%	Total N
1980	21.1	55.3	65.8	86.8	152
1981	25.0	60.1	75.0	90.5	148
1982	27.1	60.4	76.4	90.3	144
1983	35.7	71.4	88.6	98.6	140
1984	32.4	69.1	84.6	97.8	136
1985	31.8	66.7	84.8	97.0	132
1986	32.8	68.0	84.4	97.7	128
1987	25.0	55.6	72.6	90.3	124
1988	37.5	72.5	82.5	93.3	120
1989	34.5	70.7	81.9	93.1	116
1990	33.9	73.2	88.4	97.3	112
1991	32.4	72.2	88.0	96.3	108
1992	38.5	73.1	88.5	97.1	104
1993	46.0	76.0	89.0	97.0	100
1994	49.0	83.3	92.7	97.9	96
1995	68.5	92.4	95.7	100.0	92
1996	68.2	94.3	98.9	100.0	88
1997	66.7	91.7	95.2	100.0	84
1998	66.3	91.3	95.0	100.0	80
1999	63.2	90.8	97.4	100.0	76
2000	63.9	91.7	97.2	100.0	72

Figure 1: Residual fit statistics for ARIMA (1,1,0) model on homicides from 1960 – 1990

Homicide Rates in the United States 1960-2018
adjusted for population

UCR data compiled by FBI

Figure 2: Fan chart for national homicide rate predictions. The black dot shows the actual homicide rate per 100,000. The four different prediction intervals including 50, 80, 90 and 98 percent are represented with the shades of the grey in order. 50% prediction interval is displayed with the darkest band and 98% band is in the lightest grey. The bands are computed from estimated ARIMA (1, 1, 0) model on the homicides from 1991 to 2018 based on prior years actual observations.

Figure 3: *Fan chart for national aggravated assault rate predictions*

Figure 4: *Fan chart for national robbery rate predictions*

Figure 5: Fan chart for national rape rate predictions