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Testing the Validity of Demonstrated Imputation Methods on Longitudinal NIBRS Data

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The Uniform Crime Reporting (UCR) Program and the National Incident-Based Reporting System (NIBRS) are the two major sources of crime data in the United States. The UCR is a summary reporting system while NIBRS is an incident-based reporting system which was established to modernize crime reporting. The data collected by NIBRS is much more detailed. Given that law enforcement agencies across the nation voluntarily submit data to the Federal Bureau of Investigation (FBI) using either UCR or NIBRS, the presence of irregular reporting, missing data, and noncompliance are likely to compromise data quality.[1]

For many states, crime data collected using UCR or NIBRS are used to generate state and local crime reports and statistics. These data are most often reported "as is" and are thereby assumed correct. Since victimization data are typically not collected at the state or local levels to corroborate crime reports, there is an increased need for crime data to be as reliable as possible. Given the voluntary nature and inherent limitations of crime data collection systems, however, these data come with the caveat of being incomplete, or dubbed non-representative.

Previous research on state incident-based reporting (IBR) data revealed issues with completeness, resulting from partial and non-reporting agencies, and accuracy, due to irregular reporting (LaValle, Haas, Turley, & Nolan, 2013). The previous work found that imputation, particularly alternative imputation methods developed by the West Virginia Statistical Analysis Center (WVSAC), can be used to reliably estimate for missing data. In conclusion of applying imputation methods to IBR data, the study also revealed that reporting data "as is" may not be the most accurate representation of IBR data. Additional studies have been conducted on national UCR data which found similar concerns with data quality, particularly issues related to missing data (see Maltz, Roberts, & Stasny, 2006; Targonski, 2011).

Tools to detect and adjust for issues that are known to exist in crime data can improve data that are used as a basis for information and research. This research seeks to test and validate data quality techniques and imputation methods which will provide evidence that reliable and stable estimates of crime data can be attained with consistency over time. The study examines the performance of alternative imputation methods in comparison to FBI methods and provides a framework for the use of techniques on state-level IBR data. We apply

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and simultaneously test partial and non-reporting imputation methods using longitudinal data with the goal of improving the accuracy of state NIBRS data, especially when used for state and county trend analyses over time.

Background

To date, West Virginia is considered a full reporting NIBRS state with 100% population and crime covered (Justice Research and Statistics Association [JRSA], 2012). West Virginia became the sixteenth state to be certified to submit data using NIBRS in September 1998.[2] The WV state repository began only accepting data in the IBR format as of January 1999. By 2006, all policing agencies in the state were reporting IBR data, with only a small number of county and local agencies reporting no incidents. All WV Incident-based reporting (WVIBR) data are currently submitted to, compiled, and maintained by the WV State Police UCR section of the state repository.

Like WV, many states submit crime data to the FBI since converting to the NIBRS format. Including WV, 15 states are considered full NIBRS reporting states. Seventeen states are at various levels of NIBRS reporting, 12 states and the District of Columbia are either in testing and development phases for converting to NIBRS reporting, and six states have no formal plans to convert (JRSA, 2012). As more agencies convert to NIBRS and participation expands, the need for evaluating data quality and imputation methods in the context of IBR systems is in demand.

The NIBRS data, like the UCR, are not exempt from problems of data quality such as missing values. The FBI checks UCR data monthly for missing data and anomalous reporting using several layers of control. That is, missing data or data flagged as outliers are imputed (see Akiyama & Propheter, 2005). However, the data quality and imputation methods used by the FBI are quite involved and are criticized for being outdated. Furthermore, these methods are not applied to NIBRS data leaving methods specific to NIBRS data understudied.

Report Highlights...

There are inherent data quality issues due to the voluntary nature of NIBRS crime reporting.

Reporting data "as is" may distort crime trends given known issues with accuracy and completeness in state incident-based reporting (IBR) data.

Problems with data accuracy and completeness confirm the need for techniques and tools that identify and resolve data quality issues.

This study uses state IBR data to test and validate data quality and imputation methods developed by the West Virginia Statistical Analysis Center.

Systematic techniques for identifying missing and irregular data exhibit the ability to perform efficiently and with consistency over time.

This study demonstrates that imputation methods improve data accuracy and produce reliable results that are stable over time.

The impact of this research can help states optimize the utility of NIBRS data and the use of state administrative records.

Previous Research

To fill the gap in knowledge about applying data quality and imputation methods to IBR data, the WVSAC peformed a study in 2012. In the study, easy-to-use data quality techniques were developed to identify missing and irregular data in addition to measuring and comparing the accuracy of imputation methods. To identify and classify missing data, the study looked at reporting patterns in agency data and used k-means clustering to develop zero classification guidelines. Outlier detection techniques, specific to identifying irregular

Applying Imputation Methods Involves the Following Steps...

1. Obtain data. The data format should list agency data in rows and include columns for the following variable: ORI number and/or agency name, aggregate monthly crime counts (January-December), population estimate (for municipal police departments and county sheriff departments), MSA status (for all agencies other than municipal police departments).

2. Identify and classify any zero reports that may indicate missing data using zero classification guidelines. Replace missing data with a designated value.

3. Identify and classify irregular reporting using outlier detection methods. Replace irregular data with a designated value.

4. Identify non-reporting agencies (i.e., agencies that did not report data for a given year) by comparing the ORIs or names for agencies reporting data with a master agency list. Include these agency names on the data sheet.

5. Retrieve and populate population estimates for police departments in municipalities.

6. Retrieve and populate population estimates and MSA status for sheriff departments in county law enforcement agencies.

7. Apply imputation methods.

monthly reporting in IBR data, were also developed after conventional methods failed to identify known irregular values. The study proposed alternative imputation methods developed by the WVSAC which were found to be more accurate than the FBI's approach when applied to the state IBR data. The study also showed that imputation methods could adequately estimate for missing values when up to 40% of data was simulated to be completely missing due to agencies that did not report any data (LaValle, Haas, Turley, & Nolan, 2013).

The WVSAC's research identified and proposed accessible techniques to resolve critical issues in state IBR data, however, the research context was limited. Specifically, methods were examined using one year of data and imputation methods for partial reporting agencies (agencies that are missing one to nine months of data) and non-reporting agencies (agencies missing 10 to 12 months of data) were investigated separately in two separate simulation studies. Although conducting two distinct simulation studies provides a useful starting point for investigating alternative methods for imputing missing data, it is unclear whether the alternative imputation methods hold true when applied together and over time.

The current study seeks to test and verify data quality techniques and alternative imputation methods developed by the WVSAC using longitudinal data. The WVIBR data is an ideal data source given the states' level of participation and the substantial number of years data collection has been in place.

Testing partial and non-reporting imputation methods concurrently will allow us to assess the accuracy of estimates when methods are implemented together. The aim is to improve estimation precision and maintain simplicity, so that these methods can readily be employed by state repository personnel, researchers, and others working with NIBRS data. If these methods prove successful, this project will establish a systematic approach to improving the accuracy and reliability of WV crime data. However, the ultimate goal is to provide other states the means to optimize the capacity and utility of their NIBRS data, and support national initiatives to improve and expand the use of state administrative records.

Methodology

Data Source

Incident-based reporting data in WV are maintained by the WV State Police UCR section of the state repository. The WVSAC receives statewide IBR data directly from the state's repository annually.[3] The IBR data are separated into two text delimited files containing all Group A incidents and Group B arrests. The files are then imported into SPSS, where syntax files are used to read and segment the data for analysis. The SAC maintains the finalized SPSS data files for future analyses and reporting.

This research uses WVIBR data 2007 to 2011. Each data file contains incident data from Jan. 1 to Dec. 31 of the respective year. For this study, the WVIBR offenses-known crime data are aggregated into monthly totals by violent and property crime types for each reporting agency. Violent crimes consist of murder, forcible rape, robbery, and aggravated assault. Property crimes consist of burglary/breaking and entering, motor vehicle theft, all larceny, and arson.

Data with population estimates and county metropolitan statistical area (MSA) designations from the U.S. Census Bureau are used for imputation calculations.[4]

Data Quality Issues

There are two main data quality issues in WVIBR data that have an effect on analyses involving crime reporting at the local and state levels: missing data and irregular reporting resulting in data outliers. There are several approaches to identifying and dealing with suspect data, and a variety of these procedures were investigated previously using WVIBR data (see LaValle, Haas, Turley, & Nolan, 2013).

For the current study, data quality and imputation methods are tested on WVIBR longitudinal data using techniques developed by the WVSAC. The performance of alternative imputation methods are compared to methods used by the FBI. A supplemental descriptive analyses of non-reporting agency characteristics are performed to advise the appropriateness of imputation methods and can be found in Appendix F.

Classifying Zeros

There is no variable or value to solely indicate missing crime reports in WVIBR data. Therefore, a zeros observed in the WVIBR data have one of two meanings: either data were not reported (i.e., missing value) or zero crimes were reported (i.e., true zero).

For the present study, zeros in the WVIBR data are classified using zero classification guidelines

Table 1: Guidelines for classifying crime counts of zero as true zeros or missing data

Guideline 1:	For any zero reported in a given month, if the violent, property, or non-index crime counts in the same month are non-zero, the reported zero is a true zero. If there are months in which all crime counts simultaneously contain zeros, go to Guideline 2.
Guideline 2:	If zeros are observed in all crime types in the same month(s) AND the Total (property) is greater than 25, the zeros are flagged as missing (i.e., not reported) after checking Guideline 4. If Total (property) is less than or equal to 25, go to Guideline 3.
Guideline 3:	If zeros are observed in all crime types for more than 4 consecutive months, the zeros are considered missing after checking Guideline 4. Extra consideration should be given to agencies where the number of consecutive months with zero reported is equal to 4; in this scenario, it is suggested to look at the number of crimes reported in other months to assist with classification.
Guideline 4:	If the agency is a zero-population agency (colleges, universities, division of natural resources (DNR), Task Force, Turnpike, or State Police), separate examination is needed. For colleges/universities, it is not uncommon to observe crime counts of true zero for summer months (June-August) while having a total property crime count greater than 25. For DNR, Task Forces, Turnpike, and State Police, it is not uncommon for NCZ to be greater than 4 and zeros classified as true zeros due to the low volume of crime reported by these agencies.

Table 2: Description of tested automated outlier detection methods

Name	Algorithm	Details
Ratio to Median	$Yi = \frac{x_i}{\tilde{x}}$	Yi measures the number of times the monthly crime count is compared to the agency's median. The Yi test statistics is compared to a user defined critical value. No assumptions are made about the data distribution and the development of the test borrows concepts from FBI (see Akiyama & Propheter, 2005).
Ratio of Ranges	$Rr_{Top} = \frac{\lvert x_n - \tilde{x}\rvert}{\left(\frac{Total}{Range}\right)}$ $Rr_{Bottom} = \frac{\lvert x_1 - \tilde{x}\rvert}{\left(\frac{Total}{Range}\right)}$	Rr measures the ratio of 'gap' to 'range' and was developed by the WV SAC. The Rr test statistic is compared to a user defined critical value and makes no assumption about the data distribution. Rr_{Top} tests for an extremely large data point and Rr_{Bottom} test for an extremely small data point.
x_i = crime count at month i, $\tilde{x}$ = median, x_n = *ordered* monthly crime count where $x_1 < x_2 < ... < x_{12}$, Total = annual crime total, Range = $x_n - x_1$		

Table 3: Description of graphical techniques used to visualize data and detect outliers

Plot Name	Purpose	Method	Parameters	Outlier Diagnostics
Histogram	Assess the data distribution	Frequency plot of data grouped by distinct intervals or 'bins'	Number of bins = k, where $k = 1 + \log_2 n$, and n = sample size (Gentle, 2002). Bin width = data range / k, where k is the number of bins (Sturges, 1926)	Histograms that are skewed left may indicate potential outliers; skewed right or symmetric/bell shaped are supportive of the distributional characteristics we expect from count data (Poisson or Normal distributions)
Dot Plot	Assess the data spread and/or realize data clusters	One-dimension plot of monthly crime counts on the horizontal axis	Plot range set to 0 and 20 plus the maximum value rounded to the nearest 10 (allows for comparisons between plots)	Dot plots with a large spread and/or large gaps depicting data clusters may indicate outliers
Line Chart	Assess the data reporting pattern and/or seasonality	Bivariate plot of monthly crime count data and time	Plot range set to 0 and 20 plus the maximum value rounded to the nearest 10 (allows for comparisons between plots)	Line charts with sharp peaks or valleys may indicate outliers

(ZCG) developed by the WVSAC (see Table 1). The guidelines are based on the agency's monthly crime reporting patterns in violent, property, and non-index crimes and annual property crime total.[5] There are two diagnostic variables—the number of consecutive months in which all crime counts (violent, property, and non-index) are zero (NCZ), and the total number of property crime reported (TotalP)—to assist with classification. Other helper variables include crime type (i.e., violent, property, or non-index) and population coverage (i.e., population or zero-population).[6] All data identified as missing are then manually inspected and classified as either a true zero or missing value according to ZCG and the agency's annual reporting pattern. All zero data classified as missing are coded as missing values.

To validate the ZCG, the values of diagnostic and helper variables are recorded at and near cut points to determine their effectiveness for identifying missing data. The longitudinal WVIBR data are used as an additional mechanism for validating the ZCG by reviewing historical reporting patterns.

Outliers

Irregular reporting is identified using outlier detection statistics and graphical analysis.[7] Two automated outlier detection methods are used. One

Table 4: Description of imputation methods for partial reporting agencies (missing one to nine months of data)

FBI Method **CT = PCT * 12 / number of reported months**
CT = Crime Total, PCT = Partial Crime Total
WV Method **CT = PCT + Q1*(N1) + Q2*(N2) + Q3*(N3) + Q4*(N4)**
Nx* = number of missing values per period, x. Q1 = average of Dec., Jan., Feb. crime counts; Q2 = average of Mar., Apr., May crime counts; Q3 = average of Jun., Jul., Aug. crime counts; Q4 = average of Sept., Oct., Nov. crime counts. If N1 = 3, then Q1 = minimum[Q2, Q3, Q4]. If N2 or N4 = 3, then Q2 ⇔ Q4. If N3 = 3, then Q3 = maximum[Q1, Q2, Q4]. If N2 and N4 = 3, then Q2 = Q4 = average[Q1, Q3]. If data for three entire quarters were missing, the average of the remaining values are used for the respective Qx. *Nx can vary from 0 to 3. When Nx = 3, all months for that quarter are missing.

technique, the ratio of ranges, identifies the agency. The other method, the ratio of monthly count to median, identifies the month of irregular reporting. The two methods are complementary (see Table 2).

The ratio of ranges (Rr) technique is a Dixon-type test developed by the WVSAC.[8] The statistic Rr is the ratio of 'gap' and 'range' (LaValle, Haas, Turley, & Nolan, 2013). The ratio of monthly count to median (Yi) measures how many times larger or smaller a monthly crime count is compared to its median and is a simplified variation of a data quality technique used on UCR data (see Akiyama & Propheter, 2005).

Both methods require a user-defined threshold to identify outlying data. Previous research by the authors indicates the potential for outliers when Rr was greater than 2 and when Yi was greater than 4 or less than 0.25 (see LaValle, Haas, Turley, & Nolan, 2013).

Graphical analysis is used to supplement automated outlier detection methods by providing visual aids when manually inspecting potential outliers. The graphical analysis includes a histogram, dot plot, and line chart for each agency's data. The three plots visualize distinct features of monthly reporting patterns and the overall data distribution with the purpose of illustrating anomalies (see Table 3). All data classified as irregular are coded as missing values.

Distinct Imputation Methods for Estimating Missing Data

Imputation offers a systematic way to estimate for missing data. The methods used for imputing crime count data depend on the missing data scenario. That is, estimating for agencies that reported partial data (missing one to nine months of data) and estimating data for non-reporting agencies (missing 10 to 12 months of data).

The current study seeks to directly compare imputation methods developed by the WVSAC and those used by the FBI on longitudinal data to assess accuracy over time. There are prominent features that distinguish the different imputation calculations used by WV and the FBI for partial and non-reporting agencies.

For partial reporting agencies, WV's imputation method uses seasonal quarterly averages in contrast to the FBI method which uses the overall average of all reported months (see Table 4). Previous research compared the performance of the WV and FBI imputation methods for partial reporting agencies and found that the WV methods were more accurate than the FBI's when applied to one year of data. This approach anticipates that estimates will be more precise since the imputation method models data trends and implements the utility of moving averages.[9]

For non-reporting agencies, crime total is estimated by multiplying the agency's population by the crime rate for agency's population group and then dividing by 100,000. This formula is based on the assumptions that similar agencies have similar crime rates and that crime rates are related to population. There are nine population groups used for the FBI imputation methods. There are eight population groups used for the WV imputation method. To better fit the population distribution for WV, the population groups are re-scaled at one tenth the size of the FBI intervals at the national level (see Appendix A for WV and FBI population groups).[10] County and state MSA designations remained the same as the FBI's.

Simulation

Simulation is used to investigate the accuracy of imputation methods by deleting then estimating for the pseudo missing data and finding several difference measures between the original and imputed values. This simulation study uses data from agencies identified as full reporting from 2007 to 2011. Full reporting agencies are agencies that have no data classified as missing or irregular. Using data from full reporting agencies provide a context for comparing imputed and original values to assess accuracy. Since WV has been a full reporting NIBRS state for past eight years, the WVIBR data are well suited for a longitudinal study—there are ample data with consistent year to year agency reporting providing a sufficient number of cases for analysis.

To conduct the simulation study, a missing value pattern is created by checking all data for missing and irregular data and tabulating the quantity and run length of the sequence. Simulation studies using observed data and associated missing value pattern have been applied to a variety of contexts such as surveys, UCR crime counts, and health studies (see Tremblay, 1994; Targonski, 2011; Engels & Diehr, 2003).

Data from full reporting agencies are randomly deleted using the missing value pattern to simulate a dataset with pseudo missing values. Imputation methods are applied to the missing data and used to estimate the state crime totals and total crime for individual agencies. The simulation is performed using Microsoft Excel 2010 and Visual Basic for Applications and repeated 500 times to balance the chance of "good" or "bad" random draws. So results can be replicated, a string of random seeds is created to select the agencies and starting months for data to be deleted.[11]

Three accuracy measures are used to directly compare the performance of WV and FBI imputation methods from the resulting simulation: mean absolute error (MAE), root mean square error (RMSE), and bias (see Table 5). The MAE, RMSE, and bias are calculated for agency crime totals and the overall state crime total.

Student's t-test is used to compare the accuracy statistics resulting from the WV and FBI imputation methods. Significance is noted at the 0.05 level. When comparing MAE and RMSE between methods, a smaller value indicates better accuracy while bias closest to zero indicates better performance.

Results

The results of this study focus on validating and testing methods developed by the WVSAC and are presented in two sections. This section begins with a validation of the methods used for identifying data

Table 5: Formulas and descriptions of accuracy measures for imputation methods

Mean Absolute Error $= \dfrac{\lvert y_1 - \hat{y}_1\rvert + \ldots + \lvert y_m - \hat{y}_m\rvert}{m}$	The MAE is the average of the absolute distance between original and imputed values. It describes how much, on average, original values differ from imputed values. Smaller values are better.
Root Mean Squared Error $= \sqrt{\dfrac{(y_1 - \hat{y}_1)^2 + \ldots + (y_m - \hat{y}_m)^2}{m}}$	The RMSE is the standard deviation of the prediction error. It is a measure of consistency and variation and sensitive to large over- or under-estimates (Witten & Frank, 2005). Smaller values are better.
Bias $= \dfrac{y_1 - \hat{y}_1 + \ldots + y_m - \hat{y}_m}{m}$	The Bias is the average distance between original and imputed values used to indicate the tendency for a method to over- or underestimate values. Bias of zero indicates no bias, negative bias indicates underestimation, and positive bias indicates overestimation.
y_m is the original value, $\hat{y}_m$ is the imputed value, and m is the number of missing values.	

Table 6: Percent of agencies identified and classified using zero classification guidelines (ZCG) with classification rates (number of agencies classified / number of agencies identified)

Year	Total number of agencies reporting data	% of agencies **identified** using ZCG	% of agencies **classified** with missing data	Overall classification rate	Population agency classification rate	Zero-population agency classification rate
2011	266	27%	12%	44%	91%	0%
2010	254	18%	7%	39%	100%	0%
2009	237	22%	12%	53%	100%	4%
2008	263	26%	16%	60%	95%	14%
2007	260	23%	16%	69%	100%	10%
Average		23%	12%	53%	97%	6%

quality issues. First, we examine the number and proportion of agencies with missing data (classifying zeros) and outliers for the purpose of validating the previously demonstrated methods. This is followed by the results of a simulation study which is used to test imputation methods on longitudinal data.

Validation of Zero Classification Guidelines

The zero classification guidelines (ZCG) developed by the WVSAC identify data reported as zero that are suspected to be missing values. Table 6 shows the total number of agencies reporting data for each year and the percentage of agencies identified using the ZCG. The table also shows the percentage of agencies with data classified as missing and classification rates (number of agencies classified / number of agencies identified). Over the five-year span of data, the percentages of agencies identified using the ZCG are relatively consistent and on average, just more than 20% of all agencies are identified by the ZCG. After manual inspection, about half of the agencies *identified* using the criteria are *classified* as missing values. Thus, a little more than 10% of agencies are classified as having missing data (see Table 6). The stability of the results demonstrate the effectiveness of the ZCG for systematically identifying data that could benefit from imputation.

To validate the ZCG, the rate of number of agencies classified to identified are looked at for the three variables (TotalP, NCZ, and population coverage) used to assist with classification as well as agencies' historical reporting patterns.

Looking at population coverage, zeros identified in population agencies are more likely to be classified as missing data than in zero-population agencies. This pattern is illustrated with consistency in population and zero-population classification rate columns of Table 6. These patterns suggest that there are different interpretations regarding zero reporting in population and zero-population type agencies.

The historical reporting patterns of population and zero-population agencies further confirm the ZCG. Population agencies that historically reported a high volume of crime did not report zeros for any aggregate monthly crime count. For zero-population agencies, state police detachments historically report consistent crime counts but the volume of crime reported seems to be related to the size of the jurisdiction they report under. Given this, while observing zeros in some state police detachment data may be characteristic of a true zero, it is advised that the annual reporting pattern and TotalP be considered when manually inspecting data suspected as missing data. Sparse reporting and/or several consecutive months in which all crime counts are zero in zero-population agencies such as division of natural resources, task forces, and other targeted enforcement duties are typical. IT is common for agencies at higher education establishments to report decreased or no crimes in summer months so zeros in those cases are classified as true zeros.[12] Overall, these

Table 7: Percent of agencies identified as having potential outliers in violent and property crime data by outlier detection method (Yi and Rr)

		Violent crime data				Property crime data			
Year	Number of agencies reporting data	% of agencies *identified* using **Yi**	% of agencies *identified* using **Rr**	% of agencies *identified* using **Yi & Rr**	% of agencies **classified** with outlier(s)	% of agencies *identified* using **Yi**	% of agencies *identified* using **Rr**	% of agencies *identified* using **Yi & Rr**	% of agencies **classified** with outlier(s)
2011	266	12%	3%	2%	<1%	23%	13%	8%	4%
2010	254	13%	3%	2%	0%	21%	11%	3%	2%
2009	237	15%	3%	1%	<1%	20%	13%	3%	2%
2008	263	10%	2%	<1%	0%	15%	9%	3%	2%
2007	260	13%	3%	<1%	0%	18%	12%	4%	2%
Average		12%	3%	1%	<1%	19%	12%	4%	2%

results validate Guideline 4 of ZCG which points to differences in interpreting zero reporting between population and zero-population agencies.

Next, a closer review of the two diagnostics variables, TotalP and NCZ, is used to examine ZCG and cut points for population and zero-population agencies. Appendix B shows a table with diagnostic variable values (TotalP and NCZ) and the classification rates for population and zero-population agencies at each level after applying ZCG and reviewing reporting histories (see Appendix B, Table B1). There is a noticeable difference in classification rates between population and zero-population agencies. For population agencies, 100% of the cases identified by TotalP greater than 25 are classified as having missing values (see Appendix B, 'TotalP >25' column in Table B1). Likewise, all agencies identified with the NCZ greater than 4 in population agencies are classified as having missing data. In most cases, the zero-population classification rates are small, indicating a pattern of sparse reporting and the need for special consideration when classifying zeros. This gives further conformation about the differences in interpreting zero reports from population and zero-population agencies.

According to Guideline 3 of the ZCG, it is presumed that agencies with NCZ less than or equal to 4 are likely true zeros. After considering historical data, some of the population agency data in which NCZ was equal to 4 were classified as missing values (see Appendix B, 'NCZ = 4' column in Table B1). In fact, in some years, the classification rate is 100%. For cases in zero-population agencies with NCZ equal to 4, historical data validated classifying the zero reports as true zeros. This outcome supports a change to Guideline 3, particularly in cases for population agencies, and it is recommended that agencies with NCZ equal to 4 be identified as having potential missing data.

Finally, additional examination is performed on agencies not identified or classified by the ZCG. To do this, agencies are ranked in descending order by TotalP for NCZ equal to 1, 2, and 3. At each level of NCZ, the largest value of TotalP is recorded. It is expected that these agencies would have TotalP values close to 25 and the values observed confirm this (see Appendix B, Table B2). These results suggest that 25 is an appropriate cut point for TotalP when classifying zeros, consistent with Guideline 2.

Validation of Outlier Detection Methods

Automated outlier detection methods are used to systematically identify irregular data. Once potential anomalous data are identified, graphical analysis is used to guide classifying data as acceptable or irregular. Graphical analysis played a key role in deciding whether to classify identified data as acceptable or irregular (see Appendix C for examples of data identified by outlier statistics and how graphical analysis was used during

Report Highlights...

When historical data is unavailable, zero classification guidelines (developed and tested by the WVSAC) can be used to assist with identifying agencies with missing data.

About 1 out of 5 agencies are identified using the zero classification guidelines. After manual inspection, 1 out of 10 agencies are actually classified as having missing data.

About half of the data identified by zero classification guidelines are classified as missing.

Two ratio-based outlier detection methods are used to identify irregular data. These methods were previously developed by the WVSAC and found to be better suited for identifying unusual data.

For property crimes, 1 out of 5 agencies are identified by at least one outlier detection method. On average, about 1 out of 50 agencies are classified as having irregular data.

For violent crimes, 1 out of 10 agencies are identified by at least one outlier detection method. Very few agencies are classified as having irregular reporting in violent crimes.

The quantity of data identified and classified as missing or irregular was consistent throughout the five year period.

manual inspection). Visual characteristics such as histogram plots with a left-skewed distribution, dot plots with a large range, and line charts with a sharp peak(s) or valley(s) were strong indicators of irregular reporting.

The two outlier detection statistics are calculated for all agency data in the longitudinal data. One statistic, the ratio of ranges (Rr), identifies the *agencies* with potential irregular reporting. The second statistic, the ratio of monthly count to median (Yi), is used to identify the *month or months* of potential irregular reporting. Table 7 shows the percentages of agencies identified using each methods and the overall proportion of agencies classified as having irregular data. Similar to the validation of ZCG, the proportion of data identified and classified throughout the five year period is consistent. On average, 2% of reporting agencies are classified as having irregular reporting for property crimes and less than 1% for violent crimes. In all but one case, outliers are detected in population-type agencies. While the proportion of agencies determined to have irregular data is small, the outcome demonstrates that errors in NIBRS data collection do occur. These errors, that are otherwise not given any attention, can be detected using the proposed techniques. Given that at most, approximately 20% of the data will need to be examined if applying outlier detection methods, it seems worth the effort in exchange for better data quality.

Considering both methods, more agencies are identified as having potential outliers in property crime data than violent crime data. Compared to the quantity of data identified by the Rr method, the Yi method identifies more agencies. The percentages of agencies identified using the outlier detection methods is consistent year to year and comparable to the results of previous work using one year of data (see LaValle, Haas, Turley, & Nolan, 2013).

Using the threshold of 4 (and 0.25) for Yi, the method identifies an average of slightly less than 20% of agencies' property data and a little more than 10% of agencies' violent data as having potential outliers (see Table 7).

Of the agencies with data classified as irregular, the Yi values range from 0.03 to 0.41 for values that were flagged because they were lower when compared to the median, and between 5.47 and 16 for data that are larger in comparison.

For the Rr statistic, the comparison value of 2 is used. On average, 12% of agency's property data and 3% of agencies' violent data are identified as irregular. The Rr statistic range from 2.0 to 25.9 for the agencies that are identified by the method.

On average, both methods identify the same agencies in 4% of property crime data and 1% of violent crime data. All data identified by either of the outlier detection methods were manually inspected. Given that these methods are applied to the longitudinal data, the thresholds for Yi greater than 4 (and less than 0.25) and Rr greater than 2 appear appropriate for detecting outliers in the crime data.

Since the Yi and Rr outlier detection methods are complementary, an analysis of how both methods interact is examined. The majority of data classified as outliers are identified by both methods (see Appendix D). Over the five-year span of data, approximately 90% of agencies that had outliers in property data and all of the agencies with outliers in violent data are identified by both methods. The remaining 10% of agencies classified as having outliers in property data that are not identified by both methods are flagged exclusively by the Rr method. While the efficiency of using both methods to classifying irregular data is demonstrated, a small portion of data was identified by only one method. Thus, using the outlier detection methods in concert and apart gives an added layer of quality control when sifting through data.

Testing Imputation Methods Using Simulation

To measure the performance of the WV imputation methods, simulation is used to randomly delete data to test and compare imputation methods. The simulation is carried out using longitudinal data to measure the effects of imputation over time. The resulting WV imputation accuracy measures are compared directly to those found for the FBI imputation methods under the same simulation conditions. In order to calculate accuracy, having original data values is required. Therefore, the simulation study uses agencies that reported complete data with no irregularity for the five year period.

The longitudinal data set used in the simulation study resulted in 143 full reporting agencies for the property crimes and 159 agencies for the violent crimes. The missing values pattern resulting from

Table 8: Accuracy and bias results for estimating state crime totals.

	Violent						Property					
	WV Methods			FBI Methods			WV Methods			FBI Methods		
Year	MAE_{tot}	$RMSE_{tot}$	$Bias_{tot}$	MAE_{tot}	$RMSE_{tot}$	$Bias_{tot}$	MAE_{tot}	$RMSE_{tot}$	$Bias_{tot}$	MAE_{tot}	$RMSE_{tot}$	$Bias_{tot}$
2011	**367***	**485**	**18****	416	523	-137	**2,789**	**4,080**	**34***	2,986	4,146	-624
2010	**361***	**476**	**7****	413	519	-146	**2,753**	**4,030**	**55***	2,933	4,076	-558
2009	**330**	**431**	**9****	357	449	-129	**2,634**	**3,871**	**56***	2,842	3,922	-574
2008	**370**	**485**	**9****	377	476	-139	**2,783**	**4,064**	**22***	2,997	4,119	-617
2007	**365**	**477**	**11****	378	475	-131	**2,820**	**4,124**	**26***	3,060	4,191	-646
5 yr	**1,351**	**1,788**	**47****	1,479	1,865	-536	**10,928**	**16,051**	**138***	11,826	16,295	-2,461

Results in bold indicate better performance. * Significant at 0.05 ** Significant at 0.001

Table 9: Accuracy and bias results for estimating agency crime totals.

	Violent						Property					
	WV Methods			FBI Methods			WV Methods			FBI Methods		
Year	MAE_{ave}	$RMSE_{ave}$	$Bias_{ave}$	MAE_{ave}	$RMSE_{ave}$	$Bias_{ave}$	MAE_{ave}	$RMSE_{ave}$	$Bias_{ave}$	MAE_{ave}	$RMSE_{ave}$	$Bias_{ave}$
2011	**19****	**38****	**0.25****	21	46	-1.83	**151**	**319***	**0.50***	153	341	-9.05
2010	**19***	**38****	**0.09****	20	46	-1.95	**149**	**318**	**0.79***	150	335	-8.09
2009	17	**36****	**0.12****	17	40	-1.72	**145**	**299***	**0.81***	148	323	-8.31
2008	19	**41**	**0.12****	**18**	43	-1.85	**151**	**320***	**0.32***	152	340	-8.95
2007	18	**40***	**0.15****	18	43	-1.74	**152**	**325***	**0.15***	155	348	-9.49

Results in bold indicate better performance. * Significant at 0.05 ** Significant at 0.001

Report Highlights...

Missing data and irregular reporting are two main data quality issues in West Virginia IBR data.

Applying data quality and imputation methods to longitudinal data can assess the performance of methods over time.

The proposed data quality and imputation methods are designed to be accessible and resolve critical issues in state IBR data.

The methods aim to improve estimation precision and maintain simplicity so that techniques can easily be applied by analysts working with NIBRS data.

Imputation methods using quarterly averages and alternative population groups are more accurate at estimating for missing data than methods currently used by the FBI.

Using simulation to replicate missing data scenarios in state IBR serves as a platform for understanding the performance of imputation methods and comparing accuracy measures.

The tools developed by the West Virginia Statistical Analysis Center offer a systematic approach to improving the accuracy and reliability of IBR crime data.

classifying zeros and detecting outliers in the 2007 to 2011 WVIBR data is used as the model for simulating missing data (see Appendix E). Excluding agencies that reported no data, the most common missing value pattern was one missing month.

The WV and FBI imputation methods are applied to the simulated missing data for property and violent crime counts for each year and over the five year period. The performance of the WV and FBI methods are highlighted in the violent and property crime sections of Tables 8 and 9 which report the accuracy statistics MAE, RMSE, and bias for each method. Each statistic measures a particular component of accuracy calculated by the difference between original and imputed values. Table 8 includes the accuracy results for the annual state total (columns noted 'tot') and the five-year cumulative state total (row named '5 yr'). The state total is used to produce a general, statewide crime count by summing all crime reported by all law enforcement agencies within a state. Table 9 reports the results of agency totals (columns noted 'ave') which details the precision of the imputation methods to estimate data for an individual agency. Knowing the accuracy of agency totals would help determine the suitability of using estimates for smaller units of analysis.

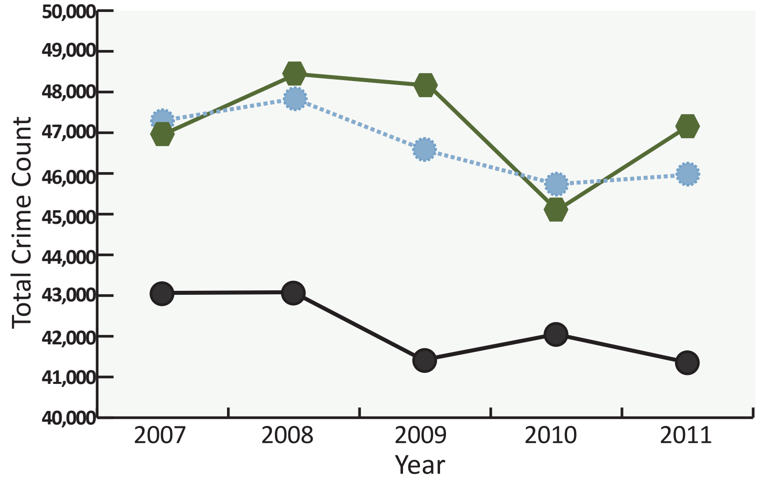
The WV imputation methods are more accurate than the FBI methods when estimating for the state and 5 year totals in violent and property crimes. In both violent and property crimes, the columns containing the resulting MAE_{tot} and $RMSE_{tot}$ values in Table 8 for the WV methods are smaller when compared to the values obtained using the FBI methods. In years 2010 and 2011, the WV imputation methods are significantly more accurate than the FBI methods when estimating for violent crimes according to the MAE_{tot}. Theses results suggest that not only are the WV methods more accurate because of smaller MAE values, they are also more consistent based on the smaller RMSE values.

The $Bias_{tot}$ columns in Table 8 for the WV and FBI methods indicate the tendency for the methods to over– or underestimate. Bias is also used as a secondary measure of accuracy — the closer bias is to zero, the more accurate the method. For all years, the $Bias_{tot}$ for the WV methods are significantly different from the FBI methods in both the violent and property crimes. While the WV methods tend to overestimate, they are much closer to zero and thus, more accurate than the FBI methods.

The precision of the imputation methods to estimate data for an individual agency is captured by the accuracy statistics for agency crime totals in

Figure 10: Five year trend for state property crime data between 2007 and 2011 with and without imputation

State Property Crimes: 5 year trend

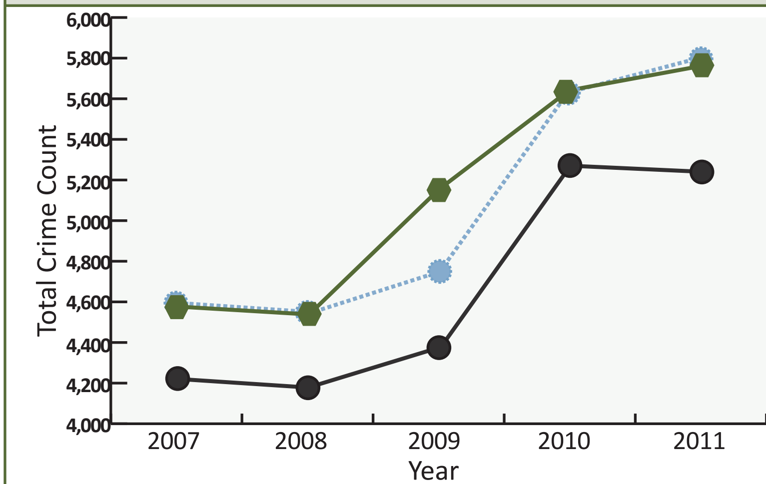


Percent change by year and imputation method.

Year	No Imputation	WV Imputation	FBI Imputation
2007-2008	0.04%	3.05%	1.25%
2008-2009	-3.83%	-0.49%	-2.64%
2009-2010	1.61%	-6.37%	-1.82%
2010-2011	-1.75%	1.90%	3.04%

Figure 11: Five year trend for state violent crime data between 2007 and 2011 with and without imputation

State Violent Crimes: 5 year trend



Percent change by year and imputation method.

Year	No Imputation	WV Imputation	FBI Imputation
2007-2008	-1.25%	-1.02%	-1.49%
2008-2009	4.91%	13.68%	4.74%
2009-2010	20.31%	9.30%	18.40%
2010-2011	-0.51%	2.06%	3.04%

Table 9. These accuracy measures for violent and property crimes are found for each method under the MAE_{ave}, $RMSE_{ave}$, and $Bias_{ave}$ columns in the table. In both the violent and property crime sections of the table, the $RMSE_{ave}$ and $Bias_{ave}$ columns between the WV and FBI methods indicate better performance for the WV methods. Specifically, the WV methods are more consistent when estimating agency totals — and in almost all years, this consistency is statistically significant.

The WV methods are more accurate in all years for estimating agency totals in property crimes as seen by the smaller values of MAE_{ave} in Table 9 when WV and FBI methods are compared. For violent crime data, the values of MAE_{ave} for the WV imputation methods fluctuate slightly year to year. In 2010 and 2011, the MAE_{ave} for the WV imputation methods are significantly less than the FBI. However, in 2007 and 2009 the MAE_{ave} values are the same and in 2008 the WV MAE_{ave} is slightly larger when compared to the FBI's.

Overall, the WV imputation methods provide strong evidence that simple modifications can be made to better the performance of imputation methods when used to estimate state totals. There is also compelling support that imputation methods can be used to estimate agency totals which aid research involving crime trends in smaller units of analysis.

The Utility and Impact of Imputation Methods on State-wide IRB Data

The WV and FBI imputation methods are applied to the 2007-2011 data to compute the state's crime trends in property and violent crimes to demonstrate the impact of applying imputation methods to IBR data. The imputed crime trends are compared to non-imputed data (noted "no imputation").

Figures 10 and 11 display property and violent crime trends and a corresponding chart with annual percent change for imputed and unimputed state crime totals. The five-year trend in both property and violent crimes show higher crime volume in the imputed trends when compared to the unimputed, or "no imputation," trend. This is illustrated by the location of the imputed crime trends plotted above the no imputation plot in Figures 10 and 11.

The year to year rates of change are shown in the percent change chart in each figure. The changes, or trajectories in the property crime trends are similar in magnitude for some years and conflicting for other years; the same is true for the direction of change (see Figure 10). It is worth noticing that the numbers of reporting agencies between 2007 and 2011 were relatively stable (around 255), with the exception of 2009 when the number of reporting agencies was 237. The "no imputation" property data crime trend displays a noticeable dip in 2009, which could possibly correspond to the decrease in the number of reporting agencies. The imputed trends also show decreases in crime reporting between 2008 and 2009; however, the downward trend continues from 2009 to 2010, whereas the "no imputation" trend increases from 2009 to 2010. These results support the suppositions that property crime trends may be affected by the number of reporting agencies and that imputation has the potential to fill in missing information. However, the different imputation methods resulted in different annual rates of change and have an impact on the trajectory and magnitude of the crime trend.

For violent crime data, the five-year crime trend among all methods are very similar with the exception of 2010 to 2011, which showed a decrease in the data reporting "no imputation" and an increase in both imputation methods. The size of change when comparing all methods does vary (see Figure 11).

Discussion and Conclusions

Data quality continues to be an issue for researchers, analysts, and stakeholders concerned with data accuracy and completeness. While WV is a 100% reporting NIBRS state, this study illustrates that upon close examination, issues of NIBRS data accuracy and completeness remain. These findings confirm the need for techniques and tools that identify and resolve data quality issues.

This research tested and validated techniques, developed by the WVSAC, and resulted in the ability to methodically and efficiently identify missing and irregular data. The study then demonstrated that imputation methods can be used reliably to estimate for missing or irregular data and produce results that are stable over time. Specifically, the imputation methods developed by the WVSAC are more consistent and accurate at estimating data when compared to conventional methods.

The techniques tested to deal with missing and irregular values in WVIBRS data were consistent at identifying and classifying suspect data over time. Historical reporting patterns were used to validate the results of zero classification guidelines and outlier detection methods and substantiate that an agency's monthly reporting pattern is a suitable resource to help determine whether there are issues in reporting (i.e., for missing data, whether a zero is a missing value or a true zero and for outlier detection, whether the a reported value is irregular or acceptable). For both zero classification and outlier detection, the regularity in performance means that the guidelines provide a systematic approach for identifying and classifying data. This,

Report Highlights...

When estimating for annual state crime totals, WV imputation methods outperformed the methods currently used by the FBI.

The WV imputation methods performed with significantly greater consistency when estimating for state and agency annual crime totals according to RMSE.

The improved performance of WV imputation methods may be explained by their sensitivity to seasonal influences observed in monthly data patterns and population distribution.

Crime trends resulting from imputed data show an obvious difference in volume of crime compared to data reported "as is".

The data trajectory observed in the five year property crime trend suggest that the crime pattern may correspond to the number of agencies reporting data. This interaction shows the effects of reporting (or lack thereof) and potential for imputation methods to improve data quality.

The shape of the five year violent crime trend is remarkably similar for imputed and non-imputed data. This exhibits the utility and capacity for imputation methods to improve data quality for more reliable estimates of crime.

Missing data, that would otherwise go undetected and uncounted, can be reasonably projected using imputation methods and offers a way to strengthen data quality.

The results of this research can help states optimize the utility of NIBRS data, improve the accuracy and reliability of crime data over time at the state and local levels, while increasing the accuracy and use of state administrative records.

in effect, provides other states with confidence that they can apply similar methods to a single year of data and obtain accurate results. These outcomes are particularly helpful to states where longitudinal data may not be available or exist, especially true in states that are converting to NIBRS reporting.

Missing data resulting from missing and irregular reporting have an impact on crime trends and statistics. Although imputation methods have long been used on UCR data by the FBI, this study looked at the application of imputation on state IBR data and challenged the accuracy of FBI methods with alternative methods. The alternative imputation methods, developed by the WVSAC, outperformed the current FBI imputation methods when applied to state IBR data. The accuracy statistics used to measure performance concluded that the WV imputation methods were more precise and consistent compared to FBI methods.

The increase in accuracy seen using the WV imputation methods may be attributed to using quarterly averages for partial reporting agency data and modified FBI population groups (i.e., scaled by 10) to estimate non-reporting agency data. The FBI methods, consequently, use broader terms such as an annual average to estimate partial reporting agency data and larger ranged population groups to estimate non-reporting agency data. The WV imputation methods seem better suited to the distinct features of state and its data which appear to be more sparse and rural in terms crime volume and population. The alternative imputation methods offer flexibility in parameter selection which can easily be adapted to fit other states and accommodate their characteristics. This is particularly beneficial since the imputation methods developed by the WVSAC rely on state data only, whereas the FBI methods are expansive and incorporate national or regional data.

When the data quality and imputation methods were applied to the five years of property and violent crime count data, differences in crime trends were observed as a result of imputation. Overall, the crime trends derived using imputation methods show an increase in the volume of crime. For the property crime trend, the unimputed data trajectory seemed to follow a decrease in number of crimes reported that may correspond to the decrease in number of agencies reporting data in 2009. This connection may support the supposition that crime totals are affected by reporting (or lack thereof) and that reporting data "as is" might not be the most accurate or reliable for depicting crime trends or calculating yearly rates of change. The crime trend for the violent crime data with and without imputation methods are remarkably similar in their trajectory. Overall, using imputation methods to estimate for missing data (that would otherwise go undetected and uncounted) is a reasonable means to improve the capacity and utility of NIBRS data, particularly when issues of data accuracy and completeness are present.

Areas of Improvement and Modification

While the zero classification guidelines, outlier detection, and imputation methods provide techniques that strengthen the quality of NIBRS data, some improvements and modification are recommended. The proposed adjustments target cut point operation in zero classification guidelines and collective performance of outlier detection methods as a result of testing and validation.

Since the structure of the zero classification guidelines are based on an agency's total number of property crimes (TotalP) and number of months with consecutive zeros (NCZ), classification decisions are guided by the values of these helper variables being greater than or less than a cut point. No change is recommended to the cut point of 25 for TotalP. The historical reporting in agencies with zero reported in all crime categories but not classified as having missing data also had TotalP less than 25. This result validates that agencies with sparse reporting may have some months were some crimes are not committed resulting in reporting zeros and a low annual total. The validity of the NCZ cut point of "greater than 4" was tested by inspecting the classification status of agencies with NCZ equal to 4. In three out of the five years, 100% of agencies with NCZ equal to 4 were reclassified as having missing data (in the other two years, 40% and 50% of data identified were classified as missing data). These results warrant the recommendation to update the zero classification guidelines to include NCZ equal to 4. Therefore, it is suggested that Guideline 3, which originally stated that agency data with the NCZ greater than 4 were suspected of signifying missing data and required manual inspection, be changed to agency data with NCZ greater than or equal to 4 be manually inspected.

This study tested two separate, yet complementary outlier detection tools: the ratio of monthly count to median, Yi, and ratio of ranges, Rr. These novel methods were chosen over traditional outlier methods, such as the standard deviation, box plots or Dixon's Q methods, because traditional methods were concluded to be unsuccessful for identifying outliers in 12 month agency data (see LaValle, Haas, Turley, & Nolan, 2013). In the outlier analysis, agency data identified by both methods, Yi and Rr, were more likely to be classified as irregular. Given this, it may be tempting to only look at data identified by both methods; however, the results suggest that there are cases where outliers were found in data only identified by the Rr method. Therefore, it is suggested that a focus should be placed on agency data identified by Rr in addition to agency data identified by both Yi and Rr.

The quantity of data identified by the outlier detection methods was more prevalent in property crime data than in violent crime data. This can be attributed to the amount of variation in data. The volume of violent crime tends to be lower and also have less variation in the number of crimes reported month to month when compared to the volume of property crimes. Relatively speaking, the volume of property crime tends to be larger which can lead to more variation and thus, more outliers identified. While the outlier statistics, Yi and Rr, use robust measures of variation, irregular data can be challenging to detect when the data range is small. Despite this, outlying data are excessively different from what is expected or typical. The outlier detection methods offer a systematic way to readily identify potential irregular data where the analyst is left to manually inspect data and conservatively determine whether the observations are reasonable fluctuations or excessive deviations.

Future Direction

Overall, the WV imputation methods are more accurate and outperform the FBI methods when estimating for the total state crime and estimating property crimes at the agency level as evidenced by the smaller MAE, RMSE, and Bias results. The accuracy statistics reveal that the WV imputation methods are able to estimate data that are closer to original values with consistency. The resulting bias measures indicate that the FBI methods grossly underestimate data which translates to continued issues with undercounting crime. Since the bias for the WV methods is closer to zero, the data estimated using these methods tends to be closer to the original values even though they slightly overestimate. The accuracy of the WV imputation methods do waver when estimating agency totals in violent crimes and additional analysis using data from other states may offer insight as to whether these results are replicable and how to make improvements to methods. It is evident that the WV imputation methods show potential for improving the process of how to estimate for missing data; however, there continues to be room for enhancement.

Future work on improving imputation methods could consider non-reporting agency characteristics and more precise methods for imputing non-reporting agency data. A descriptive analysis of non-reporting agency characteristics (including agency function, population coverage, MSA status, population size, and number of officers) can be found in Appendix F. In general terms, almost 70% of non-reporting agencies have an associated population. This finding is meaningful since population estimates are currently the most essential component of imputation methods for non-reporting agencies. Given this, incorporating regression into the non-reporting imputation methods could be considered and have a profound impact on accuracy. This is based on the results of an initial IBR imputation study, where estimating for non-reporting agencies using regression showed optimal performance at the agency level in regards to accuracy measures (MAEave). If imputation methods using regression are sought in future research, there will have to be an accompanying component within the model to estimate for zero-population agencies since the accuracy of imputation did not perform well when estimating for the state total (MAEtot). This was likely due to the regression model not including a mechanism for incorporating zero-population crime counts (LaValle, Haas, Turley, & Nolan, 2013).[13] Non-reporting agency characteristics can be used as a baseline for investigating how zero-population agencies can be incorporated into enhancing imputation methods such as measuring the relationships between crime, the number of officers at each agency, and population size. Given that the number of officers is readily available for all agencies; this type of analysis could greatly contribute to enhancing imputation methods.

This research used a statewide longitudinal data set of IBR data to test tools that were developed by the WVSAC to assess and deal with data quality. Using established criteria and guidelines to classify zero reports and identify irregular reporting patterns, the methods were shown to be efficient and effective. The WV imputation methods demonstrate the capacity to reliably estimate for missing data and produce stable crime trends over time as a means to count crime not reported. Overall, the findings of this study have the potential to help states optimize the utility of NIBRS data, improve the accuracy and reliability of crime data over time at the state and local levels, and increase the accuracy and use of state administrative records.

Endnotes

1. While states can submit data using UCR or NIBRS, national crime statistics are calculated using UCR data.

Therefore, the FBI converts data collected using NIBRS to the UCR format.

2. In addition to incorporating the data reporting standards established by the Federal Bureau of Investigation (FBI), WVIBR data also include state-specific data fields to respond to local criminal justice issues.

3. The WVIBR data are typically received every April to ensure the same lag time in reporting for greater consistency and comparability over time.

4. U.S. Census Bureau population estimates and metropolitan statistical area status were accessed from http://www.census.gov/popest/index.html .

5. The WVSAC developed an automated tool that incorporates the zero classification guidelines and diagnostics variables. The tool helps efficiently identify agencies with potential missing data using a "Data Quality" Microsoft Excel macro-embedded spread sheet. Once data are entered and the macro is executed, the tool assesses the data and creates columns for the diagnostics and helper variables. Agencies with suspected missing data are highlighted according to the zero classification guidelines and require manual inspection to classify data as missing values or true zeros.

6. Population coverage is used to categorize agencies based on whether a given agency is associated with a population estimate. There are two population coverage categories, population and zero-population. Population agencies are municipal police departments and county sheriff departments that have an associated population and zero-population agencies are those that usually fall within a city or county (e.g., campus police, fish and game police, task force, etc.), or are national or statewide agencies (e.g., state police, etc.).

7. The WVSAC developed an automated tool that incorporates the Rr and Yi outlier detection methods and graphical analysis to identify potential irregular reporting. After the process of identifying missing values has been completed in the "Data Quality" Microsoft Excel macro-embedded spread sheet, outlier detection can by performed by executing a macro. The macro calculates the Rr and Yi statistics and creates the three plots. Agencies and data exceeding the user-defined thresholds are highlighted and require manual inspection. The user-defined thresholds are set to default values based on previous work (see LaValle, Haas, Turley, & Nolan, 2013), but can be manipulated according to the user's needs.

8. Dixon-type outlier methods are derived from the Dixon-Q outlier detection test that uses the ratio of 'gap' to 'range' to detect outliers in data from a small sample size. The Dixon-Q outlier statistic uses order statistics and calculates the ratio of the absolute difference between two consecutive (or near consecutive) points and the data's range.

9. The moving average is a statistical method that calculates a series of averages using a subset of data. This method is often used in time-series data as a way to handle short term fluctuations in data (R. Yaffee & M. McGee, 2000).

10. The scalar 1/10 was selected so that all WV population groups would be represented with frequency of five or more agencies and adequate data would be available to compute crime rates.

11. A random seed is used as a fixed starting point for a random number sequence. Random seed 22314 was used for selecting agencies and random seed 921 was used for selecting the start month for removing data.

12. There was one case in which data originating from a college or university were classified as missing. In this case, the volume of crime reported was high (TotalP = 237). While the missing month was August, the historical data showed consistent nonzero reporting throughout the year.

13. Imputation methods using population groups

are able to capture zero-population crime counts by including their counts when calculating crime rates, which inflates estimates, but residually account for non-reported zero population crimes when imputing (Barnett-Ryan, 2007).

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Appendix A: West Virginia and FBI population groups for non-reporting agencies.

$$\textit{Crime Total} = \frac{\text{Population Group Crime Rate*Agency's Population}}{100{,}000}$$

Group	WV Population Groups	FBI Population Groups
1	25,000+	250,000+
2	10,000 - 24,999	100,000 - 249,999
3	5,000 - 9,999	50,000 - 99,999
4	2,500 - 4,999	25,000 - 49,999
5	1,000 - 2,499 + colleges*	10,000 - 24,999
6	Less than 1,000	Less than 10,000 + colleges
7	Not Applicable	Included with Group 6
8	Non-MSA counties & State Police	Non-MSA counties & State Police
9	MSA counties & State Police	MSA counties & State Police

*The authors' previous study concluded that the best performing WV imputation method included colleges and universities in Group 5.

Appendix B: Zero classification guidelines diagnostic variable values (TotalP and NCZ). Table B1 shows the classification rates for population and zero-population agencies. Table B2 shows characteristics of agencies not identified by guidelines by number of NCZ.

Table B1: Number of agencies identified and classification rates (number classified / number identified) for zero classification guideline variables (TotalP and NCZ) in population (top %) and zero-population (bottom %) agencies.

Year	TotalP>25	NCZ = 1	NCZ = 2	NCZ = 3	NCZ = 4	NCZ = 5	NCZ = 6	NCZ = 7	NCZ = 8	NCZ = 9	NCZ = 10	NCZ = 11
2011	11, 100%	8, 100%	NO	1, 100%	5, 40%	5, 100%	1, 100%	5, 100%	3, 100%	2, 100%	3, 100%	2, 100%
	NO	NO	NO	NO	5, 0%	2, 0%	7, 0%	2, 0%	3, 0%	7, 0%	8, 0%	3, 0%
2010	6, 100%	6, 100%	NO	NO	2, 100%	1, 100%	1, 100%	1, 100%	1, 100%	5, 100%	NO	NO
	NO	NO	NO	NO	3, 0%	5, 0%	2, 0%	4, 0%	4, 0%	3, 0%	5, 0%	3, 0%
2009	10, 100%	6, 100%	3, 100%	NO	4, 100%	5, 100%	1, 100%	3, 100%	2, 100%	3, 100%	NO	NO
	1, 0%	NO	1, 0%	NO	2, 0%	2, 0%	2, 0%	6, 17%	1, 0%	5, 0%	4, 0%	3, 0%
2008	6, 100%	3, 100%	2, 100%	1, 100%	4, 50%	5, 100%	6, 100%	9, 100%	2, 100%	1, 100%	4, 100%	2, 100%
	2, 100%	2, 100%	NO	NO	4, 0%	9, 11%	5, 0%	2, 0%	1, 0%	1, 0%	4, 0%	1, 100%
2007	13, 100%	6, 100%	4, 100%	2, 100%	4, 100%	5, 100%	4, 100%	3, 100%	4, 100%	3, 100%	2, 100%	2, 100%
	1, 0%	1, 0%	NO	NO	2, 0%	5, 20%	2, 0%	2, 0%	2, 0%	3, 0%	1, 0%	2, 0%

NO = no observed data

Notes: The TotalP and NCZ columns in this table are not mutually exclusive, meaning number of agencies that are identified and/or classified in the TotalP column are also counted in the NCZ section of the table. All agencies identified and classified for NCZ = 1, 2, or 3 had TotalP > 25. In all but three cases, agencies with NCZ > 4 where identified and classified using NCZ criteria (Guideline 3) alone.

Table B2: Maximum total number of property crimes (TotalP) and type of agency not identified by the zero classification guidelines grouped by the number of consecutive zeros (NCZ)

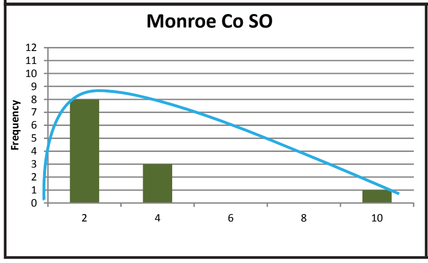
Year	NCZ = 3	NCZ = 2	NCZ = 1
2011	17, Population (CSD)	9, Population (MPD)	20, Population (MPD)
2010	19, Population (MPD)	22, Population (MPD)	24, Population (MPD)
2009	10, Population (CSD)	2, Population (CSD)	18, Zero-population (HED)
2008	22, Zero-population (HED)	21, Zero-population (HED)	20, Population (MPD)
2007	24, Population (CSD)	22, Population (MPD)	24, Population (MPD)

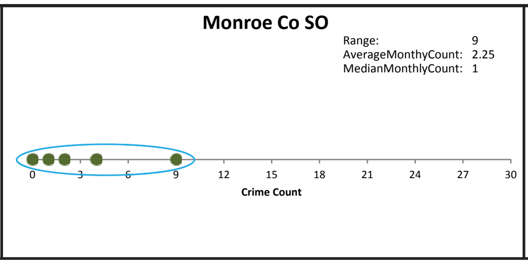
CSD = County Sheriff Department, HED = Law Enforcement at Higher Education, MPD = Municipal Police Department

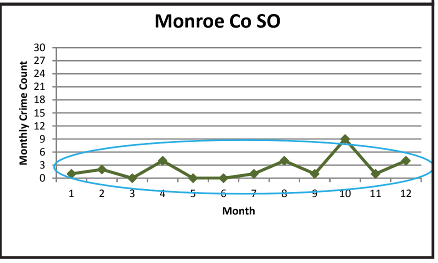
Appendix C: Plots of data (histogram, dot plot, and line chart) with acceptable reporting, irregular reporting classified by both outlier detection methods, and irregular reporting classified by Rr outlier detection methods only.

<u>Acceptable data</u> - outlier detected but **NOT classified**.

Identified by **both** outlier methods: Rr = 2.7, Yi = 9,
Histogram is *skewed right*,
Dot plot shows *reasonable spread*,
Line chart looks *fairly steady*.

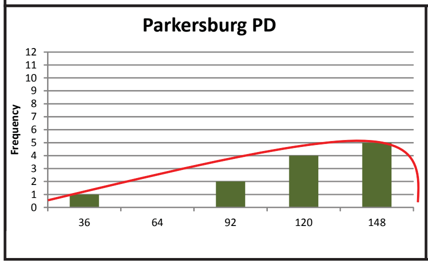


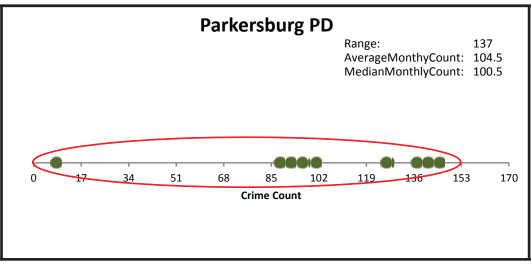


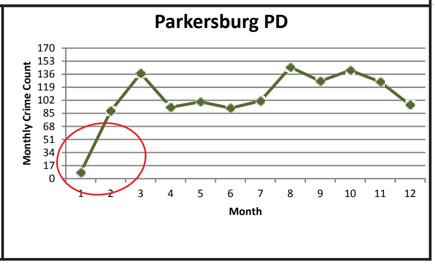


<u>Outlier detected</u> - outlier detected and classified.

Identified by **both** outlier methods: Rr = 10.1, Yi = 0.08,
Histogram is *skewed left*,
Dot plot shows *wide spread*,
Line chart shows *distinct valley*.

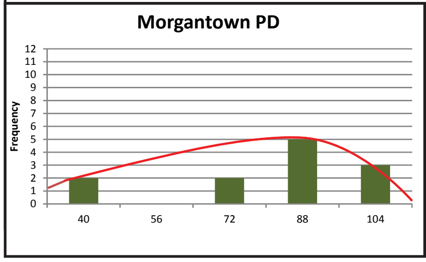


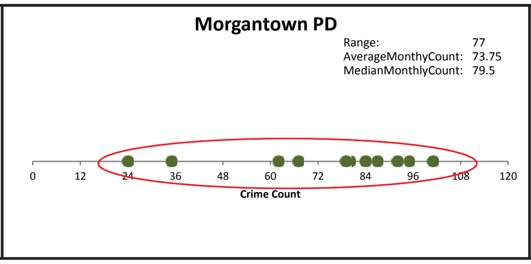


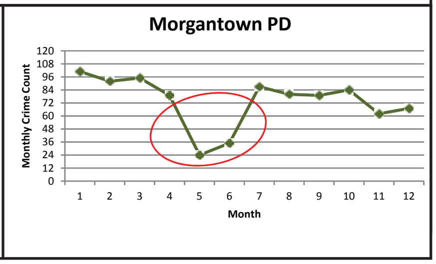


<u>Outlier detected</u> - outlier detected and classified.

Identified by **Rr outlier** method: Rr = 4.8, Yi = 0.3,
Histogram is *skewed left*,
Dot plot shows *wide spread*,
Line chart shows *distinct valley/sharp drop*.



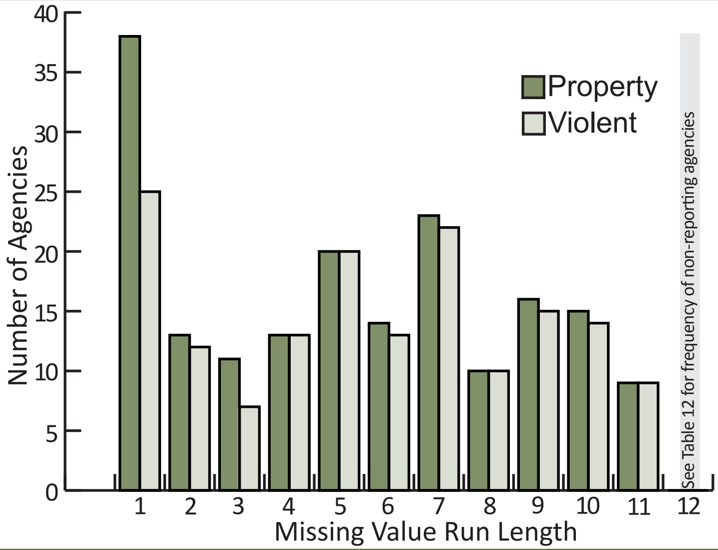




Appendix D: Summary of agencies with data classified as having outliers in violent and property crime data that were identified using both outlier detection methods, Yi and Rr.

	Violent crime data		Property crime data	
Year	Number of agencies with data **classified** as outliers	Percentage of agencies that were identified using Yi and Rr AND **classified** as outliers	Number of agencies with data **classified** as outliers	Percentage of agencies that were identified using Yi and Rr AND **classified** as outliers
2011	1	100%	10	90%
2010	0	na	4	100%
2009	1	100%	5	100%
2008	0	na	6	67%
2007	0	na	4	100%
Average				91%

Appendix E: Property and violent crime data missing value pattern and corresponding percentages for 2007 to 2011 West Virginia IBR data.



Missing Value Run Length	Percentage Missing (Property)	Percentage Missing (Violent)
1	0.019	0.013
2	0.007	0.006
3	0.006	0.004
4	0.007	0.007
5	0.010	0.010
6	0.007	0.007
7	0.012	0.011
8	0.005	0.005
9	0.008	0.008
10	0.008	0.007
11	0.005	0.005
12	0.344	0.344

Appendix F: Non-reporting agency descriptive analysis - methods and results.

Descriptive Analysis of Non-reporting Agencies

The need for investigating the characteristics of non-reporting agencies, or agencies that reported no data for a particular year, stems from the mechanics of imputation methods and the results of prior work done by the WVSAC investigating alternative imputation methods.

First, imputation methods for non-reporting agencies that use population group crime rates and population to estimate missing data are not able to directly imputing data for zero-population non-reporting agencies. This is because population group crime rates are able to capture zero-population crime counts by including their counts when calculating crime rates, thereby inflating estimates and residually accounting for non-reported zero-population crimes when imputation is applied (Barnett-Ryan, 2007). Both the alternative imputation methods develop by the WVSAC investigated in this study and the current FBI imputation methods use population groups.

Second, the WVSAC investigated regression based imputation methods for non-reporting agencies which outperformed all other methods when estimating for agency totals but performed with diminished accuracy when estimating for state totals (see LaValle, Haas, Turley, & Nolan, 2013). The performance of regression based imputation methods for estimating the state total was theorized to falter because the methods had no variable to incorporate zero-population agencies, therefore those estimates were not imputed and remained zero. The resulting conclusion was that by understanding the characteristics of non-reporting agencies, imputation methods could be improved and alternative information, other than population, could be incorporated into imputation methods. Since the performance of the imputation methods is achieved through simulation, where all agencies have equal chance of being simulated as missing, this analysis offers an investigation of the true nature of non-reporting agencies in IBR data to further guide the exploration of alternative imputation methods.

Descriptive analyses of non-reporting agencies are performed to develop a basis for non-reporting agency characterization. Data used for characterization include population size and number of law enforcement officers for each agency from the West Virginia State Police annual report titled, "Crime in West Virginia," (http://www.wvsp.gov/about/Pages/Publications.aspx) and Metropolitan statistical area status was obtained from the U.S. Census Bureau (http://www.census.gov/population/metro/about/).

Population and Functional Characteristics of Non-Reporting Agencies

Non-reporting agencies are identified by comparing originating agency identification numbers (ORIs) that reported WVIBR data and a master list of agency ORIs maintained by the West Virginia State Police. The master list included 421 agencies, however, 31 indicated "No PD." This resulted in the agency population of 390 and is used to define the population of law enforcement agencies in West Virginia.

To assist with characterizing non-reporting agencies, all agencies are grouped according to their function into seven categories: municipal police departments (MPD), county sheriff departments (CSD), state police detachments (SP), division of natural resources (DNR), higher education police departments (HED, consisting of agency names with key words "college," "university," "campus," or "Tech"), targeted enforcement agencies (TEA, including agencies with key words "Task Force," "BCI," or "Unit"), and other agencies (including "County Parks" and "Capital Protective Services" agencies).

Agencies are also grouped by whether they cover an associated population: population (MPD and CSD agencies) and zero-population (SP, DNR, HED, TEA, and other agencies).

County sheriff departments are categorized by their metropolitan statistical area (MSA) status. The MSA status is assigned to counties by the U.S. Office of Management and Budget and helps identify geographical areas with a larger population density and high degree of social and economic integration (U.S. Census MSA). While the MSA status of a county can change from year to year due to population, social, and economic growth, all MSA designations for WV's 55 counties stayed the same during the 2007 to 2011 period.

Data used to describe non-reporting agencies included population size and number of officers which are obtained from the WV State Police annual reports. The mean population size and number of officers data from non-reporting and reporting agencies are compared using Student's t-test in SPSS. Due to the nature of data distributions for population and number of officers (i.e., count data with a skewed distribution), a log (x + C) transformation is applied to the data before running the comparison tests, where C = 0 for the population data and C = 1 for the number of officers data to meet the assumption of normality.

Utility of Methods for Identifying Characteristics of Non-reporting Agencies

Developing a context to describe agencies that do not report data for a given year can assist with generalizing agency non-reporting characteristics to better understand missingness and guide the development of more accurate imputation methods. Understanding non-reporting characteristics may help determine the appropriateness of imputation methods and how the methods can be improved. For example, the imputation methods investigated in this study use population size to estimate for missing data. If it is found that a significant portion of non-reporting agencies are from zero-population agencies, then future work involving imputation methods should work towards using data other than population to improve the methods.

Using the agency name and ORI provided by the West Virginia State Police, we placed each agency into one of seven categories based on the agencies' function, one of two categories based on population coverage and placed each county sheriff department in one of two categories based on MSA status.

Municipal police departments and law enforcement at the division of natural resources have the highest instances of non-reporting; state police detachments, targeted enforcement agencies, and county sheriff departments tended to have much smaller percentages of non-reporting (see Table F1). These results suggest that the majority of non-reporting agencies are municipal police departments followed by division of natural resources.

Nearly 70% of non-reporting agencies were population agencies and the remaining 30% were categorized as zero-population. Compared to the percentages of reporting agencies and from complete West Virginia State Police agency list, there seems to be an over-representation of population type agencies and under-representation of zero-population agencies in the non-reporting data (see Table F2 for reporting agency and Table F3 for all agencies listed on the West Virginia State Police agency list).

The majority of West Virginia's counties are designated as non-MSA (62%) and the percentages of sheriff offices in non-MSA and MSA counties are similar among reporting agencies and the West Virginia State Police agency list (see Tables F2 and F3). Nearly 70% of non-reporting sheriff agencies were in non-MSA counties (see Table F1). While there are very few county sheriff agencies that do not report data, sheriff departments in non-MSA counties are less likely to report data than sheriff departments in MSA counties.

The number of officers and population size of an agency also gave useful information about agency characteristics. In general, the average number of officers at non-reporting agencies was smaller than the number of officers at reporting agencies (see Table F4).

For municipal police department and county sheriff departments, the average numbers of officers at non-reporting agencies are significantly less than at reporting agencies at the 0.05 level (see Tables F5 and F6 for additional descriptive statistics).

Differences in population size between non-reporting and reporting municipal police departments and county sheriff agencies are also examined. For all years, the average population size of non-reporting agencies was significantly less than the average population of reporting agencies in both municipal police and county sheriff departments (see Table F7; see Tables F8 and F9 for additional descriptive statistics).

The descriptive analysis of non-reporting agencies offers an initial look at characteristics such as agency function, population served, MSA status, officer totals, and population size. The results suggest that non-reporting agencies tend to be smaller jurisdictions based on the number of officers at the agency, population size, and MSA status. The tendency for non-reporting agencies to be smaller or less populated is consistent with what was found in other studies that used national UCR data and population groups to determine patterns of crime data missingness (Maltz, Roberts, & Stasny, 2006). Within the WVIBR data, it was found that on average, over 60% of non-reporting agencies were municipal police departments and nearly 25% were DNR offices. The percentages of agency characteristics for non-reporting agencies were consistent in the longitudinal data, which may offer valuable insight for improving imputation methods performed on crime count data.

Table F1: Summary of **non-reporting** agencies by agency function, population reporting, and MSA status.

Year	n	MPD	CSD	SP	DNR	HED	TEA	Other	Pop	ZPop	MSA	non-MSA
2011	124	71%	5%	1%	18%	1%	4%	1%	76%	24%	33%	67%
2010	136	68%	3%	1%	24%	1%	3%	1%	71%	29%	25%	75%
2009	153	66%	4%	1%	24%	2%	2%	1%	70%	30%	33%	67%
2008	127	61%	6%	1%	28%	1%	3%	<1%	67%	33%	29%	71%
2007	130	58%	5%	1%	33%	1%	2%	<1%	63%	37%	33%	67%
Average		64%	5%	1%	25%	1%	4%	<1%	69%	31%	30%	70%

n = number of non-reporting agencies, MPD = Municipal police department, CSD = County Sheriff, SP = State Police Detachment, DNR = Division of Natural Resources, HED = Law Enforcement at Higher Education, TEA = Targeted Enforcement, Pop = Population agencies, ZPop = Zero population agencies, MSA = Metropolitan Statistical Area

Table F2: Summary of **reporting** agencies by agency function, population reporting, and MSA status.

Year	n	MPD	CSD	SP	DNR	HED	TEA	Other	Pop	ZPop	MSA	non-MSA
2011	266	33%	18%	24%	13%	4%	7%	<1%	52%	48%	39%	61%
2010	254	33%	20%	26%	9%	4%	7%	<1%	54%	46%	39%	61%
2009	237	32%	21%	27%	8%	3%	8%	<1%	53%	47%	39%	61%
2008	263	38%	18%	25%	8%	4%	7%	1%	56%	44%	40%	60%
2007	260	39%	19%	25%	5%	4%	8%	1%	58%	42%	39%	61%
Average		35%	19%	25%	9%	4%	7%	1%	55%	45%	39%	61%

Table F3: Summary of **ALL** agencies (West Virginia State Police complete agency list) by agency function, population reporting, and MSA status.

	n	MPD	CSD	SP	DNR	HED	TEA	Other	Pop	ZPop	MSA	non-MSA
All WV law enforcement agencies	390	45%	14%	17%	14%	3%	6%	1%	59%	41%	38%	62%

Appendix F: Non-reporting agency descriptive analysis - methods and results. (Continued)

Table F4: Average number of officers at non-reporting and reporting agencies (average non-reporting (SD); average reporting (SD))

Year	MPD	CSD	SP	DNR	HED	TEA
2011	2 (3); 14 (24)*	5 (1); 21 (17)*	0 (na); 7 (6)	1 (1); 2 (1)	2 (na); 12 (14)	1 (2); 4 (3)
2010	2 (2); 15 (25)*	4 (1); 20 (17)*	0 (na); 7 (5)	2 (1); 2 (1)	3 (1); 13 (13)	3 (3); 4 (4)
2009	2 (2); 16 (26)*	6 (2); 20 (17)*	0 (na); 7 (6)	2 (1); 2 (1)	3 (2); 14 (16)	1 (2); 3 (4)
2008	2 (2); 13 (23)*	6 (3); 20 (18)*	0 (na); 7 (6)	2 (1); 2 (2)	1 (na); 12 (15)	3 (3); 2 (4)
2007	2 (2); 12 (23)*	6 (2); 19 (17)*	0 (na); 7 (5)	2 (2); 2 (2)	1 (na); 12 (15)	4 (2); 1 (2)

*Significant at 0.05, MPD = Municipal Police Department, CSD = County Sheriff, SP = State Police Detachment, DNR = Division of Natural Resources, HED = Law Enforcement at Higher Education, TEA = Targeted Enforcement

Table F5: Descriptive statistics (maximum, minimum, average, median) for number of officers at **non-reporting** agencies by agency function.

Year	MPD				CSD				SP				DNR				HED				TEA			
	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med
2011	14	0	2	1	6	3	5	5	0	0	0	0	5	0	1	1	2	2	2	2	5	0	1	0
2010	11	0	2	1	5	3	4	4	0	0	0	0	4	0	2	1	3	2	3	3	6	0	3	2
2009	11	0	2	2	10	4	6	6	0	0	0	0	5	0	2	2	5	2	3	2	3	0	1	0
2008	13	0	2	1	9	1	6	5	0	0	0	0	5	0	2	1	1	1	1	1	6	0	3	3
2007	13	0	2	1	9	3	6	5	0	0	0	0	10	1	2	2	1	1	1	1	5	2	4	4

Table F6: Descriptive statistics (maximum, minimum, average, median) for number of officers at **reporting** agencies by agency function.

Year	MPD				CSD				SP				DNR				HED				TEA			
	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med	Max	Min	Ave	Med
2011	161	1	14	6	102	3	21	16	29	0	7	5	6	0	2	2	49	3	12	7	13	0	4	4
2010	175	0	15	6	102	3	20	15	25	0	7	5	4	1	2	2	45	5	13	7	16	0	4	3
2009	179	1	16	7	100	2	20	16	26	0	7	5	4	1	2	2	52	3	14	8	15	0	3	2
2008	176	0	13	6	99	2	20	16	25	0	7	5	9	0	2	2	52	2	12	7	14	0	2	0
2007	180	0	12	5	93	2	19	16	24	0	7	5	6	1	2	2	51	2	12	7	7	0	1	0

Table F7: Average population size at non-reporting and reporting agencies (average non-reporting (SD); average reporting (SD))

Year	MPD	CSD
2011	1,051 (1,140); 5,949 (9,296)*	10,056 (5,240); 24,094 (19,276)*
2010	877 (620); 6,339 (9,466)*	8,274 (1,544); 23,675 (19,595)*
2009	969 (782); 6,709 (9,683)*	10,487 (5,407); 23,482 (19,141)*
2008	1,002 (1,113); 5,373 (8,822)*	10,326 (4,911); 23,681 (18,877)*
2007	990 (1,111); 5,295 (8,752)*	10,401 (5,457); 23,399 (18,780)*

*Significant at 0.05 MPD = Municipal Police Department, CSD = County Sheriff Department

Appendix F: Non-reporting agency descriptive analysis - methods and results. (Continued)

Table F8: Descriptive statistics (maximum, minimum, average, median) for population size at **non-reporting** agencies by agency function.

Year	MPD				CSD			
	Max	Min	Ave	Med	Max	Min	Ave	Med
2011	7,740	160	1,051	673	20,605	7,075	10,056	8,047
2010	2,821	228	877	691	10,163	6,665	8,274	8,135
2009	5,538	222	969	736	21,264	6,631	10,487	8,666
2008	7,230	225	1,002	690	21,188	6,776	10,326	8,880
2007	7,230	225	990	690	21,188	6,623	10,401	8,812

Table F9: Descriptive statistics (maximum, minimum, average, median) for population size at **reporting** agencies by agency function.

Year	MPD				CSD			
	Max	Min	Ave	Med	Max	Min	Ave	Med
2011	51,466	355	5,949	2,447	93,334	5,663	24,094	19,586
2010	50,822	785	6,339	2,585	96,785	5,452	23,675	18,651
2009	50,132	781	6,709	2,958	94,497	5,261	23,482	18,055
2008	50,510	246	5,373	2,242	94,104	5,300	23,681	18,948
2007	50,510	246	5,295	2,242	94,104	5,300	23,399	18,060