Addressing Data Quality in Ohio's Incident-Based Reporting System:

Application of Akiyama and Propheter (2005) Outlier Detection Methods

Authors:
Kristina Nicholson, M.S.
Alan Wedd, M.S.
Charles Partridge, Ph.D.

Ohio Department of Public Safety
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Office of Criminal Justice Services

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Abstract

Crime data are collected nationally through the Federal Bureau of Investigation's Uniform Crime Reporting Systems and the National Incident-Based Reporting System. Law enforcement agencies in Ohio have been submitting data to the federal system since 1989 through the Ohio Incident-Based Reporting System. These crime data are used to construct crime reports, provide data for crime mapping, and ultimately provide support to inform policy and practice throughout the state. Given the importance of crime data, continuous data quality and improvement is also a high priority. Federal and state systems implement logical checks on the data submitted by law enforcement agencies, but currently only the federal system has automated checks in place to determine the reasonableness of the data that submitted by local agencies. At the local level, the onus of these checks is put on the data systems coordinator through manual inspections. The current project moves to fill this gap by applying Akiyama and Propheter's (2005) federally-used outlier detection methods to Ohio's incident-based data. Additionally, the project expanded beyond Akiyama and Propheter (2005) by adapting methods to account for critical cut points that limit the number of agencies identified as outliers. This report summarizes the methods applied to Ohio's 2014 and 2015 OIBRS data and discusses the next steps in automating implementation of additional data quality checks at the state-level.

Introduction

Collecting and sharing crime data has been a national priority for the last century, with the conception of the Uniform Crime Reporting (UCR) Program in 1929 and implementation by the Federal Bureau of Investigation in 1930. Since then, the program has been building a database of information submitted voluntarily by law enforcement agencies throughout the United States with annual reports spanning the last eighty years. The data collected through the UCR program is limited however, in that it provides summary data on crime and information is collected based on a hierarchy of crimes, meaning that agencies report only the highest offense of crime within an incident for the summary data. To address these limitations, the Federal Bureau of Investigation (FBI) created the National Incident-Based Reporting System in 1988 to improve the quality of crime data collected and reported by law enforcement (Federal Bureau of Investigation, 2018). With its introduction, the FBI began reporting specific details on separate offenses within the same incident such as information on victims, offenders, and property-involved crimes. With the addition of NIBRS, crime data moved beyond a monthly aggregate of crime to the ability to examine specific circumstances for crimes (Federal Bureau of Investigation, 2017A).

In contribution to NIBRS, the Ohio Office of Criminal Justice Services has maintained the Ohio Incident-Based Reporting System (OIBRS), a state-level system of the NIBRS since 1999. OIBRS is a voluntary crime-reporting program that allows state and local law enforcement agencies to submit crime statistics directly to the state and federal government, with approximately 54% of Ohio's law enforcement reporting to OIBRS, covering approximately 77% of Ohio's population. Given the population coverage, OCJS is able to provide state-level crime reports, local crime reports for reporting agencies, as well as benefits such as crime mapping and improved tools for local crime analysis.

Addressing Data Quality

To ensure accurate and reliable data, information submitted by local law enforcement agencies to the state go through validation processes before final inclusion in NIBRS and UCR reporting (pg. 128-66, Office of Criminal Justice Services, 2017). Law enforcement agencies must use a reporting management system (RMS) vendor that is certified by the state, meeting requirements set by the OIBRS administrator including a sustained submission error rate of four percent or less for three consecutive monthly submissions (Office of Criminal Justice Services,

2004). If errors in reporting are present, they are identified upon submission of data to OIBRS through a data validation process.

This validation process includes three groups of edits (i.e. rules that must be met for the submitted report to be considered accurate): incident-level edits, data element-level edits, and offense-level edits (Office of Criminal Justice Services, 2017). Incident-level edits validate the consistency of the incident as a whole to determine if all of the required segments are submitted, and that the relationships between the segments are logical. Data element-level edits validate the codes entered for specific data elements as well as test the relationships among data elements within specific report segments. Lastly, offense-level edits validate the information that is submitted for specific offenses, such as the crime type (e.g. crime against an individual, society or property) and implied edits. Implied edits validate that the implied information of the offense are also included in the report. For example, if homicide is the offense reported, then additional information such as weapon type/force used and aggravated assault/homicide circumstances must also be reported with the incident. If any of these rules are violated, an error is sent back to the reporting agency providing the opportunity to fix the reporting element and resubmit. If the agency does not resubmit, then these data are excluded from the agency's reported data.

The data validation process occurs automatically. However, once data are submitted and have passed the logical edits, additional checks are needed at the local level to identify data that may be unreasonable due to reasons outside of logical errors. While questions around incident-based reporting data quality have historically been a topic of interest (Maltz & Weiss, 2006; Maltz, 1999), recent research has offered guidance for database administrators to address data quality concerns, specifically with regards to the presence of missing and irregular data. Maltz (1999) references visually checking local data for potential errors, referencing excessively high or low figures compared to surrounding data. More recently, Akiyama and Propheter (2005) provided guidance on conducting reasonableness tests for outlier detection, or rather, the occurrence of data identified as much higher or lower than what would be expected when compared to data from agencies with similar characteristics. It is important to note that data identified as outliers are not automatically considered inaccurate or infeasible. Rather, outlier detection is only one step in determining the reasonableness and utility of the data that have been submitted (Akiyama & Propheter, 2005).

In 2005, Akiyama and Propheter identified three primary methods of detecting outliers, namely cross-sectional outliers, longitudinal outliers and distributional outliers (Table 1). In cross-sectional comparisons, an agency's crime rate for a given time period are compared to the median crime rate for similar agencies in the same reporting period. Similarly, distributional outliers are determined by examining the ratio of certain crime types within an agency compared to the ratio for similar agencies within a given reporting period. Longitudinal outliers take into account changes in crime rates over time. In efforts to address data reliability, the FBI has implemented outlier detection methods that examine an agency's crime data from month to month and year to year, compared to other agencies of similar characteristics (Federal Bureau of Investigation, 2017A). With regard to Ohio data however, these methods apply only to those agencies that have passed through Ohio's validation methods and are subsequently submitted to the federal system.

Table 1. Description of Outlier Types as detailed in Akiyama and Propheter (2005) Methods of Data Quality Control: For Uniform Crime Reporting Programs

Outlier Type	Description
Cross-Sectional Outlier	An agency's crime rates for a given time period are compared to the median crime rate for similar agencies in period.
Longitudinal Outlier	An agency's crime rates are compared to the agency's preceding crime rates to determine consistency in reporting over time.
Distributional Outlier	An agency's proportion of designated crimes or distributions of reported crimes are compared to proportions/distributions of similar agencies within a given time period.

Given that Ohio does not currently have automated methods for examining data quality outside of the data validation process, the current project tested the methods from the Department of Justice, Criminal Justice Information Services Division of the Federal Bureau of Investigation (i.e. Akiyama and Propheter, 2005) for identifying cross-sectional, longitudinal, and distributional outliers on Ohio incident-based reporting data. This method will inform an additional check-and-balances system by prompting law enforcement review of data submitted to the Ohio Incident-Based Reporting System that have been flagged as outliers. Once applied, researchers worked with the state's OIBRS program coordinator to determine the feasibility of automating a process in which law enforcement agencies are notified of potential data quality

issues prior to data submission in the Ohio system. The methods applied to the data and subsequent results are described on the following pages.

Methods

Data Overview

Outlier detection methods for this study were applied to OIBRS data from 2014 to 2015 (Office of Criminal Justice Services, 2018). Crime totals were first determined for participating agencies by querying incident-level information from the years of interest. Crime totals were then aggregated by month (January through December) and year (2014 and 2015), across multiple crime types. Crime types were determined by the Uniform Crime Reporting program definitions of property crime and violent crime, as well as all offenses (i.e. non-index crimes), regardless of crime type. See Table 2 for an overview of offense types and UCR code designations for property and violent crime.

Table 2. Overview of offense type by crime category

Offense Type	UCR code
Violent Crime	
Aggravated assault	13A
Murder/Non-negligent manslaughter	09A
Robbery	120
Rape	11A
Property Crime	
Arson	200
Burglary	220
Larceny	23A
Motor vehicle theft	240

Missing Data

Prior to applying the Akiyama and Propheter (2005) methods to the OIBRS data, an additional data quality step was applied to identify agencies that had complete data compared to those agencies that did not report or were missing data. Identifying agencies with missing data compared to agencies with true zeros within incident-based reporting systems can be a challenge, given that zeros are populated in the database when no crime is reported by an agency. If no crime is reported by an agency for a given time period, it may be that there was truly zero crime within the agency's jurisdiction, or it could indicate that the data are missing for the agency within a given timeframe.

To determine if zeros within the database represented zero crime totals or missing data (i.e. zero classification), methods developed by LaValle and colleagues (2014) were applied. The guidelines applied included:

1) If an agency reported a monthly violent, property or non-index crime count that was non-zero, any zero reported for that month is considered a true zero.
2) If the violent, property or non-index crime totals for an agency are all zero for a particular month, and the total number of annual property crimes for that agency is great than 25, then the zeros were considered missing.
3) If an agency reported zeros for all crime types for at least four consecutive months (i.e. one quarter within the year), then those zeros are considered missing.
4) Guidelines 2 and 3 do not apply to agencies that have zero populations within the reporting system, such as universities/colleges and parks.

After monthly OIBRS crime totals were determined in a Microsoft Excel Worksheet, a macro-enabled workbook from the Justice Research and Statistics Association Incident-Based Reporting Resource Center was used to apply the zero classification guidelines (LaValle, 2014). These methods identified months that contained potentially missing data. Once months were identified, the data were then manually inspected and classified as either missing data or true zeros, resulting in a "completeness" indicator within the dataset. Given the types of analyses to be completed, data were categorized as *complete* for an agency if there were two complete years of data available for the agency. Using these methods, 457 agencies in the OIBRS system between 2014 and 2015 were identified as having complete data, however, analyses excluded "zero-population" agencies, such as state-level law enforcement (e.g. Ohio State Highway Patorl, Bureau of Criminal Investigation), colleges and universities, and parks (e.g. Butler County Metro Park, Cedar Point, Cleveland Metroparks Ranger Department, etc.). With these agencies excluded, 433 agencies were included in final analyses.

Agency Strata Development

One of the basic premises of outlier detection is determining if a given agency's data is substantially different compared to the expected based on agencies with similar characteristics. To make this comparison, agency classifications or stratifications were developed. Akiyama and Propheter (2005) determined agency stratification based on four factors including jurisdictional

size (i.e. agency's population size), geographic area where an agency is located (i.e. geographic regions/U.S.), the degree of urbanization (i.e. Metropolitan Statistical Area or not) and the agency type (i.e. sheriff's office or police department). Given that the current study only examined Ohio agencies, compared to Akiyama and Propheter methods that examined law enforcement agencies across the United States, the number of agencies on which the strata are based are limited. Applying the four factors to the 433 Ohio agencies with completed data would limit the overall number of agencies within a given strata for comparison in a way that would severely hinder the ability to determine outliers. To mitigate the potential of low agency representation within a given strata, the following factors were used when developing strata for the current study.

1) Jurisdiction size of agencies; and
2) Geographic level of coverage (i.e. county sheriff's offices or city/local police).

Jurisdiction size classification was determined by percentile cuts to create five groups for the county level agencies. This method was also used for city/local police agencies, however given that there were several metropolitan agencies skewing the overall data, a sixth strata was created to account for local agencies with population sizes over 75,000 people. In total, eleven strata were developed as the foundation for the Akiyama and Propheter (2005) outlier detection methods. Table 3 indicates the population cut points for each strata as well as stratum frequency.

Table 3. Strata characteristics and frequencies

Level	Strata	Population Size	Frq	%
Sheriff Offices	1	Less than 18,953	15	3.5
	2	18,954 – 25,643	11	2.5
	3	25,644 – 33,543	16	3.7
	4	33,544 – 53,341	14	3.2
	5	More than 54,331	15	3.5
Local/City Police Departments	6	Less than 1,357	65	15.0
	7	1,358 – 2,736	71	16.4
	8	2,737 – 6,310	68	15.7
	9	6,311 – 14,057	71	16.4
	10	14,068 – 75,000	74	17.1
	11	More than 75,000	13	3.0

Outlier Detection Methods

Once missing data were addressed and strata developed, cross-sectional, longitudinal and distributional outliers were identified using the Akiyama and Propheter (2005) methods. These methods are described in the following sections.

Cross-Sectional Outliers

To determine cross-sectional outliers for 2014 and 2015 violent crime and property crime, the median annual violent and property crime rate for each strata was calculated, then the annual violent and property crime rate for each agency was divided by the median for its strata using the formula $y_i = \frac{x_i}{m}, i = 1, 2, \ldots, n$. Where y_i represents the ratio, x_i is a given agency's crime rate and m represents the median for the strata (Akiyama & Propheter, 2005). This produced a ratio that was used to determine if an agency rate was identified as an outlier. Agencies with a ratio that was either greater than 4 or less than 0.25 were flagged as outliers. While Akiyama and Propheter (2005) provided the foundation for outlier detection within the context of this report, a slightly modified method of creating critical values was used to detect cross-sectional outliers. The Akiyama and Propheter (2005) approach sets the proportion of outliers of a given strata to the top and bottom 2% of ratios. While conservative, it is problematic because it assumes that the rate of outliers is both small and unchanging. To address this issue, comparison values of 4 and 0.25 were used. LaValle and colleagues (2014) demonstrated that these ratios were appropriate for detecting monthly outliers in state-level NIBRS data applying a *Yi* outlier detection method similar to the Akiyama and Propheter (2005) method (LaValle et al., 2014, LaValle et al., 2015).

Longitudinal Outliers

The Akiyama & Propheter (2005) algorithm for longitudinal outliers detects excessive changes in an agency's reports between the two most recent reporting periods. For the purposes of this project, comparisons were made between two consecutive years of data (i.e. 2014 and 2015). To identify outlier agencies, standard scores (i.e. z-scores) were obtained by examining the change in crime totals (e.g. total crime, property crime and violent crime) from 2014 to 2015, taking into account the anticipated standard deviation of crime applying the below formula to a given agency:

$$z_0 = \frac{X_0 - Y_0}{\sqrt{X_0 + Y_0 + 1}}$$

Where X is the number of offenses (e.g. property offenses, violent offenses or all offenses) for 2015 and Y represents the number of offenses for 2014 for the respective crime category. Agencies' resulting z-scores were compared within each stratum, identifying the top and bottom 2% as outliers. Given the small number of agencies within certain stratum there were several strata, particularly when representing county-level agencies, where no outliers were identified. To address this limitation, the ratio method was adapted to longitudinal analysis in which a ratio of the difference between 2014 and 2015 and the median difference in years observed within a given strata was obtained. Outliers were identified when the resulting ratio was larger than 4 or less than .25. The Akiyama and Propheter (2005) and LaValle and colleagues (2014) method are compared in the results below.

Distributional Outliers

The distributional outlier detection method was applied to determine which agencies had a substantial difference in the way that crimes were distributed across violent and property crime when compared to the norm of the strata. In instances where an agency falls within the norm of the strata either when examining cross-sectional or longitudinal outliers, it is possible that the makeup of the agency's crime (e.g. the distribution) is significantly different than what would be expected of the strata. This method can be used not only when looking at overall crime totals/rates, but also when breaking crime down into more specific elements, such as the types of weapons used, types of victimization, etc.

The norm of the strata was identified as the median ratio of violent crime rate to property crime rate. Each agency's outlier statistic was determined using the formula $\hat{X}^2 = \sqrt{n}\left[\frac{(p_j-\pi_j)^2}{\pi_j}\right]$ where n is the total crime rate of the agency, p_j references the agency's given ratio of violent crime to property crime and π_j is equivalent to the median ratio of violent crime rate to property crime rate for the agency's strata. Resulting scores were then compared within each stratum, using the top and bottom 2%. To address the limitation in strata where the number of agencies did not allow for identifying outliers in such a restrictive scope, additional methods were utilized to identify outliers.

Rather than expanding the cutoff point to a higher percent, the following method is an adaptation of the cross-sectional method in which a ratio is created between the observed ratio and the norm observed within the strata. This method differs from the above in that a chi-value is

not obtained and the ratio can be directly compared, similarly to the Y_i method developed by LaValle and colleagues (2013) while still taking into account the ratio of property crime rates to violent crime rates. The method was applied utilizing the formula $y_i = \frac{p_i}{\pi}$ where p_i is the ratio of property crime rate to violent crime rate and π is the median for the strata. Once y_i was determined, those values higher than 4 and less than .25 were designated as outliers.

Results

Results for each of the different methods indicated a varying number of law enforcement agencies identified as outliers within their given stratum. A totally of 170 of the 433 agencies were identified as an outlier at least once between the different types of outlier detection. The total percent of agencies identified as outliers by strata appears in Figure 1, whereas the percent of agencies identified as an outlier within a given strata is shown in Figure 2. Strata with the highest percent of outliers are those that are made up of agencies at the local level (i.e. city and township) with a population size less than 2,736 (i.e. Strata 6 and 7). Given that the smaller strata are less likely to have outliers flagged by the Akiyama and Propheter method, and larger strata more outliers flagged, this observation is in alignment with what would be expected given the methods that were applied.

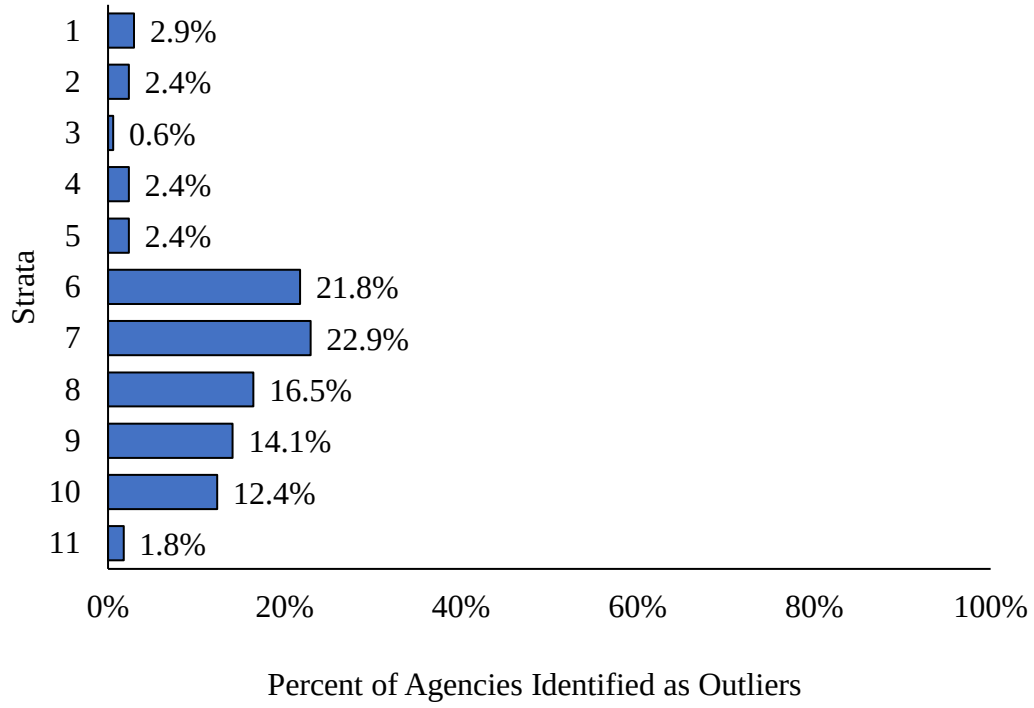

Figure 1. Percent of outliers identified across all strata (*N* = the total number of outliers).

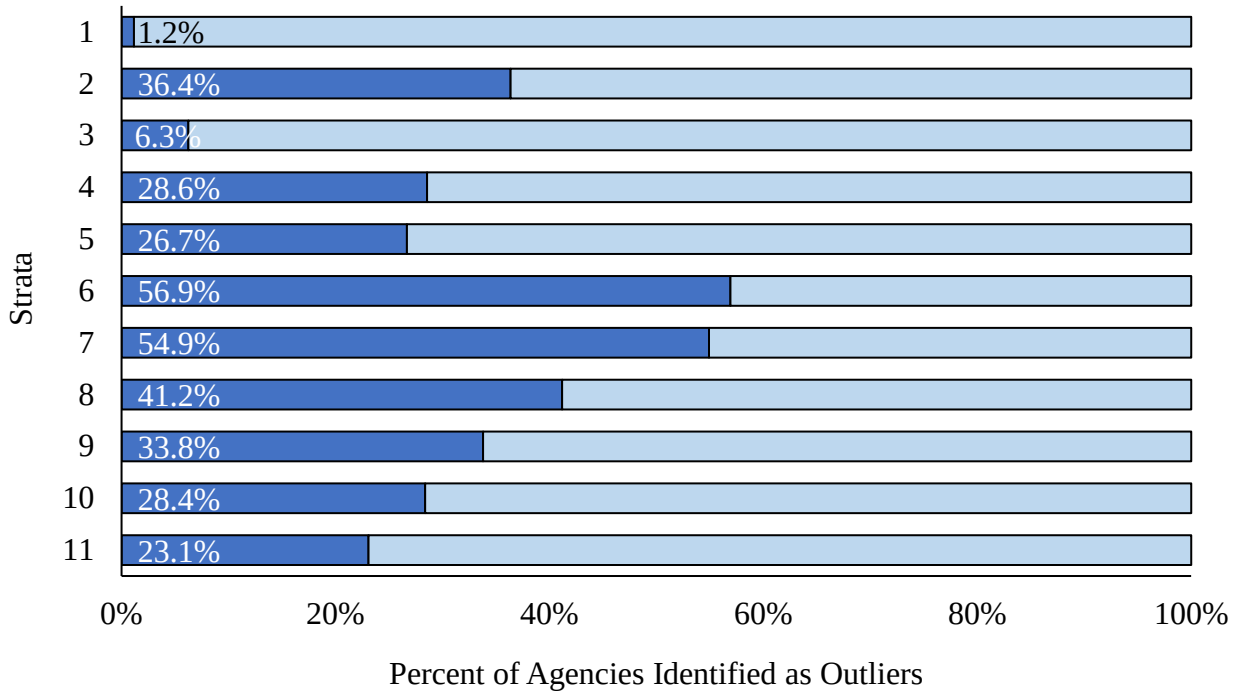

Figure 2. Percent of agencies identified as outliers out of all agencies within their respective strata (*N* = the total number of agencies within a given strata).

Cross-Sectional Outliers

Cross-sectional outlier detection methods compare an agency's crime rate for a given time period to the median crime rate of agencies within the same strata in the same period of time. The results from the cross-sectional outlier analysis are shown in Table 4. Depending on crime type, crime rates from between 27 and 50 agencies were considered outliers using this method; this corresponded to between 5.9 and 10.9% of all complete agencies for a given year.

Table 4. Number and frequency of agencies with cross-sectional outliers

Condition	N	%
Violent Crime 2014	32	7.0
Violent Crime 2015	27	5.9
Property Crime 2014	35	7.7
Property Crime 2015	50	10.9

Longitudinal Outliers

Longitudinal outliers compare an agency's crime rate from one year to the agency's crime rates from a previous reporting period. In the case of the current study, an agency's crime rate from 2015 was compared to their respective crime rate in 2014 to examine the agency's

consistency in crime reporting over time. The results from the longitudinal outlier analysis are shown in Table 5. Depending on the type of crime analyzed, between 3.2% and 4.6% of the 433 agencies with complete data for the 2014-2015 reporting years were identified as outliers.

Table 5. Number and percentage of agencies with longitudinal outliers

Condition	N	%
Violent Crime 2014-2015	16	3.7
Property Crime 2014-2015	13	4.6
All Crime 2014-2015	14	3.2

In strata with a higher number of law enforcement agencies, the outlier detection method with a cutoff point of the top and bottom 2% consistently detected outliers as expected. However, given the smaller number of agencies of the county-level strata, the consistent cutoff value of 2% in many of the strata did not reveal any outliers. In order to identify cases of the ranked data in strata with a lower frequency of agencies, the cutoff point would have to be increased to 20%. In these instances, it was beneficial to apply the additional outlier method previously discussed. Table 6 shows the results of the adapted Y_i method, which resulted in outlier designation that was much more liberal compared to the Akiyama and Propheter (2005) method. This method aligns with results of LaValle and colleagues (2013) when looking at all crime in a given year, given that it similarly identified nearly a quarter of agencies as outliers.

Table 6. Number and percentage of agencies with longitudinal outliers identified using the adapted Y_i (i = year) method for annual crime count

Condition	N	%
Violent Crime 2014-2015	45	10.3
Property Crime 2014-2015	67	15.4
All Crime 2014-2015	100	23.1

One difference observed in implementing the adapted ratio and the Akiyama and Propheter (2005) method is that the two methods are not complementary, meaning that a majority of the agencies identified in the more conservative method were not designated as outliers when using the adapted ratio method. More specifically, 10 out of the 14 (All Crime 2014-2015), 14 of the 16 (Violent Crime 2014-2015) and 8 of the 13 (Property Crime 2014-2015) outlier agencies identified using the Akiyama and Propheter methods were not identified as outliers using the adapted ratio method.

Distributional Outliers

Distributional outlier detection methods examine the distribution of one crime to another compared to the distribution seen in the agency's respective strata. In the current study the distribution of violent crime to property crime was examined. Distributional outliers were determined using two methods, namely the Akiyama and Propheter (2005) method, as well as an adaptation of the Yi method, which examines the ratio of violent crime rate to property crime rate of the given agency compared to the median of the agency's respective stratum. The Akiyama and Propheter (2005) method, was the most conservative in the number of outliers it detected, with only 1.2% of agencies identified as outliers for 2014 and 2.5% of the agencies as outliers identified in 2015 (Table 7). Utilizing such small critical values for the Akiyama and Propheter (2005) method was determined to be too conservative and that outliers may be missed. As such, an adapted *Yi* (i.e. ratio) method was utilized. The latter of the two methods in determining distributional outliers was more liberal in that it identified 7.1% of agencies in 2014 and 14.1% of agencies in 2015 as outliers (Table 7).

Table 7. Number and percentage of agencies identified as potential distributional outliers

	Condition	N	%
Akiyama & Propheter (2005)	Violent Crime to Property Crime 2014	5	1.2
	Violent Crime to Property Crime 2015	11	2.5
Adapted Ratio Method	Violent Crime to Property Crime 2014	31	7.1
	Violent Crime to Property Crime 2015	61	14.1

As observed when applying the adapted ratio method compared to the Akiyama and Propheter (2005) method, there were substantial differences not only in the number of potential agencies identified but also in the agencies that were identified as outliers. For each year, only two of the outliers identified in the Akiyama and Propheter (2005) methods belonged to the group of outliers when using the adapted ratio method. While this may be the case, both methods identified outliers outside of those identified through the longitudinal and cross-sectional method. So while an agency's violent or crime totals may have been in alignment with the stratum's for a given year, the ratio of those crimes to one another were not.

Discussion

The purpose of the given study was to demonstrate the outcomes of applying outlier detection methods to Ohio's incident-based data. Methods were applied with the intent of

determining the practicality of implementing sustainable methods with Ohio data through automating systematic outlier checks. The methods applied in the current study identified agencies that have submitted data that differed substantially from agencies of similar characteristics. Depending on the applied methods and crime type and/or year, between 1% and 23% of the agencies were identified as outliers. While identified as outliers, additional steps must be taken to determine if the data are accurate or if corrections by the agency should be made prior to the data being used in the state's reporting system. These additional steps include manual inspection of the data, which has historically been completed by a research team (e.g. LaValle et al, 2013, LaValle et al, 2014) or the UCR program coordinator locally when outliers are identified through the UCR system (Federal Bureau of Investigation, 2017B).

The need for manual inspection paired with the desire for sustainable implementation of identifying outliers locally led to collaboration with the state's Ohio Incident-Based Reporting System program coordinator to discuss an online interface in which agencies are alerted of outliers when data are submitted to the state system. In the summer of 2019, OIBRS interfacing will be updated to allow for agencies to interact with their data more directly once submitted. This will include not only a data dashboard, but also the ability to upload agency data into the Ohio system through the website rather than emailing data to the program coordinator to then be uploaded into the system. Data will still be validated using the data edits and logical tests described on page 4, however, the goal is to also add the outlier detection methods to flag outliers for agencies and then notify the agency that their data are irregular or substantially different compared to agencies of similar characteristics. This will then prompt and guide the agency to review their data submission and then verify that the data are correct. If implemented and an agency does not verify that the flagged data are accurate and approved for use in the state data, then they will be excluded from Ohio's publishable data, recognizing that data quality is ultimately in the hands of the law enforcement agencies that submit the data.

While the current project addresses data quality within the Ohio Incident Based Reporting System, it is not without its limitations. One of the key differences between the Akiyama and Propheter (2005) implementation and the current study was the scope of the project. The current project focused on law enforcement agencies within Ohio whereas Akiyama and Propheter (2005) references a national pool of law enforcement agencies. When it comes to developing strata based on the characteristics of the law enforcement agencies, the Akiyama and

Propheter recommend characteristics that are typically used for Uniform Crime Reporting crime estimation and are reliant on stable and available factors that do not require continuous updates, including MSA, population coverage, city/county level and region. When applying these methods to a national sample of agencies, each strata has a large sample for comparison while maintaining a relatively low level of variance between agencies of a given strata. When these two things are both taken into consideration, looking at the top and bottom 1% or 2% of agencies does not result in strata with zero outliers identified. With Ohio crime data however, the implementation of characteristics beyond population size and city/county level resulted in small strata sizes with higher variability of crime occurrence within strata. In these cases, applying methods that are unassuming of the strata's distribution (i.e. ratio methods) were more appropriate.

As previously mentioned, the Akiyama and Propheter (2005) method as demonstrated limits outlier detection to agencies who fall within the top and bottom 1% to 2% of tested values, under the assumption that these are agencies presenting with unlikely deviations that should be examined more closely. As is the case with other methods, determining the critical values for reasonableness is user defined. If the critical values are too conservative, meaning that less agencies are identified as outliers, the likelihood of designating outliers that should be examined further is limited. However, if the critical value is too liberal, meaning that a high number of outliers are designated, the likelihood of agencies being falsely flagged increases. In addressing data quality, it seems reasonable to prefer over-designation of outliers for additional examination rather than conservative critical values that overlook outliers, given that corrections will be missed if an outlier is not identified. The importance of the practical implications of outlier designation is not lost, however. The time and resources of those completing manual inspection of the outlying agencies must be kept in mind when determining designation, particularly when less conservative methods will ultimately increase the resources needed to manually review the data. With the balance between the resources needed for manual inspection and data quality in mind, determining the critical value for outlier detection arises as a limitation. In the current study, between 3.2% and 23.1% of agencies were identified as outliers depending on the type of methods used, which tended to be more conservative in application. When automated on the state website, methods that utilize the ratio method will likely be implemented over the 1% or 2% cutoff points given that they tended to be more inclusive when identifying outliers.

Another challenge commonly referenced in outlier detection is the inability of determining outlier scores of strata with a median crime rate or frequency of zero (Akiyama & Propheter, 2005; LaValle et al., 2013). This study was no exception, as the agencies within Strata 6 (i.e. cities/local police agencies with population 1,347 or less) typically had little to zero crime reported. In instances where the median of crime or crime ratio for the strata was zero, comparisons were unable to be made utilizing the above methods. Instead, manual inspection of the data needed to be made to determine if agencies should be flagged as outliers.

In conclusion, the current study is a critical first step in determining the best methods for implementing automated outlier detection upon data submission to OIBRS. It applied FBI methods for outlier detection to state level data, as well as additional methods developed specifically for application to state NIBRS data with the intent of identifying agencies that have submitted data that is irregular compared to norms established by examining agencies with similar characteristics. As a necessary step in addressing data quality for the state's incident-based reporting system, it offers a foundation to build upon the ability to identify specific agencies for further examination, with the ultimate hope of improving the accuracy and reliability of law enforcement data that is shared with the public.

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