City of Boulder's Warrant Clustering Pilot Program Evaluation

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Executive Summary:

This report provides an evaluation of the impact of an intervention with homeless defendants in Boulder, Colorado with the intended goal to keep these individuals out of jail. The program, called Warrant Clustering, involves a judge "staying" warrants related to municipal crimes for homeless individuals. If, after six months, no new charges are filed, these cases are dismissed. However, if the defendant accumulates three "stayed" warrants in a six-month period, all three are "clustered" together or prosecuted by the city prosecutor's office. This report evaluated Warrant Clustering's impact on municipal jail bookings in the City of Boulder and compared them to jail booking for similar municipal offenses in the nearby City of Longmont.

Using Boulder County Jail booking data for municipal crimes as the primary outcome variable for this evaluation, an interrupted time series design using time-series data analyses were used to determine if the number of municipal jail bookings was impacted by the start of the Warrant Clustering Program pilot beginning in March 2019. The analysis compared the 62 weeks of municipal offenses prior to the implementation date to the 53 weeks after implementation for the City of Boulder and the City of Longmont. Results were as follows:

- **The Warrant Clustering program led to an average reduction of 4.32 municipal bookings per week in Boulder after its implementation on March 1, 2019.**
  - Multiple time series design models were constructed to compare the predicted number of jail bookings (based on the prior 62 weeks of data) to the actual number of bookings
    - Results showed statistically significant differences. Municipal bookings were lower during the Warrant Clustering Pilot.
      - These results were strong in magnitude (Cohen's d = 1.40) meaning that the implementation of the program had a large impact on municipal jail bookings
- **Municipal bookings from Longmont (control group) were unaffected during this time period.**
  - There was no statistically significant difference in average books per week for Longmont before and after the intervention ($p > .05$). The average books per week remained stable over 115 data points ($M = 1.76$).
- **It is estimated that the Warrant Clustering Program led to cost savings of at least $107,852.16 but as high as $492,524.86**
  - Based on average cost to house an inmate in Boulder County Jail being $160 a day. Low end based on median of 3 days detention for municipal offenses, high end based on average stay of 13.7 days for municipal booking defendants.
- **It is estimated that the Warrant Clustering program saved between 4.3 – 7.2 hours per week (224.69 – 374.49 hours per year) of police officer time in arresting and booking defendants**

- Based on estimates ranging from 60 minutes to 100 minutes of arrest and booking the warrant clustering program reduced the time an officer spent from arrest to booking from 4 to 7 hours weekly. This range of time savings enhances efficiency of community patrol resources.

This report is broken into four sections. The first provides a background of the project including an explanation of the program and data compiled for the analysis. Part two provides descriptive statistics for the sample who were eligible to take part in the Warrant Clustering program. Part three includes the detailed analysis and results for this study. This section explains the models selected and run to compare municipal jail booking rates before and after the implementation of the Warrant Clustering pilot, a comparison of Boulder municipal cases compared to Longmont municipal cases during the same time frame. Finally, part four examines cost savings calculations that show the amount of money and law enforcement time is estimated to be saved through the on-going implementation of the Warrant Clustering program.

Part 1: Background of Project:

Starting March 1, 2019, Christopher Reynolds and the City of Boulder piloted a project called Warrant Clustering. Warrant clustering is a discretionary tactic used with homeless cases in the City of Boulder. The judge "stays" a warrant for municipal crimes if the defendant is homeless, not ordering an immediate bench warrant for that individual. After 6 months, if no new charges are filed, the original charge is dismissed. However, if the defendant accumulates three "stayed" warrants, all three are clustered together and prosecuted.

The goal of the Warrant Clustering program is to reduce the number of homeless individuals who are arrested due to bench warrants and booked into the Boulder County Jail. The types of crimes reported homeless individuals are arrested for often include trespassing, having an open alcohol container in public, illegal camping, cannabis use in public, and cigarette use in public. Individuals were identified as eligible for warrant clustering based on information captured by a law enforcement officer at the time of writing a ticket. On the section of the ticket where an individual's address is requested, officers will write "homeless", "transient", list the address of a homeless shelter or food bank, or leave that section blank. These individuals are identified by the city prosecutor's office as eligible for warrant clustering.

In January 2020, Christopher Reynolds met with Drs. Kyle Ward and Paul Hawkins to discuss the possibility of evaluating this program. The pilot of the program officially ended March 1, 2020. The data used for this evaluation will cover that time period. However, on March 24th, 2020 the City of Boulder instituted a lockdown to mitigate the spread of COVID-19. This impacted the criminal justice system for all those who, according to District Attorney Michael Dougherty, "didn't demonstrate an immediate risk to community safety" and were released from jail. Based on data from the Boulder County website, in February 2020 the average number of bookings in Boulder County Jail were 22.8 per day. This dropped to 15.3 average bookings in March and 5.8 in April. Despite these changes, the pilot time period was unaffected. However, due to the six- month follow-up period for defendants participating in the Warrant Clustering program, a reduced timeframe of this study was developed when examining descriptive statistics related to defendants whose warrants were "clustered" or "stayed". Instead of the full year, March 2019 to March 2020, this evaluation used March 2019 to September 2019 as a data collection phase, with a follow up period of October 2019 to March 2020 to study those who successfully have their cases dismissed after six months of no new charges. This timeframe did not interfere with any enforcement effects due to COVID-19.

Data from this report were provided by the City of Boulder's prosecutor's office. There were two datasets used in this study. The first entailed Boulder County Jail booking data from 1/1/2009 until 3/1/2020. This dataset included the individual's name, date of birth, jail ID, booking date, charge, arresting agency, court date, and release date. The second dataset was compiled by the city prosecutor's office and consisted of individuals who had a recorded Failure to Appear in court for a "jailable offense." This dataset consisted of 759 individuals and 1,848 cases between 1/29/2019 and 9/1/2020. Variables in this dataset included the individual's name, case number, case status, charge(s), attitude based on police officer's perception on interaction (i.e., poor, fair, good, or excellent), gender, date of birth, age, indication of homelessness, offense information, review date, and number of cases prior to pilot and during the pilot.

Part 2: Descriptive Statistics

There were 759 individuals who had interactions with Boulder PD and were determined to be eligible for the Warrant Clustering program during the pilot period. This resulted in a total of 1,840 cases. These data were gathered from a database curated by the City of Boulder's Prosecutor's office. During this period, a total of 1,067 cases were "stayed", 773 had a warrant issued and 459 were clustered. Of the cases examined in this period, 446 were deposed with good behavior diversion and 225 with housing focused diversion. A total of 980 cases were closed, 146 were dismissed and 833 either pled or were found guilty.

The program intervention time period spanned March 1, 2019 to September 30, 2019. During this 6-month time period, 201 cases were clustered and 677 were stayed in total. Of the 759 total individuals eligible for the program, 161 had warrants clustered at least once and 403 of them had at least one warrant stayed. The case outcomes during the program intervention time period included 227 diversion sentences, 502 guilty decisions and 97 case dismissals or not guilty decisions. In the 62 weeks prior to the intervention, the City of Boulder had an average of 11.29 (*SD* = 4.4) municipal jail bookings per week in Boulder County Jail. During the intervention period, this dropped to 7.61 (*SD* = 3.35) municipal jail bookings per week, and 6.18 (*SD* = 2.5) after the intervention period of this report (October, 2019) (See Appendix A).

Table 1 includes the descriptive statistics of the 759 individuals who were eligible to take part in the Warrant Clustering Program.

A total of 70% of all individuals examined during the pilot time period were determined to be homeless. There were a total of 71 individuals who were determined to be high utilizers. These individuals had at least 6 criminal cases during the pilot period.

Of the sample, 78.39% were male and 21.48% were female. The average age of the defendants during the pilot was 38 years old (*SD* = 13.24) with a range of 19 to 80 years old.

Officer ratings of the interactions with defendants were mostly rated as Good (39%, *n* = 296), with 18.31% (*n* = 139) rated Fair, and 15.28% (*n* = 116) rated Poor. A total of 112 interactions (14.76%) were rated as Excellent by law enforcement. Most offenses occurred in the morning, between 5am and 11am (37.12%) followed by afternoon (11:01am – 4pm; 28.33%), evening (4:01pm – 9pm; 18.71%), or night (9:01p, - 4:59am; 15.81%).

Table 1. Descriptive Statistics of those eligible for Warrant Clustering Program

Variable	n (%)	$\overline{x}$ (SD)	range
1. Attitude (per officer interaction) (n = 759)			
Excellent	112 (14.76)		
Good	296 (39.00)		
Fair	139 (18.31)		
Poor	116 (15.28)		
2. Age (n = 759)		38.10(13.24)	19 – 80
3. Time of offense (n = 759)			
Morning (5a – 11a)	282 (37.12)		
Afternoon (11:01a – 4p)	215 (28.33)		
Evening (4:01p – 9p)	142 (18.71)		
Night (9:01p – 4:59a)	120 (15.81)		
4. Homeless (indication of homeless dichotomous (n = 759)			
Yes	531 (69.93)		
No	228 (30.04)		
5. Sex (n = 758, 1 missing value)			
Male	595 (78.39)		
Female	163 (21.48)		
6. New Cases: Violence or serious public safety (n = 129, during the pilot time period)			
Yes	23 (17.83)		
No	106 (82.17)		
7. High Utilizer (n = 759, during the pilot time period)			
Yes	71 (.35)		
No	688 (90.65)		
8. Cases filings (n = 759)			
Prior to the pilot (3/1/19)		4.82 (12.92)	0 - 141
During the pilot (3/1/19 – 2/29/20)		2.34 (2.79)	1 - 25

Part 3: Time Series Analysis Results

A time-series analysis for municipal jail bookings from the City of Boulder was developed to examine the impact of the Warrant Clustering program. Data from 62 weeks before and 53 weeks after program implementation were used for the analysis (see Figure 1). Data from 62 weeks before program implementation were used to build three forecasting models. These models predicted what the number of weekly municipal jail bookings would have been if no intervention was implemented (i.e., if warrant clustering was never piloted). Data from 53 weeks after program implementation were compared to the forecasts produced by the models to examine the effectiveness of Warrant Clustering. The analysis was completed using SPSS 27 Time Series Modeler.

A note on reading figures. In examining the figures in this report, the dark vertical line represents the time of the intervention. The section left of the line represents the 62 weeks prior to the start of the Warrant Clustering Pilot, while the section right of the line represents the 53 weeks post Warrant Clustering pilot. Figures 1 and 4 are the only figures that display daily jail bookings. These figures represent a visual test of the data to display the variability of the data. For analysis purposes, weekly averages were used. The remaining figures reflect these weekly booking averages located on the x-axis.

Pre and post intervention jail bookings.

Prior to developing the forecasting models, the data were preliminarily examined both visually and statistically for differences in the pre- and post-intervention time period. First, the daily municipal jail bookings for the City of Boulder were examined in a visual format. Figure 1 displays this data. A visual test of Figure 1 shows an apparent decrease in jail bookings after the intervention. Further examination of weekly municipal jail bookings in Figure 2 displays a more prominent decrease. To determine if this apparent difference is statistically significant, an independent t-test was run. This test compares the average weekly bookings prior to the intervention (M = 11.29, SD = 4.41) and post Warrant Clustering (M = 7.01, SD = 3.09) (see Table 2). Finding meaningful differences (e.g., statistical significance) in the averages between time periods indicates that there are likely differences present in the larger population of homeless individuals.

The results found a statistically significant drop in the average weekly municipal jail bookings in the 52 weeks after the intervention ($t(108.98) = 6.08$, $p < .001$). Furthermore, the effect size (Cohen's d = 1.11) was found to be large, meaning that the two time periods differed by more than one standard deviation and indicating that Warrant Clustering may play a large role in these time period differences. While these differences are important, a more robust analysis for determining the impact Warrant Clustering may have on jail bookings involves Time Series Analysis.

Time series analysis is an analytical technique used for data collected over time with at least 50 observations. This data may have internal structures (e.g., random shocks, seasonal trends or variations, autocorrelation, lags, and moving averages). that need to be accounted for (i.e., reduced to error in the model) prior to using the data to make forecasts or to assess the effect of an intervention over time on the structure of the data. The steps involved in time-series analysis include model identification, estimation, and diagnosis. Findings from this type of analysis can provide statistical and counterfactual evidence of whether the trends in bookings before and after the warrant clustering program was administered meaningfully differ between Boulder and Longmont. If a meaningful difference is identified in Boulder but not in Longmont, this means that the reduction of jail bookings in Boulder County can be at least partially attributed to the Warrant Clustering pilot program. This next section will describe the time series model that was developed to predict an expected weekly municipal jail booking average based on the 62 weeks of data prior to the intervention for Boulder and Longmont.

Figure 1. Visual Test: Boulder Jail Bookings Time Series by day

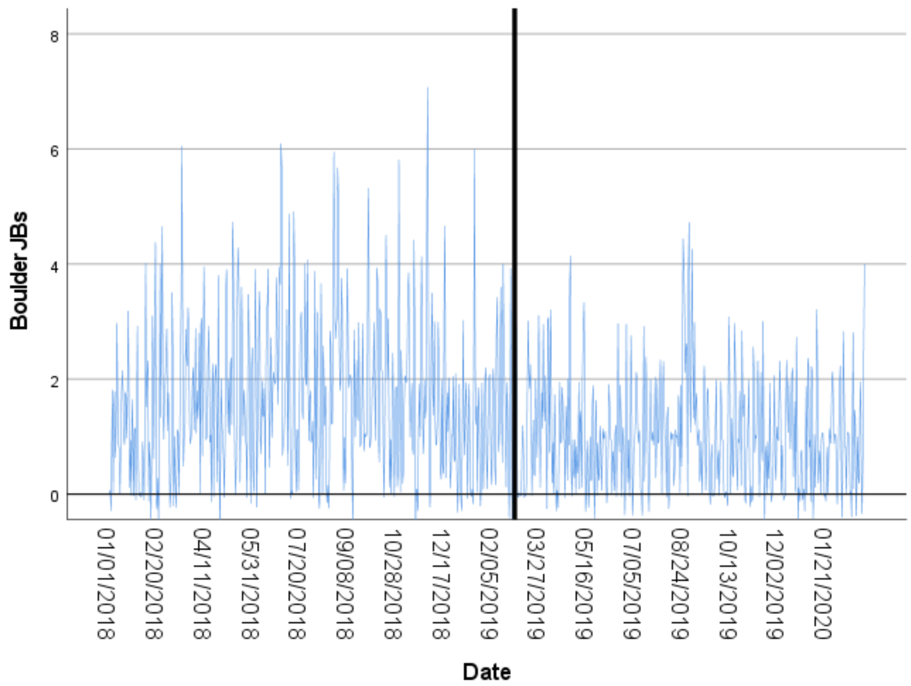


Figure 2. Boulder Jail Bookings Full Time Series by week

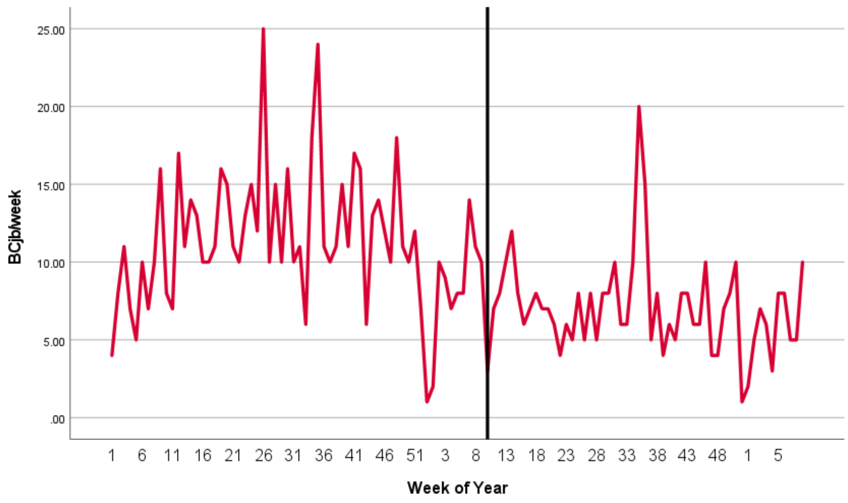


Table 2. Average number of municipal jail bookings from Boulder pre and post Warrant Clustering intervention

City of Boulder weekly municipal jail bookings	Mean	Standard Deviation
Pre-Intervention	11.29	4.41
Post-Intervention	7.01	3.09

Note: $t(108.98) = 6.08$, $p < .001$. Mean difference = 4.27, effect size = 1.11 (Cohen's *d*)

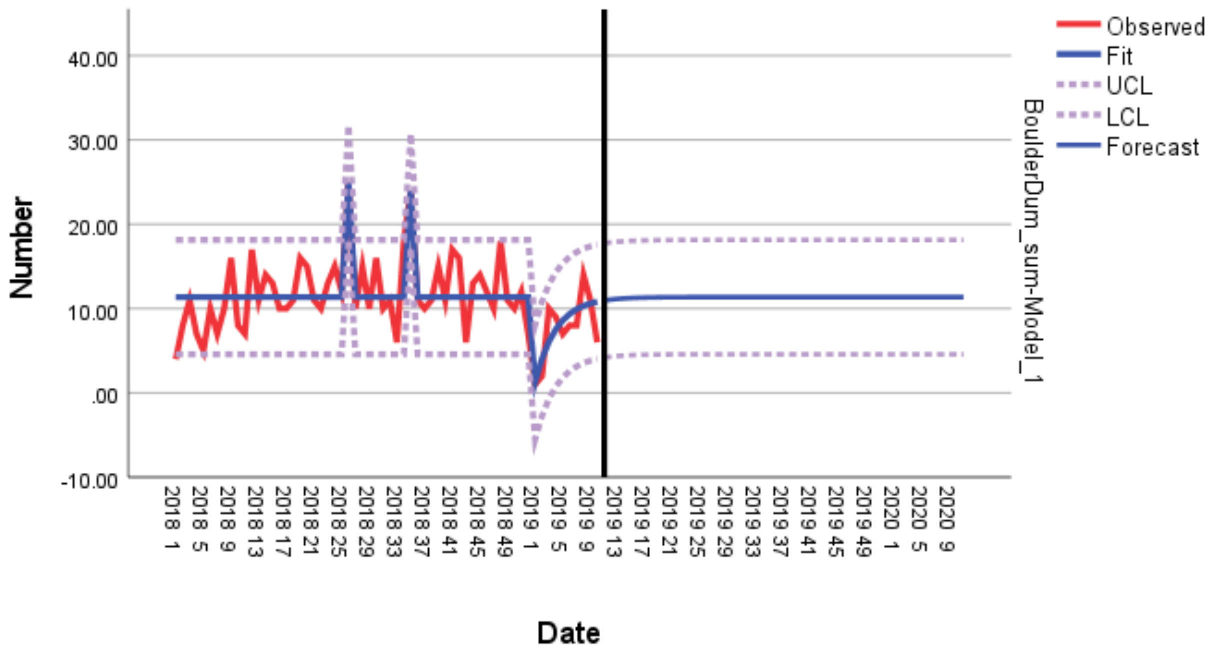
Time Series Expert Modeler.

Using SPSS Time Series expert modeler, a series of three models were modeled, identified, and diagnosed to obtain the best possible unbiased prediction line. This line represents the average municipal bookings in Boulder County Jail if the warrant clustering pilot was never implemented. The three models developed are explained in more detail below and include the Winter's Additive model, an auto-regressive, integrated, and moving average (ARIMA) model without statistical outliers modeled, and an ARIMA model that included modeled statistical outliers. The best predictive model was found to be the ARIMA model that included modeled statistical outliers. That model is highlighted below. The additional Winter's Additive model and ARIMA model without statistical outliers modeled can be found in Appendix B at the end of this report.

The SPSS Time Series Expert Modeler identified an ARIMA (0,1,1) model as the appropriate forecasting procedure. This model excluded exponential smoothing models but identified and modeled statistical outliers. This model revealed three statistical outliers (2 additive, 1 transient) from the pre-intervention data that were considered in the model and forecast. As can be seen in Figure 3, the pre-intervention data does not appear stationary (i.e., no constant mean and variance over time), thus the modeler identified 1 integrated/differencing component to achieve stationarity. Further, this model identified a moving average order of 1, suggesting that a seasonal cycle/trend, or the observation for jail bookings per week experienced 1 persistent random shock from one observation to the next that must be accounted for in the model. This model was determined to be the best predictive model among the three, based on the following criteria.

The analysis for this model revealed that the interruption was not a significant predictor of any change in the structure of the forecasted data post interruption ($p > .05$). A Stationary R Square value of .378, and although not statistically significant, indicates that the preintervention time period explains 38.8% of the proportion of the total variation in the post-intervention series. A Ljung-Box Q test, (13.162, 17, $p = .725$) showed that there was randomness of the residual errors in the model, indicating a good fit for the data to the model, and therefore, is quite acceptable for additional analyses. Taking these statistical findings together indicates that there is no underlying structure in the data that has gone unidentified or not considered in the model through either the ARIMA identification, estimation, and diagnosis components, or the tests of the goodness of fit of the model. Further, the root mean square error (RMSE = 4.379) indicates that actual values of the time series do not substantially differ from the values predicted by the model, indicating support for an acceptable model. Additional goodness of fit measures includes the mean absolute percentage errors (MAPE = 50.309) and its maximum values (MaxAPE = 1033.297), which in this case suggests that the data varies from its model-predicted level by 50.31% to 1,033.3%. Next, the mean absolute error and its maximum values (MAE = 3.341; MAXAE = 12.549) provide insight into the worst-case scenario forecast errors relative to the same units (e.g., jail bookings per week) modeled in the forecast. Finally, the Normalized Bayesian Information Criterion (BIC = 3.021) provides insight into the complexity of the model compared to the others. In comparison with other models, the difference in BIC is less 1, and therefore becomes negligible in-terms of model selection. In other words, the other two models assessed for this time series had relatively similar goodness of fit and BIC measures, therefore, we opted to use the model that took into account the most amount of noise, without overfitting the model, relative to the other models, to provide the best linear unbiased forecasts.

Figure 3. ARIMA (0,1,1) with outliers modeled



Results of forecast vs observed post-intervention

A paired-samples t-test was performed to assess the relationship between the 53 weeks of observed post intervention data to the three forecasts of the post intervention data. As Table 3 displays, the mean differences between each group decreased after the intervention. There was a statistically significant difference between the observed post intervention weekly municipal jail bookings and all three forecasts ($p < .001$), indicating that the observed post intervention data were significantly lower than the projected post intervention data. The mean difference in the ARIMA model was 4.32 jail bookings. With a mean difference of 4.32 weekly municipal jail bookings and a large effect size of 1.402 (Cohen's *d*), there is strong evidence that the Warrant Clustering intervention significantly impacted the number of municipal bookings for the City of Boulder. For further evidence, a counterfactual was examined. In the next section, municipal jail bookings for the City of Longmont will be examined. As Longmont did not implement Warrant Clustering during the examination period, they serve as a control group for this study.

Table 3. *Predicted vs. Observed Weekly Average Municipal Jail Bookings from Boulder Based on Time Series Model.*

City of Boulder weekly municipal jail bookings		Mean Bookings	Standard Deviation
Observed Pre and Post	Pre-Intervention	11.29	4.41
	Post-Intervention	7.01	3.01
ARIMA (0,1,1) with outliers modeled[2]	Pre-Intervention	11.34	0.07
	Post-Intervention	7.02	3.09

[1] $t(108.98) = 6.08$, $p < .001$. Mean difference = 4.27, effect size = 1.11 (Cohen's d)

[2] $t(52) = -10.20$, $p < .001$. Mean difference = 4.32, effect size = 1.402 (Cohen's d)

Control Group: Longmont Municipal Bookings

To further examine the impact of Warrant Clustering, an additional location was included to serve as a control group. The City of Longmont is the second biggest city in Boulder County and is also served by the Boulder County Jail. As Longmont did not implement Warrant Clustering or, as far as the researchers have found, implemented any additional initiatives during the pilot period that could influence municipal jail booking rates, they serve as a control group to compare municipal jail bookings to the City of Boulder. Following the same format as the analysis above for the City of Boulder, Longmont municipal jail bookings will be examined. Figure 4 shows the visual test of daily jail bookings for municipal crimes in Longmont. In addition, Figure 5 displays average weekly municipal jail bookings. From these figures, municipal jail bookings do not seem markedly different from pre to post intervention. To test this, an independent samples t-test was run and found no differences between the time prior to Boulder's implementation of Warrant Clustering and the period after, $t(113) = 0.861$, $p = .39$ (see "Observed Pre and Post in Table 4).

Figure 4. Longmont Municipal Jail Bookings Time Series by day

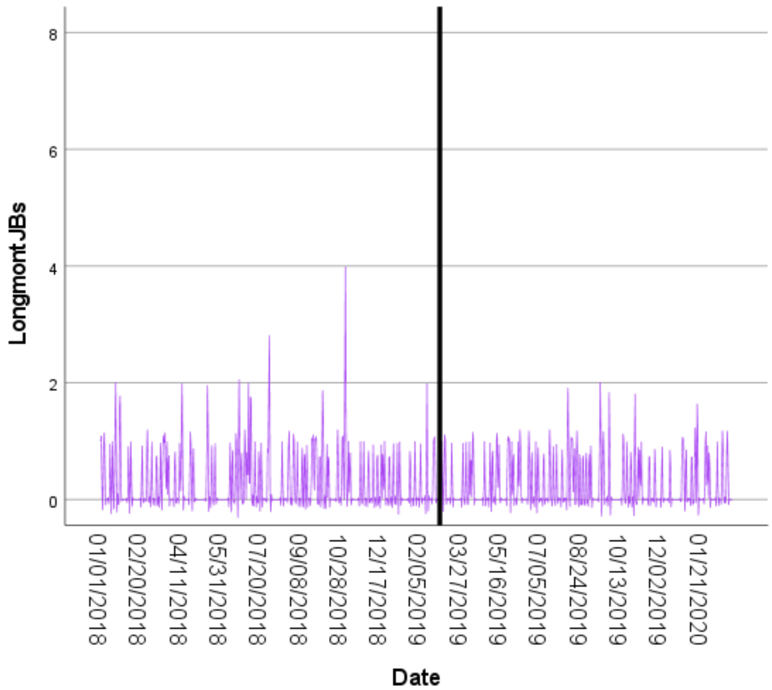
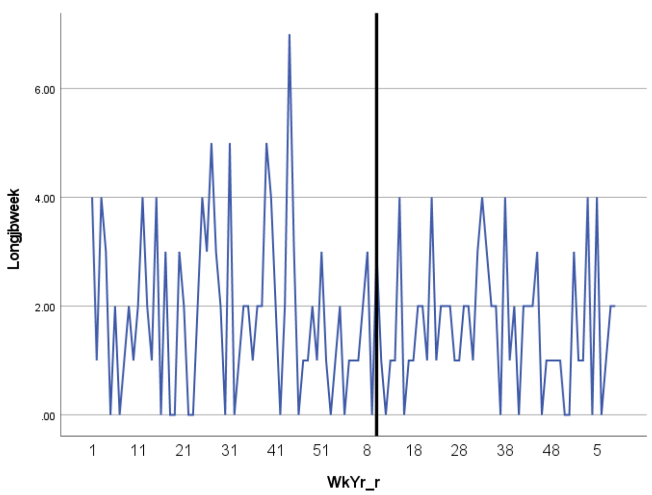


Figure 5. Longmont Municipal Jail Bookings Full Time Series by week



Using SPSS Time Series expert modeler, a series of three models were modeled, identified, and diagnosed to obtain the best possible unbiased prediction line. This line represents the average municipal bookings for Longmont in Boulder County Jail if the warrant clustering pilot was never implemented. The three models developed are explained in more detail below and include the Winter's Additive model, and an auto-regressive, integrated, and moving average (ARIMA) without outliers modeled and an ARIMA model with outliers modeled. There was one additive statistical outlier identified in the Longmont time-series data. The best predictive model was found to be the ARIMA (0,0,0) model with the one additive statistical outlier included in the model. That model is highlighted below. The additional Winter's Additive model and non-outlier modeled ARIMA (0,0,0) can be found in Appendix C at the end of this report.

The SPSS Time Series Expert Modeler identified an ARIMA (0,0,0) model as the appropriate forecasting procedure for the Boulder time-series data. This model included an evaluation of exponential smoothing models and ARIMA models, which identified one additive outlier in the data. As can be seen in Figure 4, the pre-intervention data appears stationary (i.e., constant mean and variance over time), therefore no manipulations were made to the data. Additionally, no auto-regressive or moving average components were identified in the model. This model was determined to be the best predictive model among the three based on the following criteria.

The analysis for this model revealed that the interruption was not a significant predictor of any change in the structure of the forecasted data, post interruption ($p > .05$). A Stationary R Square value of .175, and although not statistically significant, indicates that the preintervention time period explains 17.5% of the proportion of the total variation in the post-intervention series. A Ljung-Box Q test, (25.752, 18, $p = .106$) showed that there was randomness of the residual errors in the model, indicating a good fit for the data to the model, and therefore, is quite acceptable for additional analyses. Taking these statistical findings together indicates that there is no underlying structure in the data that has gone unidentified or not considered in the model. Further, the root mean square error (RMSE = 1.450) indicates that actual values of the time series do not substantially differ from the values predicted by the model, indicating support for an acceptable model. Additional goodness of fit measures includes the mean absolute percentage errors (MAPE = 44.175) and its maximum values (MaxAPE = 78.689), which in this case suggests that the data varies from its model-predicted level by 44.17% to 78.69%. Next, the mean absolute error and its maximum values (MAE = 1.162; MAXAE = 3.213) provide insight into the worst-case scenario forecast errors relative to the same units (e.g., jail bookings per week) modeled in the forecast. Finally, the Normalized Bayesian Information Criterion (BIC = .877) indicates that this model is the least complex (lower value, less likelihood of error) among the others and therefore provides the best fit and estimate moving forward.

Similar to the City of Boulder analysis above, a paired-samples t-test was performed to assess the relationship between the 53 weeks of observed post intervention data to the three forecasts of the post intervention data. As displayed in Table 4, the mean differences did not decrease after the implementation of Warrant Clustering in Boulder. There were no statistically significant differences between the observed post intervention weekly jail municipal bookings in either the observed or forecasted model. Figure 6 shows the best predictive ARIMA model used for Longmont Municipal Jail Bookings.

These results, coupled with the results from the City of Boulder municipal bookings above, indicate that the introduction of Warrant Clustering in Boulder caused a significant reduction in municipal jail bookings in the Boulder County Jail. Comparatively, not engaging in warrant clustering did not result in a similar reduction in bookings in a neighboring jurisdiction, thus providing statistical and counterfactual evidence for the impact of Warrant Clustering on the county jail. Next, we estimate the potential savings in money and law enforcement officer time may have resulted from Warrant Clustering.

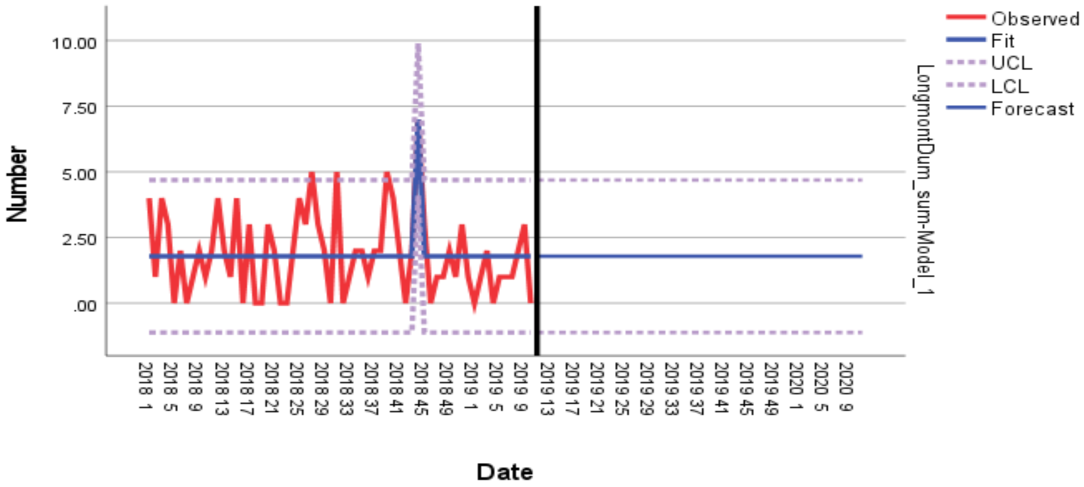
Table 4. *Average Number of Municipal Jail Bookings from Longmont Pre and Post Warrant Clustering intervention in Boulder including Predicted Based on Time Series Models.*

City of Longmont weekly municipal jail bookings		Mean Bookings	Standard Deviation
Observed Pre and Post[1]	Pre-Warrant Clustering Time	1.87	1.58
	Post-Warrant Clustering Time	1.64	1.21
Model 3) ARIMA (0,0,0) with outliers modeled[2]	Observed Post-Warrant Clustering Time	1.64	1.66
	Predicted Post-Warrant Clustering Time	1.79	< 0.001

[1] $t(113) = 0.861$, $p = .39$. Mean difference = .23, effect size =.16 (Cohen's *d).*

[2] $t(52) = -.87$, $p = .39$. Mean difference = .15, effect size = -.120 (Cohen's *d*)

Figure 6. ARIMA (0,0,0) (1 additive outlier detected and modeled)



Part 4. Potential Savings Attributed to Warrant Clustering

Cost Savings Analysis

A goal of this study was to determine the amount of potential savings the Warrant Clustering pilot had on jail expenses and law enforcement officer time. First, the mean difference in the predicted vs. actual weekly municipal jail bookings (M = -4.321, $SD = 3.08$) was used. This resulted in an average weekly municipal booking reduction of 4.321 (95% CI = 3.47 – 5.17). According to the Boulder County Sheriff's Office 2020 Annual Report, it cost $160 per day to house an inmate in Boulder County Jail[1]. Based on correspondence with City Prosecutor Christopher Reynolds, the average length of stay for a municipal defendant is 13.7 days, with the middle of the range of days, a median of 3 days. Using the average reduction in jail bookings (M = 4.321), the average reduction in jail costs would be $2,074.08 per week ($107,852.16 per year) using the median of 3 days per municipal defendant.

If calculating based on the average (13.7 days) instead of the median, the average jail cost savings would result to $9,471.62 per week ($492,524.86 per year).

Other monetary cost savings estimates:

The calculations above use the average number of municipal jail reductions per week as a point estimate. While this number provides a tangible estimate for use in the calculations above, the use of confidence intervals provide a fuller picture of the true municipal jail booking estimates. The confidence intervals comparing the strongest predictive ARIMA model to the observed output ranged from a 3.47 to a 5.17 reduction in weekly municipal jail bookings. This means that we are 95% confident that the true average reduction in weekly municipal jail bookings lies between 3.47 and 5.17.

Lower Estimate (conservative): Taking the lower bound of the confidence interval as a new mean to calculate the average cost savings provides a conservative estimate, or lower limit, of the savings to Boulder County Jail. Using the same calculations above with the new lower estimate of 3.47, the average savings would be $1,165.6 per week in savings based on the median length of stay of 3 days ($86,611.2 per year in saving) or $7,606.24 per week in savings ($395,524.48 per year) based on the average length of stay of 13.7 days.

Upper Estimate: Conversely, taking the higher bound of the confidence interval as a new mean for calculating average cost savings provides the largest, or upper limit, of the savings to Boulder County Jail. Using the same calculations above with the new lower estimate of 5.17, the average savings would be $2,481.60 per week in savings based on the median length of stay of 3 days ($129,043.20 per year in saving) or $11,332.64 per week in savings ($589,297.28 per year) based on the average length of stay of 13.7 days.

Time Savings Analysis:

[1] https://assets.bouldercounty.org/wp-content/uploads/2020/06/sheriff-annual-report.pdf

In order to determine the average time reduction in arrest and booking (in hours) for law enforcement, the mean difference in the predicted vs. actual weekly municipal jail bookings (*M* = -4.321, *SD = 3.08*) was used. This resulted in an average weekly municipal booking reduction of 4.321 (95% CI = 3.47 – 5.17) bookings. From correspondence with City Prosecutor Christopher Reynolds, it takes an estimated 100 minutes for an officer to arrest and book a defendant in the Boulder County Jail. During this time law enforcement officers are tasked with general steps for processing an arrested person into jail detention, and other unanticipated time requirements including but not limited to processing an arrested person for medical clearance, delay in entering the jail sally port or limited staffing of booking officers. Using the numbers above, the Warrant Clustering program led to an estimated 4.3 to 7.2 hours of law enforcement time saved per week (224.69 – 374.49 hours per year). Those are hours that law enforcement officers can spend on other community service not related to municipal arrests.

Other Time Savings Estimates: Similar to the calculations above on the cost savings estimates, the 95% confidence intervals of 3.47 and 5.17 were used to create upper and lower bounds of time savings for officers. Lower (conservative estimate) = 3.47 to 5.78 hours per week (180.44 – 300.73 hours per year. Upper estimate = 5.17 to 8.62 hours per week (268.84 – 448.07 hours per year).

Using this 100 minute average booking time estimate, a single booking equates to 4.17% of an officer's total 40 hour work week. Policing expenditure by local and state governments for the state of Colorado has been estimated to range $250 - $350 annually.[2] Using the middle of this range $300, a single 100 minute booking per officer is estimated to cost $.006 per capita Colorado resident annually. The estimated average weekly reduction in bookings of 4.321 results in an annually reduction in bookings of 225, and cumulative reduction in cost per capita to Colorado of $1.35 annually.

Based on 2021 population estimates for the city of Boulder with 105,003 residents, the reductions in bookings as a result of Warrant Clustering could produce a cost-savings of $141,754 for city residents. Applying the confidence interval surrounding the average reduction ranging from the lower estimate of 3.47 to upper estimate of 5.17 reduction in weekly bookings. An annual reduction in law enforcement time-savings cost to the residents of the city of Boulder could range from $113,403 to $170,104.

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[2] Urban Institute.(2018) "Criminal Justice Expenditures: Police, Corrections, and Courts" https://www.urban.org/policy-centers/cross-center-initiatives/state-and-local-finance-initiative/state-and-local-backgrounders/criminal-justice-police-corrections-courts-expenditures#Question1Police

Appendix A

Table 5. *Descriptive Statistics of Municipal Jail Bookings for Boulder and Longmont*.

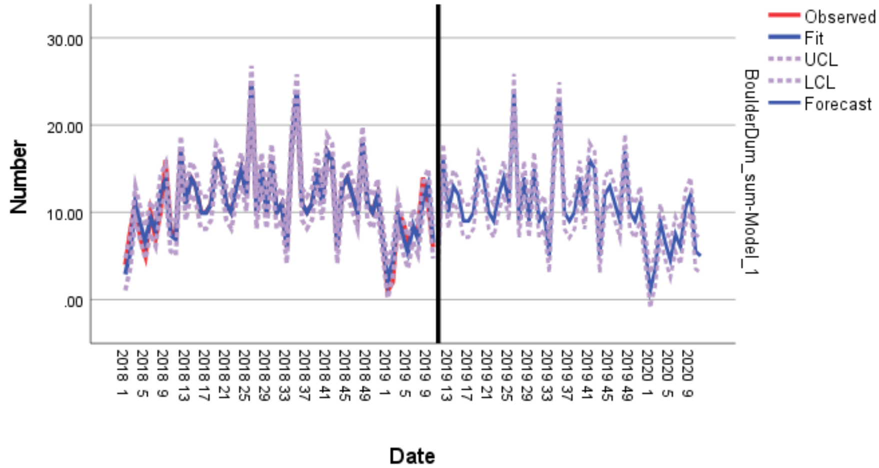
Time Series Descriptive Statistics

Intervention		Boulder	Longmont
Pre-Intervention	Mean	11.2903	1.8710
	Weeks	62	62
	Std. Deviation	4.40710	1.58356
Intervention	Mean	7.6129	1.8065
	Weeks	31	31
	Std. Deviation	3.35338	1.16674
Post-Intervention	Mean	6.1818	1.4091
	Weeks	22	22
	Std. Deviation	2.50022	1.25960
Total	Mean	9.3217	1.7652
	Weeks	115	115
	Std. Deviation	4.39407	1.42244

Appendix B
Additional Time Series Analysis Designs

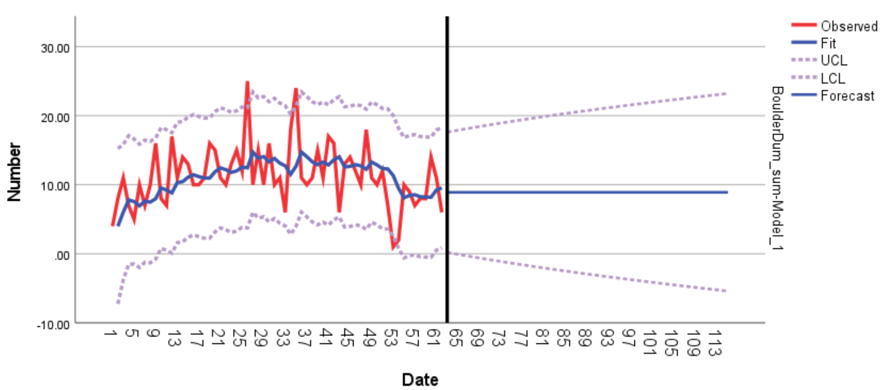
Winter's Additive Model. First, the SPSS Time Series expert modeler identified Winter's Additive exponential smoothing model as the appropriate forecasting procedure. This model did not consider statistical outliers or ARIMA components of the time-series (see Figure 7).

Figure 7. Winter's Additive Time Series Model.



ARIMA with no outliers modeled. Second, the SPSS Time Series Expert Modeler identified an ARIMA (0,1,1) model as the appropriate forecasting procedure. This model excluded exponential smoothing models and statistical outliers. As can be seen in Figure 8, the pre-intervention data does not appear stationary (i.e., no constant mean and variance over time), thus the modeler identified 1 integrated/differencing component to achieve stationarity. Further, this model identified a moving average order of 1, suggesting that a seasonal cycle/trend, or the observation for jail bookings per week experienced 1 persistent random shock from one observation to the next that must be accounted for in the model.

Figure 8. *ARIMA (0,1,1) no outliers modeled*



Three paired-samples t-tests were performed to assess the relationship between the 53 weeks of observed post intervention data to the three forecasts of the post intervention data. As Table 6 displays, the mean differences between each group decreased after the intervention. There was a statistically significant difference between the observed post intervention jail booking data and all three forecasts ($p < .001$), indicating that the observed post intervention bookings were significantly lower than the projected post intervention. The mean differences in each model ranged from 1.89 to 4.32, with the ARIMA with outliers modeled serving as the best predictive model. With a mean difference of 4.32 weekly municipal jail bookings and a large effect size of 1.402 (Cohen's *d*), there is strong evidence that the Warrant Clustering intervention significantly impacted the number of municipal bookings for the City of Boulder.

Table 6. *Predicted vs. Observed Weekly Average Municipal Jail Bookings from Boulder Based on Time Series Models.*

City of Boulder weekly municipal jail bookings		Mean Bookings	Standard Deviation
Model 1) Winter's Additive Model[1]	Predicted Post-Intervention	10.64	4.41
	Observed Post-Intervention	7.02	3.09
Model 2) ARIMA (0,1,1) no outliers modeled[2]	Pre-Intervention	8.91	0.00
	Post-Intervention	7.02	3.09
Model 3) ARIMA (0,1,1) with outliers modeled[3]	Pre-Intervention	11.34	0.07
	Post-Intervention	7.02	3.09

[1] $t(52) = -5.33$, $p < .001$. Mean difference = 3.62, effect size = 0.73 (Cohen's *d*)

[2] $t(52) = -4.47$, $p < .001$. Mean difference = 1.89, effect size = 0.61 (Cohen's *d*)

[3] Best predictive model. $t(52) = -10.20$, $p < .001$. Mean difference = 4.32, effect size = 1.402 (Cohen's *d*)

Appendix B

Additional Time Series Models for the City of Longmont

Similar to the City of Boulder models in Appendix A, a Winter's Additive and ARIMA with no outlier modeled were run. Figures 9 and 10 display these forecasts.

Figure 9. Winter's Additive for the City of Longmont Municipal Jail Bookings

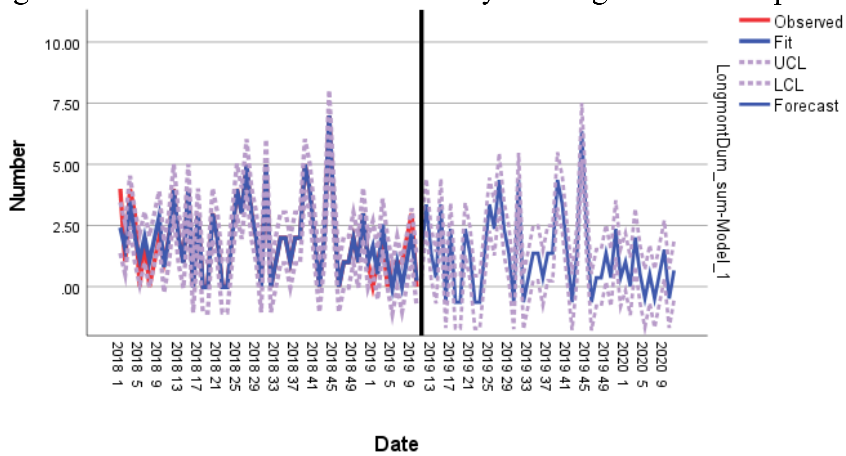
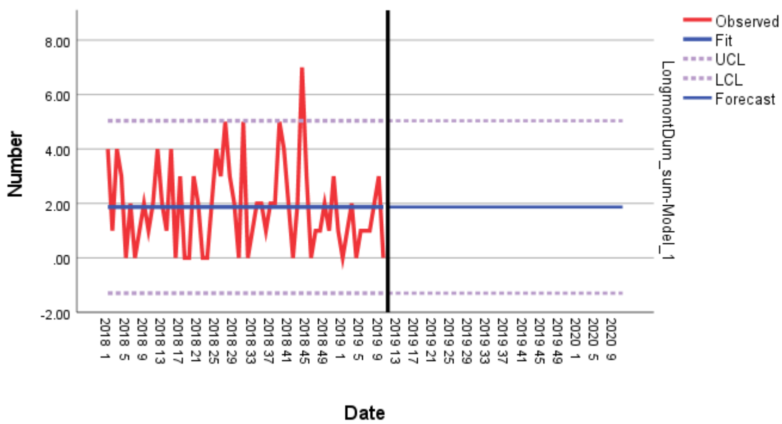


Figure 10. ARIMA (0,0,0) (no outliers modeled) for the City of Longmont Municipal Jail Bookings.



Similar to the City of Boulder analysis above, paired-samples t-tests were performed to assess the relationship between the 53 weeks of observed post intervention data to the three forecasts of the post intervention data. As displayed in Table 7, the mean differences between each group did not decrease after the implementation of Warrant Clustering in Boulder. There were no statistically significant differences between the observed post intervention data and any of the three forecasts among the observed time periods.

Table 7. *Average Number of Municipal Jail Bookings from Longmont Pre and Post Warrant Clustering intervention in Boulder including Predicted Based on Time Series Models.*

City of Longmont weekly municipal jail bookings		Mean Bookings	Standard Deviation
Observed Pre and Post[1]	Pre-Warrant Clustering Time	1.87	1.58
	Post-Warrant Clustering Time	1.64	1.21
Model 1) Winter's Additive Model[2]	Observed Post-Warrant Clustering Time	1.64	1.21
	Predicted Post-Warrant Clustering Time	1.24	1.59
Model 2) ARIMA (0,0,0) no outliers modeled[3]	Observed Post-Warrant Clustering Time	1.64	.166
	Predicted Post-Warrant Clustering Time	1.87	< 0.001
Model 3) ARIMA (0,0,0) with outliers modeled[4]	Observed Post-Warrant Clustering Time	1.64	1.66
	Predicted Post-Warrant Clustering Time	1.79	< 0.001

[1] $t(113) = 0.861$, $p = .39$. Mean difference = .23, effect size =.16 (Cohen's *d).*

[2] $t(52) = 1.45$, $p = .15$. Mean difference = .40, effect size = .199 (Cohen's *d*)

[3] $t(52) = -1.38$, $p = .17$. Mean difference = .23, effect size = -.190 (Cohen's *d*)

[4] $t(52) = -.87$, $p =.39$. Mean difference = .15, effect size = -.120 (Cohen's *d*)