CRIMINAL JUSTICE COORDINATING COUNCIL
AMENDED AGENDA

Date & Time of Meeting: **Thursday, January 19, 2023, at 8:00 a.m. – 9:30 am**

Meeting Location**: Courthouse Assembly Room, (B105), Courthouse, 500 Forest Street, Wausau WI**

Council Members: Chair Suzanne O'Neill, Vice Chair Kurt Gibbs, Lance Leonhard, Matt Bootz, Michelle Van Krey Chad Billeb, Ben Bliven, Theresa Wetzsteon, Kelly Schremp, Kat Yanke, Cati Denfeld-Quiros, Vicki Tylka, Jane Graham Jennings, Kenneth Grams, Yauo Yang, Daniel Tyler, Liberty Heidmann.

Marathon County Mission Statement: *Marathon County Government serves people by leading, coordinating, and providing county, regional, and statewide initiatives. It directly or in cooperation with other public and private partners provides services and creates opportunities that make Marathon County and the surrounding area a preferred place to live, work, visit, and do business. (Last updated: 12-20-05)*

Council Mission Statement: *To improve the administration of justice and promote public safety through community collaboration, planning, research, education, and systemwide coordination of criminal justice initiatives.*

1. **Call Meeting to Order**
2. **Public Comment** *(not to exceed 15 minutes)*
3. **Approval of the November 17, 2022, CJCC Meeting Minutes**
4. **Operational functions required by bylaws**
5. **Operations Issues**
   A. Defense Attorney Whitepaper – Judge O'Neil
   B. Opioid Funding Work Group – Laura Yarie
6. **Policy Issues for Discussion and Potential Council Action**
   A. Root Cause Analysis on Marathon County Arrests – Ruth Heinzl
7. **Educational Presentations/Outcome Monitoring Report**
   A. Marathon County D.A. Theresa Wetzsteon- 2022 District Attorney of the Year – Administrator Leonhard
   B. Workforce Innovation and Opportunity Act (WIOA) Presentation – Forward Service Corporation Career Planner Nicky Lindman and Tyler Leiskau.
   C. Public Defender Project Position – Attorney Manager Kat Yanke
   D. Update from NCHC Managing Director of Community Programs (Vicki Tylka)
      1) What is our "desired future state" and how do we intend to achieve it?
8. **Adjournment**

**Any person planning to attend this meeting who needs some type of special accommodation to participate should call the County Clerk's Office at 261-1500 or e-mail countyclerk@co.marathon.wi.us one business day before the meeting*

SIGNED: /s/, Judge Suzanne O'Neill
Presiding Officer or Designee

EMAILED TO: Wausau Daily Herald, City Pages, and other Media Groups
EMAILED BY: Toshia Ranallo
DATE & TIME: 1/17/2023 at 9:15 am

NOTICE POSTED AT COURTHOUSE
BY: Toshia Ranallo
DATE & TIME: 1/17/2023 at 9:15 am

MARATHON COUNTY
CRIMINAL JUSTICE COORDINATING COUNCIL MINUTES

Thursday, November 17, 2022, at 8:00 a.m. – 9:30 am
Courthouse Assembly Room, (B105), Courthouse, 500 Forest Street, Wausau WI

Members	Present/Web-Phone	Absent
Chair Suzanne O'Neill	X	
Vice Chair Kurt Gibbs		X
Lance Leonhard	X	
Matt Bootz		X
Michelle Van Krey	X	
Scott Parks	X (designee Chad Billeb)	
Ben Bliven	X (designee Todd Baeten)	
Theresa Wetzsteon	X	
Kelly Schremp	X	
Kat Yanke	X	
Cati Denfeld-Quiros	X	
Vicki Tylka	X	
Mort McBain	X	
Jane Graham Jennings	X(designee Ashley Bores)	
Daniel Tyler	X	
Yauo Yang	X	
Liberty Heidmann	X	

Also present: Ruth Heinzl, Nikki Delatolas, Greg Grau, Laura Yarie, Jacob Chittum.

1. **Call Meeting to Order**
   The meeting was called to order Judge O'Neill at 8:00 a.m.

2. **Public Comment** *(not to exceed 15 minutes)*
   No public comment is received.

3. **Approval of the Minutes of the September 15, 2022, CJCC meeting**
   MOTION BY LEONHARD, SECOND BY BILLEB TO APPROVE THE SEPTEMBER 15, 2022, CJCC MEETING MINUTES. MOTION CARRIED.

4. **Operational functions required by bylaws – None**

5. **Operations Issues - None**

6. **Policy Issues for Discussion and Potential Council Action-**
   A. **Public Safety Strategic Plan regarding attorney shortage**

***Discussion**:*

Leonhard discussed Marathon County Objective 7.1 to Provide Cost Effective and High-Quality Public Safety Services and the Public Safety Committee goal to issue a whitepaper by December 31, 2023, regarding strategies to outline what counties can do to address the public defender shortage. Leonhard asks for anyone interested in assisting with this to send him an email as he is looking for staff research and input for outside the box solutions and incentives. Wetzsteon requests that Judges in the interim come up with a consistent policy between the branches for county appointments for indigent defendants. She states that currently some are being required to pay back attorney costs and others are not, and it is known that this will affect budgets and the State will not reimburse the County for these appointments. The group discusses ongoing issues with defendants applying for an attorney. Yanke states concerns about consistent access to jail inmates prior to intake, and the 22% increase in those not qualifying due to the use of the poverty level from 2010-2011. Leonhard mentions the possibility of having someone from the Public Defender's Office at intake court to determine eligibility for out of custody defendants. Yanke states current staffing levels would not allow for this. Wetzsteon advocates for having someone available at initial appearances and the value of the county investing in this as the cost is significant when considering case delays for those who don't get an attorney.

Action:

Lance requests those interested in working on solutions for the whitepaper to email him directly.

Follow Up:

None

7. Educational Presentations/Outcome Monitoring Reports

A. Police Assisted Addiction & Recovery Initiative (PAARI) – Wausau PD

Discussion:

Jacob Chittum, Supervisor of the Wausau PD Community Resource Unit, attended and presented on PAARI. He states this is a grant program to reduce overdose deaths. The Wausau PD visited Plymouth County in Massachusetts to learn about the program as they have had great success there. The program provides outreach to individuals within 72 hours of an overdose. This is an optional program and participation is not forced. Officers visit with a recovery coach and are not there to investigate but to help. Recovery coaches hand out harm reduction kits and resources for the individual to call for help. In Massachusetts they get individuals into treatment beds within 48 hours, and they are hoping to expand their work to people who have not yet overdosed. Chittum states that there is currently a need for a list of qualified recovery coaches and additional resources for treatment beds locally. The group discussed funding for and development of recovery coaches within the community as well as the way this program can partner with the Deflection Program being developed with NCHC. Yarie mentioned that Drug Court has been approached by the Recovery Coach Program through AmeriCorps and there are opportunities to host recovery coaches locally for a stiped. Baeten states that the PD is working on strategic planning to recruit recovery coaches. Yang suggests tapping in to NTC students in the AODA field. Denfeld-Quiros suggests presenting PAARI to F.O.R.T (Fatality Overdose Review Team).

B. Final 2023 County Budget Update – Administrator Leonhard

Discussion:

Administrator Leonhard reports the 2023 Marathon County budget has been finalized. Resources have been allocated to a limited term Victim Witness position within the District Attorney's office as well as a Data Officer position within County Administration. Leonhard hopes to begin hiring for the data position the first quarter of 2023. County funding for the Court Mediation Program for eviction cases remained in the 2023 budget as well as contracts with The Women's Community.

C. Criminal Case Backlog Update – Judge O'Neill

Discussion:

Judge O'Neill reports a shout out to Marathon County at a recent Judicial Conference. Marathon County is second in the State as far as reducing criminal case backlog from the pandemic. Waukesha County is the only county to have a higher rate for disposing of cases.

D. NCHC Program Update – Mort McBain

Discussion:

McBain distributes a handout titled NCHC Wausau Campus Renovation Update (attached). He discusses a reorganization of positions at NCHC to better coordinate services between the counties and NCHC. It is believed that the new structure will better allow the organization to be accountable and responsive to the needs of each county. The five leadership positions consist of Managing Director of Finance, Chief Medical Officer, Managing Director of Nursing Homes, Compliance Officer and Managing Director of Community Programs. McBain states that there needs to be a clear understanding of what NCHC does and how to do it better as well as for the counties to understand what can and can not be provided. McBain feels the lack of understanding causes on going problems between agencies and that NCHC needs to improve communication. NCHC is a very complex organization with 850 employees, he feels the Managing Director of Community Programs position will help with staying aligned with the agency purpose for existing. He discusses the major difficulties the agency is experiencing with hiring and staffing programs.

E. Pretrial Program Update – Laura Yarie

Discussion:

Yarie presented current numbers from the Pretrial Program. She stated the ongoing need to close cases quickly and the burden to case manager resources when cases stay open. She further discussed the issues with data comparison due to increased length of pretrial supervision. Yarie reports that DOJ has hired a pretrial data position to evaluate the effectiveness of the pretrial pilot. This individual will be visiting Marathon County December 6, 2023, from 12:00 -2:00p.m. at the office of ATTIC. Wetzsteon questions if there is data to determine which supervision levels are having the most FTA and New Criminal Activity as it is important to understand if we are working with the right people and if the assessment is predicting accurately.

8. Adjournment

MOTION BY BILLEB, SECOND BY LEONHARD TO ADJOURN THE MEETING AT 9:30 a.m. MOTION CARRIED.

CRIMINAL ARRESTS ON THE RISE:
AN EXPLORATORY ANALYSIS ON A POST-COVID INCREASE IN ARRESTS

by
Ruth Heinzl

A capstone submitted to Johns Hopkins University in conformity with the requirements for the degree of Master of Science in Data Analytics and Public Policy

Baltimore Maryland
December 2022

Abstract

Arrest rates fluctuate throughout time and across jurisdictions due to changes in policy, environmental circumstances, or other catalytic events. Knowing how these events change the makeup of how many individuals are arrested can lead to better law enforcement practices. This study uses data from Marathon County, Wisconsin, and conducts time series analysis and logistic regression to determine whether the severity of the crime is a statistically significant predictor variable of the probability of arrest, as well as look at the impact of major policy changes on the variance in these arrest rates.

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Figures

1. Introduction

Arrest rates fluctuate throughout time and across jurisdictions. Policies change regularly, impacting arrests through events such as the implementation of evidence-based practices or in response to life-altering events. Marathon County, Wisconsin has enacted a few major policy changes over the last five years, with the application of an evidence-based actuarial tool to determine offender risk levels and arrest restrictions in response to the COVID pandemic. This analysis looks into two hypotheses. First, the severity of the crime is a statistically significant predictor of custodial arrests. Second, imposing large policy changes can have a considerable impact on arrest rates, positively and negatively.

1.1 An Increase in Arrests

Over the last six months, many criminal justice stakeholders in Marathon County have expressed perceiving an increase in arrests and jail population. As a key performance indicator, the number of arrests should be investigated if concerns arise to mitigate any issues that arise. There are many consequences to criminal arrests, including personal, familial, community, and taxpayer consequences.

1.2 History of Policy Changes

1.2.1 Actuarial tools. The first critical decision point examined in this study was the enactment of the Proxy Risk Assessment Tool to assist in determining whether to cite or summon an alleged offender or make a custodial arrest. Stakeholders noticed unnecessary arrests of low-risk first-time offenders and explored alternative options. The decision to use this tool was because it is evidence-based and simple to administer by only asking three questions based on age and criminal history to calculate a risk score. A policy and decision tree for utilizing this tool was enacted on March 1, 2019.

1.2.2 Authorization of COVID Restrictions. The second major critical decision point explored is the authorization of imposing COVID restrictions. Along with Wisconsin's Safer at Home Act, the Marathon County Sheriff's Office instituted restrictions on the type of offender they would accept to book into jail. The jail was not allowed to accept bookings based solely on warrants or probation holds and was only to accept bookings where the alleged offender was an immediate danger to the public. These restrictions were put in place on March 15, 2020.

1.2.3 Lifting COVID restrictions. The final critical decision point studied is the lifting of the COVID restrictions. With a consistently low COVID-positive census, the Marathon County Sheriff's Office determined it was safe to lift all COVID restrictions on August 30, 2021. The order was to allow all previously allowed bookings with the encouragement to follow the proxy guidelines.

2. Literature Review

2.1 Actuarial Tools Influence on Arrest

This study will look at the impact of implementing a pre-arrest actuarial tool on arrest rates. Any study on actuarial tools most often looks at recidivism and not the actual rate of arrests. Therefore, to my knowledge, there are no studies pertaining specifically to the impact of actuarial tools on criminal arrests.

2.2 COVID Restrictions Influence on Arrest

This study will also look at how COVID restrictions affected criminal arrest rates. Studies have looked at the consequences of COVID restrictions on domestic violence rates and other crime patterns, but not on the overall arrest rates. Therefore, to my knowledge, there are no studies pertaining specifically to the impact of COVID on arrest.

2.3 Criminal History's Influence on Arrest

In terms of external factors influencing arrest, the research considers criminal history as contributing to increasing the odds of arrest. Research shows that an individual with a history of criminal convictions is more likely to be arrested in the future. Many studies consider the relationship between criminal history and recidivism, but there was only one research study that analyzed the relationship between criminal history and arrest. This analysis found that individuals with a criminal record are 29 times more likely to be arrested.[1]

This same study presumed that individuals with previous criminal convictions are more likely to be arrested due to being more criminally predisposed.[2] Another assertion found in the study identifies the strong influence of criminal history on arrest as indicating a chronicity that should be considered by decision-makers.[3] To decrease criminality in the community, decision-makers should consider other evidence-based practices to decrease criminal behavior, even if those practices seem like a major deviation from the classic framework.

2.4 Demographic Factors that Influence Arrest

Various individual observable characteristics appear to increase the likelihood of an individual being arrested. Demographics considered by the research include race, age, and gender (redefined as sex in this analysis) as potential contributors to an increased probability of arrest. Firstly, race as a contributing factor yields mixed results. One study reviewed for this research paper found no significance between race and odds of arrest.[4] Otherwise, numerous other studies found that Black, Hispanic/Latinx individuals, and individuals living in Black

[1] Lisa Stolzenberg, Stewart J. D'Alessio, and Jamie L. Flexon. "The Usual Suspects: Prior Criminal Record and the Probability of Arrest." *Police Quarterly* 24, no. 1 (Mar, 2021), 41

[2] Ibid., 15.

[3] Ibid., 35

[4] Stolzenberg, 41

neighborhoods are more likely to be arrested. A meta-analysis found that Black individuals were 1.4 times more likely to be arrested and Hispanic/Latinx individuals 1.25 times more likely to be arrested.[5] A regression analysis found that Black individuals were 1.32 times more likely to be arrested than white individuals.[6] While a different regression analysis found, when controlling for all other variables, that an arrest was 1.71 times more likely to occur in a primarily Black neighborhood.[7] The inconsistencies and lack of consensus in the research present an unclear understanding of what role race plays in the odds of arrest and, ultimately, does not offer a direct pathway to alleviating disparity or reinforcing best practices.

Studies theorize that BIPOC (Black, Indigenous, and People of Color) are arrested more frequently than white individuals for a couple of reasons. A comprehensive study examined a range of community, school, family, and individual characteristics.[8] The study found a greater "impact of neighborhood racial composition in influencing racial/ethnic disparities of arrest above and beyond socioeconomic indicators of poverty, unemployment, vacant housing, and school quality." [9] Other studies have also found the significance of the racial composition of neighborhoods and an increase in arrest rates.[10] Something not often considered regarding the accuracy of this data is that oftentimes law enforcement does not ask offenders, victims, and witnesses which race they identify with, but instead assume either by their own perception or by default. Furthermore, many articles reviewed for this study sidestep the causality of race as a

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[5] Daniel J. Lytle. "The Effects of Suspect Characteristics on Arrest: A Meta-Analysis." *Journal of Criminal Justice* 42, no. 6 (Nov, 2014): 589-597., 595

[6] Lauren NicholGase, Beth A. Glenn, Louis M. Gomez, Tony Kuo, Moira Inkelas, and Ninez A. Ponce. *Understanding Racial and Ethnic Disparities in Arrest: The Role of Individual, Home, School, and Community Characteristics*. Vol. 8 Springer Science and Business Media LLC, 2016., 301

[7] Jessica Huff. "Understanding Police Decisions to Arrest: The Impact of Situational, Officer, and Neighborhood Characteristics on Police Discretion." *Journal of Criminal Justice* 75, (Jul, 2021): 101829., 10

[8] Gase et al., 298

[9] Ibid., 309

[10] Huff, 10

risk factor for arrest and can only conclude that the tangled web of systemic racism and slow institutional change lies at the root.

Secondly, with some mixed results, numerous studies found that age is not a significant predictor of arrest. The prevailing school of thought reflects age as a predictor for committing criminal offenses, but age might also increase the chances of someone being given a citation instead of being arrested when other factors come into play alongside age, like a lack of criminal history. In one meta-analysis, there was no significant relationship between age and probability of arrest across all studies.[11] Another study found that being older in age increased the likelihood of being arrested in certain types of offenses, such as possession of drug paraphernalia, theft, and criminal damage.[12] Often, first-time offenders are not being arrested and this could be where the discrepancy in age as a factor truly lies. Obtaining a significant enough criminal history that, in turn, makes you more likely to be arrested takes time in itself. Therefore, age and time pose a potentially curvilinear effect.

Third, few studies have reviewed sex as a predictor of arrest. A meta-analysis found that males were 1.49 times more likely to be arrested than females.[13] A regression analysis in a different study found that males were 2.2 times more likely to be arrested than females.[14] Another study found that females were 0.6 times as likely to be arrested, which ultimately presents being female as a protective factor against arrest.[15] In accordance with the previous

[11] Lytle, 593

[12] John D.Crum, and David M. Ramey. "Impact of Extralegal and Community Factors on Police Officers' Decision to Book Arrests for Minor Offenses." *American Journal of Criminal Justice* (Apr 19, 2022): 1-30. , 18

[13] Crum and Ramey., 593

[14] Sonja Starr. *Estimating Gender Disparities in Federal Criminal Cases*. Vol. 17 Oxford University Press (OUP), 2012. doi:10.1093/aler/ahu010., 6

[15] Melissa Hamilton and Meredith G. F. Worthen. "Sex Disparities in Arrest Outcomes for Domestic Violence." *Journal of Interpersonal Violence* 26, no. 8 (May, 2011): 1559-1578., 1567

study, another controlled for all other variables and concluded that females were .72 times as likely to be arrested.[16]

The phenomenon at work as to why males are arrested more often than females can go in many directions. One study theorized that males may commit more violent crimes with more force because of physical strength differences.[17] Not only considering physical pathways of thought, this study also theorizes that females are less likely to be arrested due to parental responsibilities because they are more cooperative, or that they are more often considered less culpable than males involved in the incident. The social element in this study's research links complexities in the perception of female offenders along with their assigned roles in society.[18]

2.5 Critical Gaps

As alluded to throughout this literature review, most studies look at individual characteristics of the offender when studying the variable impact on criminal arrests at the expense of other influential factors. Arrest rates may change as a result of agency policy changes due to ideology, functionality, need, or, ideally, the implementation of evidence-based best practices. A less well-known direction for research is the relationship between arrests and the number of active warrants. Amid COVID policies and bail reform causing fewer people to be brought into custody, it stands to reason that more individuals are not showing up to court as frequently, which directly increases the number of bench warrants issued. An increase in bench warrants is indicative of a loss of valuable court time and significant delays in proceedings.

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16 Lisa Stolzenberg and Stewart J. D'Alessio. "Sex Differences in the Likelihood of Arrest." *Journal of Criminal Justice* 32, no. 5 (2004): 443-454., 450

17 Starr, 14

18 Starr, 14-16

3. Data and Methods

The research site for this study is Marathon County, Wisconsin, the 10th largest county in the state, with a population of 137,648.[19] Marathon County's Criminal Justice Collaborating Counsel has been in existence for over a decade, and with between 4,000 and 5,000 new criminal cases per year, criminal case processing has always been a priority. Criminal arrest is the first step in the criminal process and the focus of this analysis.

3.1 Wisconsin Incident-Based Reporting System (WIBRS)

The WIBRS database is the Wisconsin repository for the National Incident-Based Reporting System (NIBRS) and part of the FBI's Uniform Crime Reporting (UCR) Program.[20] This dataset includes important information regarding the cited/summonsed versus arrested populations; however, there are significant sections of data that are missing to be the only dataset used in this analysis. This includes cases from arresting agencies outside of the Marathon County area, most significantly, the Wisconsin State Patrol. This dataset also does not capture the whole criminal justice population and thus will not tell the complete story of the Marathon County arrest practices. Proportion tables for all variables in the dataset can be viewed in Appendix A and Appendix B.

3.1.1 Dependent Variable. The dependent variable is a binary measure of arrest. This includes arrests on new charges and arrests on warrants or probation holds. Individuals not arrested in this dataset were issued a citation/summons to appear in court for their Initial Bond Hearing and released without booking.

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[19] "Quick Facts: Marathon County, WI". United States Census Bureau. Accessed November 1, 2022. https://www.census.gov/quickfacts/marathoncountywisconsin

[20] "WIBRS Data". Wisconsin Department of Justice. Accessed November 1, 2022. https://www.doj.state.wi.us/dles/bjia/wibrs-data

3.1.2 Independent Variables. The major predictor variable used for this analysis is based on the severity of the crime. This "severity scale" was weighted using the offense categories of violent victim crime, non-violent victim crime, drug crime, and other crimes. The weights of this scale range from one to four. Other independent variables used as controls in the study were the originating law enforcement agency, as well as the race, age, and sex demographics of the alleged offender.

3.2 PROsecutor TEchnology for Case Tracking (PROTECT)

The PROTECT database is a case management system for Wisconsin prosecutor offices. The difference about the dataset pulled from this database is that it is a more representative population of the whole criminal justice system. This dataset includes the arrested and cited/summonsed cases, as well as cases that are referred to the District Attorney's Office through other means. The proportion table for all variables in the dataset can be viewed in Appendix C.

3.2.1 Dependent Variable. The dependent variable is a binary measure of whether an individual is in custody at the time of their bond hearing. This is used as another measure to determine a type of arrest rate. All of the individuals in custody at the time of their Initial Bond Hearing were arrested, so this variable makes sense as a determinate of arrest, however, there is a significant population of arrested individuals missing due to posting bail and signing their bond before their Initial Bond Hearing.

3.2.2 Independent Variables. The main predictor variable used for this dataset is the variable that is based on the severity of the crime. This "severity scale" was calculated by combining the severity of the crime (Misdemeanor or Felony) and the class of the offense (A:U) and weighting them based on the alphabet (two sets total), ranging from five (Class U

Misdemeanor) to fifty-two (Class A Felony). The other control variables used are the originating law enforcement agency, whether there was a warrant, as well as the race, age, and sex of the alleged offender. Whether an individual was on a probation hold as part of their in custody status is another variable looked at from this dataset, but not included in any regression analysis due to 100% of probation holds being in custody.

3.3 Methods

3.3.1 Logistic Regression. Along with an initial Pearson Chi-Square test, a multivariate logistic regression was utilized to examine the statistical significance of using severity of the crime as a predictor of whether someone was arrested or in custody during their Initial Bond Hearing. All models include control variables to increase the accuracy of the regression model.

Model fit will be calculated using Pseudo-R-Squared (Pseudo R2), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Variance Inflation Factor (VIF). There is no comparison number to determine model fit for the Pseudo R2, AIC, and BIC, but the VIF must be under five to show that multicollinearity does not exist between the independent variables. Pseudo R2 is interpreted by comparing each model and the higher the number, the better the model fits the data. While AIC and BIC are also interpreted by comparing each model where the lower the number the better the model fits the data.

3.3.2 LOcal regrESSion (LOESS) Segmented Time Series Analysis. The first analysis utilized a local regression on a segmented time series analysis. The LOESS model is a computer algorithm that calculates a trend line by using a linear least squares regression with a nonlinear regression by using degrees of local polynomials and a weight function to find a slope that is the best fit for the model. This analysis will show the mean trend of the total arrest and in custody population.

3.3.3 Predicting. Utilizing a logistic regression alone is not useful for understanding probabilities of arrest. Therefore, we will run a prediction function on the logistic regression results and plot the predicted probability of arrest based on the severity of the crime.

3.3.4 Proportion and Means Analysis. For this analysis, we create a proportion chart and plot the mean of each category of the variable to see changes in mean proportions over each time segment.

4. Results

4.1 Logistic Regression Show Statistical Significant in Severity of the Crime

4.1.1 WIBRS Regression Table Model Fit Results. Utilizing Pseudo R2, AIC, BIC, and VIF, the Pseudo R2 (Appendix D) supports the last two models as being the best fit for the data, while the AIC and BIC significantly support the second model. The VIF score for all models supports very little correlation between independent variables if any.

4.1.2 WIBRS Regression Results. The regression model seen in Appendix D shows statistical significance between the severity of a crime and arrest to the 1% level, other than during the time period before the implementation of the actuarial tool, supporting the initial hypothesis. Age was the only variable with any significance before the implementation of the actuarial tool showing the variable that was most influential in determining arrest was not included in this analysis or arrests were mostly random during that time period.

Examining demographic characteristics in the WIBRS regression table, there was a statistically significant relationship between Black and white populations in relation to arrest, which shows while holding the Asian population constant, both of these populations were less likely to be arrested. The male population also shows statistical significance in being more likely to be arrested than females, while age shows a positive significance, where the older an alleged offender is, the more likely they are to be arrested.

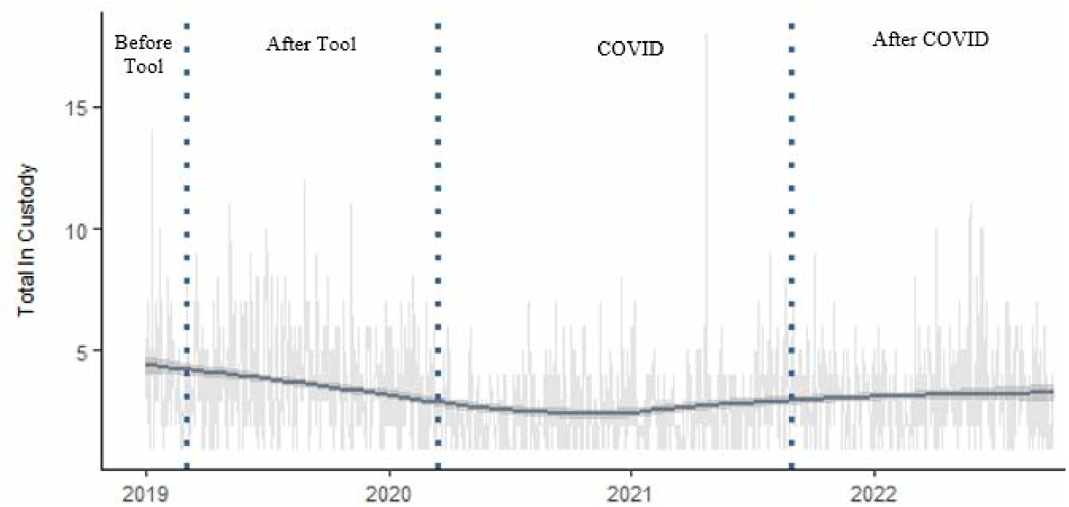
4.1.3 PROTECT Regression Model Fit Results. As seen in the regression model in Appendix E, the AIC and BIC calculations determine that the last three models (After tool implementation, during COVID restrictions, and after COVID restrictions) were the best fit for the data. The Pseudo R2 supports the after tool implementation model as being the best fit. The VIF score for all models supports very little correlation between independent variables if any.

4.1.4 PROTECT Regression Results. The regression model shows statistical significance between crime severity and the in custody population at the time of the Initial Bond Hearing at the 1% level, supporting the initial hypothesis. With all models support this, the data that best fits these models is during the time period after the tool implementation showing the impact on how the tool assisted an increased consistency in arrest based on risk as the main determining factor.

Examining demographics in this dataset, looking at the last time segments, there was a statistical significance in the increased likelihood for Native American individuals to be arrested. As well as a statistical significance in the likelihood of arrest for both the Hispanic/LatinX population and the Native American population wherein the Hispanic/LatinX population is less likely to be arrested and the Native American population is more likely to be arrested. This dataset also supports the statistical significance in the increased likelihood of arrest for males over females. Additionally, there is some significance during the 26 to 35 age range.

4.2 LOESS Segmented Time Series Analysis. This analysis shows Changes Correlated with the Enactment of Substantial Policy Changes. As seen in Figure 1, starting at a mean of approximately five daily arrests, the actuarial tool's implementation decreased the average of daily arrests until COVID restrictions caused the mean to level out. Consequently, repealing COVID restrictions caused the average to have a slight temporary increase, but has begun to stabilize near the end of the after COVID restrictions period.

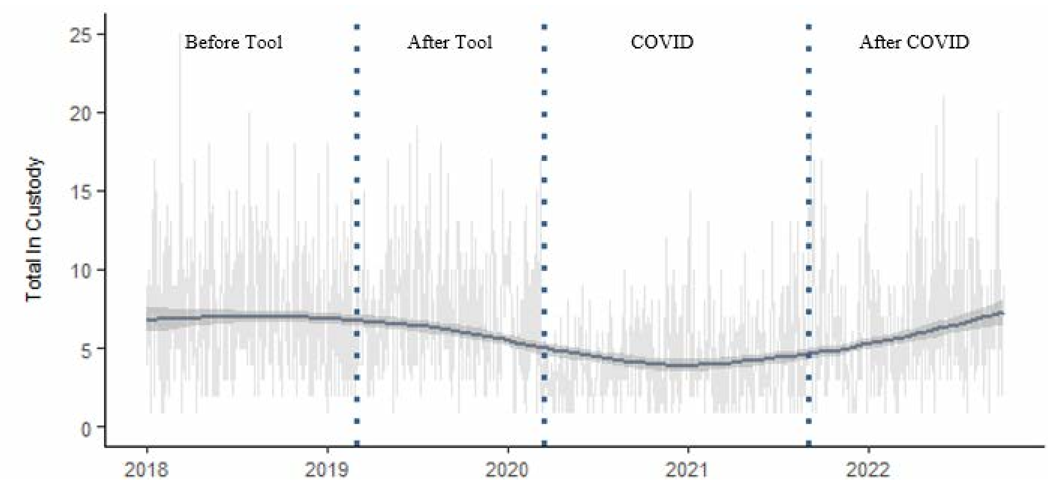
Figure 1. Critical Decision Points Impacts Number of Custodial Arrests



This model only slightly supports the concern of Marathon County criminal justice stakeholders of an increase in arrests. There could be an assumption that this increase is based on the restrictions on warrants and probation holds being lifted. In support of this claim, Wisconsin has a domestic violence mandatory arrest law. These individuals are allowed to pay a cash bail based on the Wisconsin bail schedule and bond out of jail prior to their Initial Bond Hearing. However, individuals arrested on warrants and probation holds are unable to do the same.

Figure 2 also shows visible trend shifts after the enactment of substantial policy changes. While the average daily in custody population maintained stability before the implementation of the actuarial too, the period after shows a marked decrease. The average decreased further throughout the COVID-19 Pandemic and later drastically increased after the restrictions were lifted.

Figure 2. Critical Decision Points Impacts In Custody Population at Initial Bond Hearings

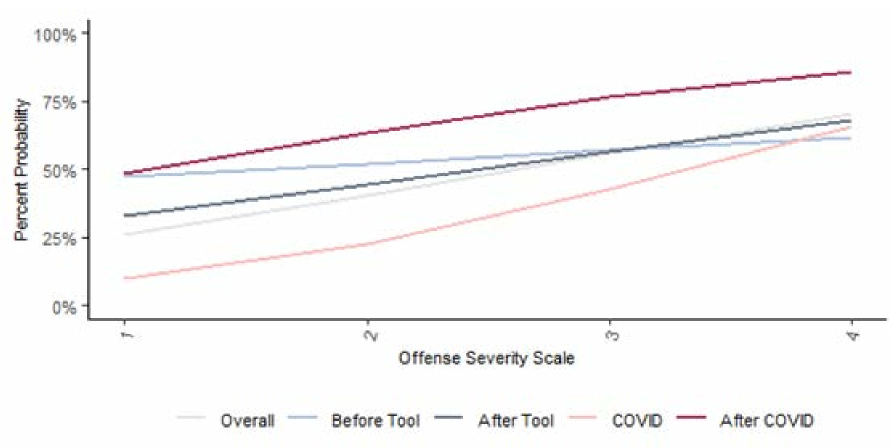


Marathon County criminal justice stakeholders are concerned about arrest increases and this upward trend in the average warrants further exploration. This could also support the same as Figure 1, where there is an increase in warrants and probation holds, while other arrests remain the same. With this hypothesis, this number should increase or level out until the system "catches up" on warrant arrests, then subsequently decrease to the after-tool implementation period.

4.3 Predicting Arrest and In Custody Population

After running a regression analysis on all models, using the predict function to show the probability of arrest based on the severity of the crime, Figure 3 shows a significant difference in this relationship. Before the implementation of the actuarial tool, there seems to be very little difference in the probability of arrest based on the severity of the crime, while after implementation there is a very linear relationship. During COVID, the probability of arrest greatly decreases for the lowest crime severity, while the highest remains about the same. However, after the restrictions were lifted, the likelihood of arrest for low-level offenses increased to pre-actuarial tool levels.

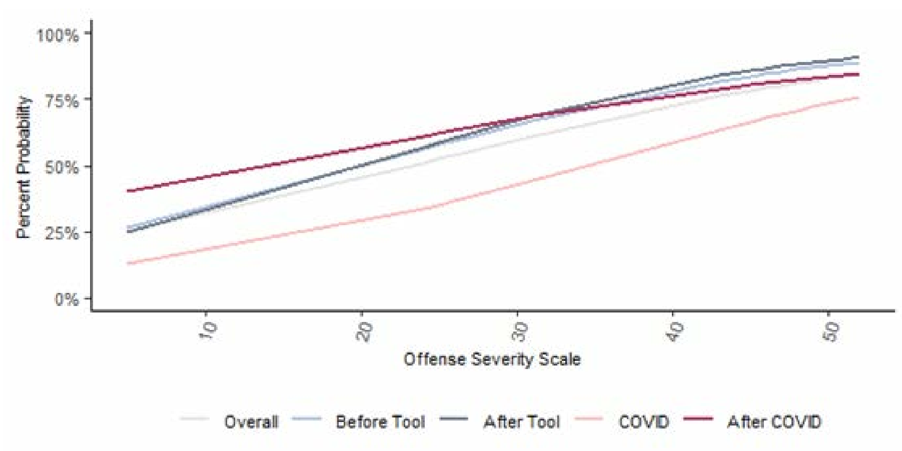
Figure 3. Critical Decision Points Impacts Probability of Custodial Arrests



This significant increase in the probability of arrest after COVID restrictions were lifted also supports the claim by Marathon County criminal justice stakeholders, that arrest rates have increased. However, this overall increase could support the theory that this increase is based on the backlog of warrants. Individuals with warrants often are caught based on low-level offenses.

Figure 4 shows there wasn't much of a change in the probability to be in custody at the Initial Bond Hearing before and after the implementation of the actuarial tool. This difference compared to figure 3 could be explained through the population that was no longer arrested after the utilization of the tool are individuals that would have bonded out previously. During COVID, the likelihood of arrest made a significant drop, even more significantly for low-level felonies, which would score somewhere around thirty on the severity scale. After the COVID, the whole population increased in the probability of arrest with a greater increase in low-level offenses.

Figure 4. Critical Decision Points Impacts Probability of in Custody Population at Initial Bond Hearing

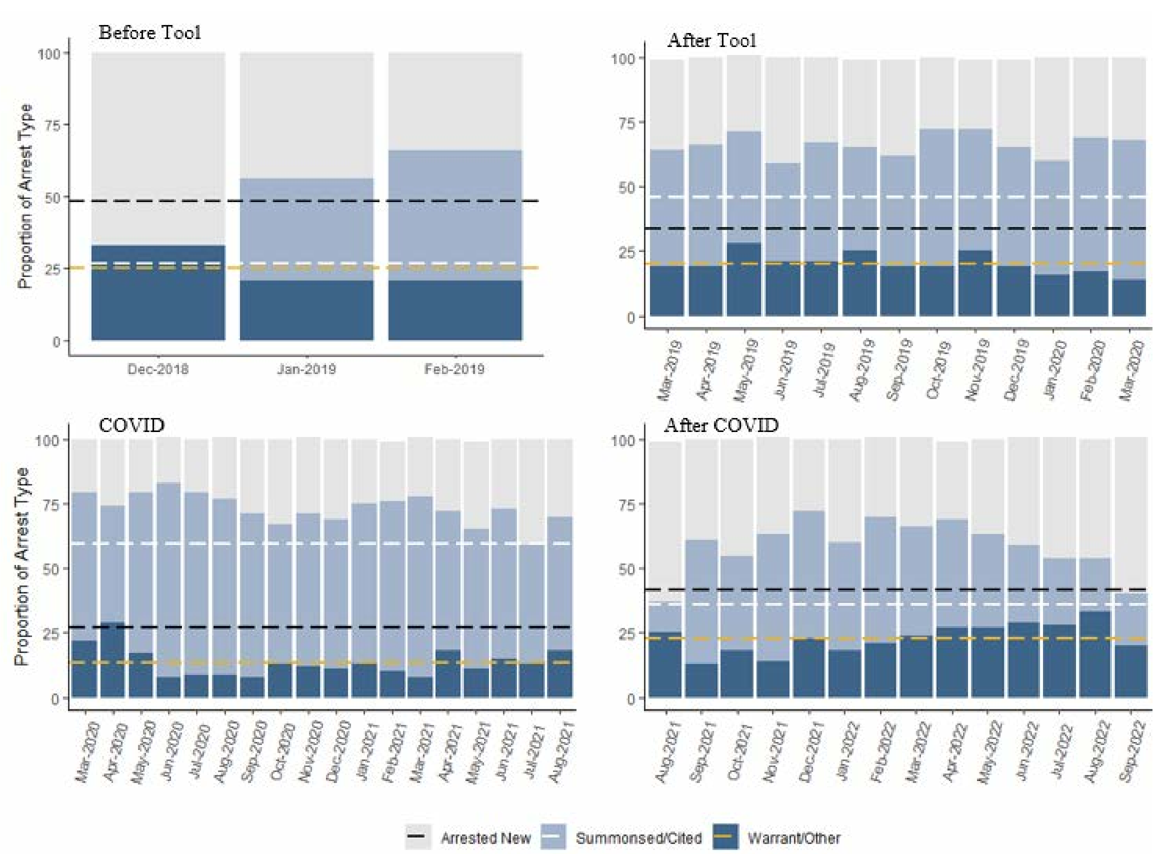


This significant increase after lifting restrictions further supports the claim by Marathon County criminal justice stakeholders that arrest rates have increased. The significant increase in low-level offenses also supports the theory that this increase is based on the ability to book individuals with warrants into custody. This will be investigated further through the proportion graphs.

4.4 Proportion Charts Over Time and Means Analysis

The important things to consider when interpreting the charts in Figure 5 are the mean lines. The white line represents the cited or summonsed population, where this mean was equal to arrests on warrants and notably less than the mean of the arrested population. This mean jumps to almost 50% after the implementation of the tool and then to approximately 60% during COVID. Proportionally the mean for the cited or summonsed population greatly decreases after the restrictions ended.

Figure 5. Proportions of Arrest Type and Means Analysis Shows Significant Fluctuations Between Critical Decision Points

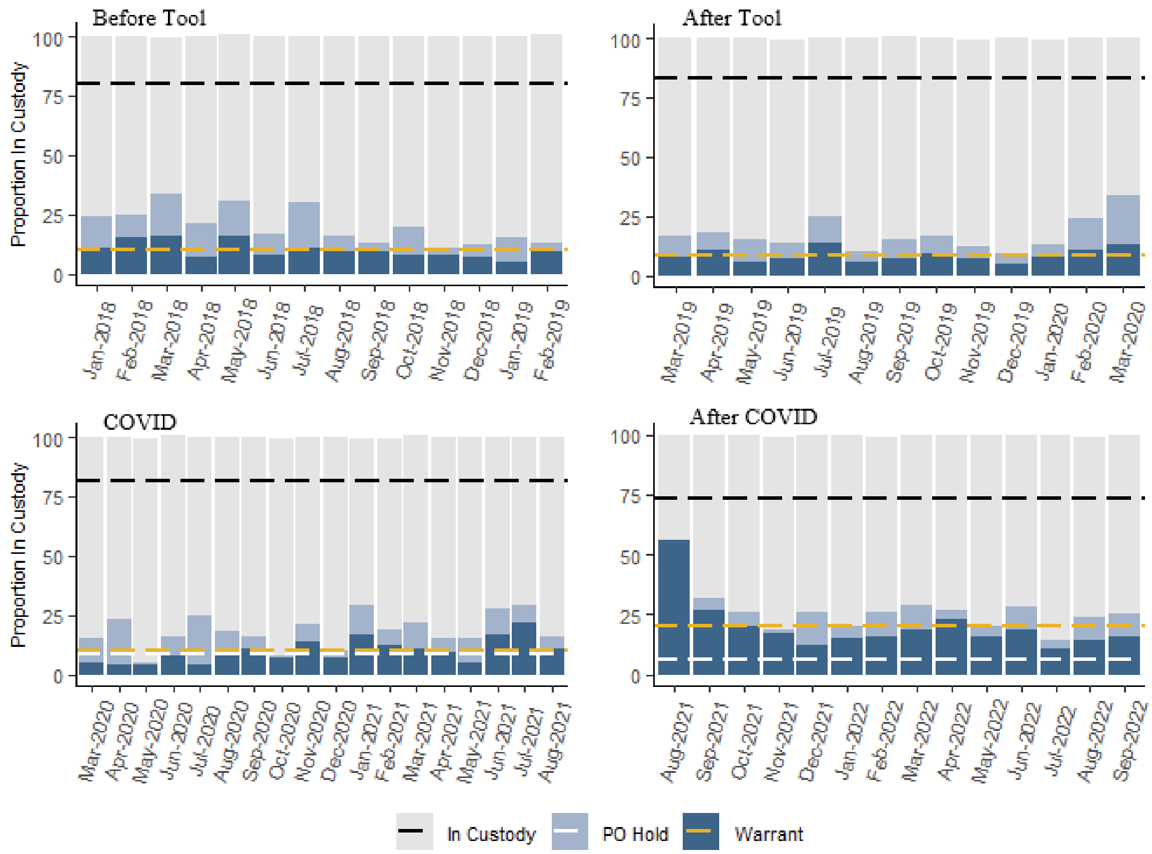


The mean of the arrested populations based on new criminal offenses, in figure 5, also changes drastically between periods. The mean begins at around 50% of the population and subsequently decreases to approximately 30% after the actuarial tool's enactment. It further decreases to approximately 25% during the pandemic. Then, the mean rebounds to 55% post-pandemic. Concurrently, the mean for the warrant population remains about the same and only decreased during COVID.

These charts do support the concerns of the Marathon County criminal justice stakeholders, but do not support the theory of warrants being the reason for the increase in arrests. In the final graph depicting post-pandemic restrictions, a drastic increase in both individuals arrested on warrants and new charges in the last six months displays a greater amount of variability in the data. This phenomenon skews the data to appear to be lower overall. This may warrant further investigation into other possible reasons behind this increase.

Figure 6 looks at the PROTECT data and the makeup of the population that is in custody during their Initial Bond Hearing. The mean proportion of people that are in custody based on new charges only remains relatively consistent throughout all four time periods, varying between approximately 75% to 80%. The proportion of people with warrants or probation holds remains relatively consistent for the first three periods at approximately 10% of the population. It should be noted that the warrant and probation hold lines overlap in the first two graphs. The proportion of individuals appearing in custody on warrants drastically increased to approximately 20% post-pandemic.

Figure 6. Proportions of In Custody Population at the Initial Bond Hearing and Means Analysis Shows Significant Fluctuations Between Critical Decision Points

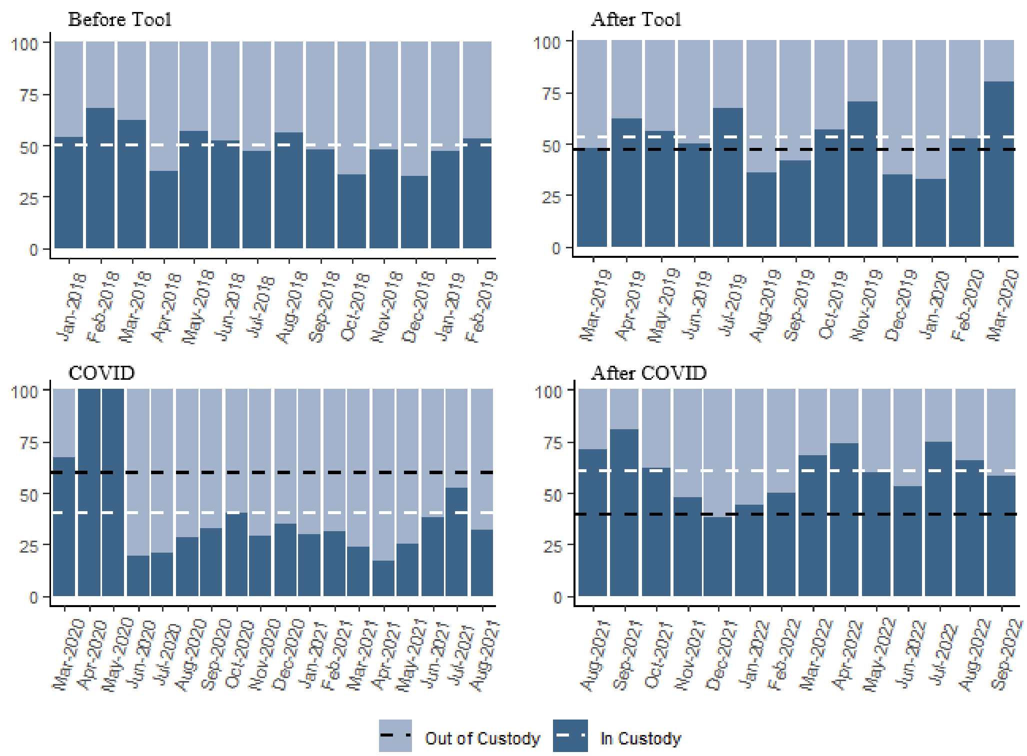


These charts neither support nor fail to support the concerns of whether there is an increase in the number of arrests. What figure 6 does support is the theory of the increase in arrests being based on the increase in individuals arrested on warrants. The first four months after the restrictions were lifted were far greater than the remaining eleven months in this dataset, showing that the proportion of warrants is leveling off, but still greater than before COVID.

4.5 Proportion Charts Over Time and Means Analysis of Warrants

The final figure in this analysis (Figure 7) looks at the proportions of individuals appearing on warrants at their Initial Bond Hearing and whether they are in custody or out-of-custody at the time their warrant is quashed. There are some significant differences between the proportions over the four time periods. Before the actuarial tool was implemented, the in custody and out-of-custody warrant appearances were exactly equal, at 50%. The mean proportion for the individuals appearing out-of-custody on their warrants decreases after the implementation of the actuarial tool, increases during COVID, then drastically decreases after the restrictions were lifted.

Figure 7. Proportions of In Custody vs. Out-of-Custody Warrant Appearances at the Initial Bond Hearing Shows Significant Fluctuations Between Critical Decision Points.



The mean proportion of individuals appearing in custody to quash their warrant decreased during COVID, but dramatically increased after the restrictions were lifted. In turn, this supports the stakeholders' concerns and the theory that the increase in arrests is based on the backlog in COVID restrictions era warrants.

5. Conclusion

This analysis explored two specific inquiries. The first was on whether the severity of the crime is a statistically significant predictor of arrest as well as in custody status at the Initial Bond Hearing. The second was on how critical policy changes may have impacted the arrested population. With both datasets, the severity of the crime was determined to be statistically significant at the 1% level. Through computing a prediction function on the regression results, this significance supported the concerns of Marathon County stakeholders on seeing an increase in arrests.

Furthermore, using local regression smoothing on segmented time series data showed notable changes in arrest and the in custody populations in alignment with particular policy changes. To investigate this further proportion graphs with means analysis were examined and showed the fluctuation in these populations over these segmented time periods. These analyses confirmed that the implementation of the actuarial tool did create a positive impact on these rates. Therefore, the analysis confirmed Marathon County stakeholders' concerns that there has been a marked increase in arrests over the last six months. The explanation for this increase is presently unknown. A signification portion of this uptick may be due to higher rates of arrest for individuals with warrants.

5.1 Implications

These results suggest ending COVID restrictions initially influenced higher arrest rates, but has since leveled off. Whether or not arrest rates will naturally decrease based on the current status of the criminal justice system as a whole without further intervention is unknown. Policies could be considered on finding ways for individuals with active bench warrants to appear and quash their warrant without arrest, focusing on individuals that habitually fail to appear for their court appearances.

5.2 Critical Limitations

One of the major limit of the datasets in this analysis was the lack of a common variable accuracy in order to combine datasets. Even though there is a common variable of agency case number, this number is imputed differently by each law enforcement agency and does not get transferred through the law enforcement and Protect interface with the same value. Being able to combine datasets could increase the accuracy of the data and would create better efficiencies instead of duplicating work.

Another limitation is the inability to get data based on who is arrested and bonds out of jail prior to their Initial Bond Hearing. To get a full picture, it is important to understand this subset of people and their impact on the system. Without this data, this decreases the understanding of how many people are arrested out of the criminal justice population as a whole. On this same note for the WIBRS dataset, the inability to obtain data on cases that are referred to the District Attorney's Office outside of the traditional arrest or cite and release fails to capture the full understanding of who is arrested versus who isn't and greatly inflates the arrest ratio.

5.3 Areas for Future Research

5.3.1 Bond Hearing Assessment. Finding a way to gather data on whether a defendant bonds out of jail before the Initial Bond Hearing would be beneficial to seeing the whole picture of what is happening when an individual is arrested. Different states have various laws on whether an individual can sign a bond before going in front of a judge. In Wisconsin, individuals are allowed to sign bonds based on a bond schedule. An analysis on the impact of this bond schedule could help with other states passing similar laws and reducing the pretrial detention population.

5.3.2 Arrest Decision's Impact on Court Case Processing. Prior research fails to document how the decision to arrest affects case outcomes and taxpayer costs throughout the criminal justice system. Stakeholders are concerned with an increase in arrests mostly based on costs. However, this may also impact the rest of the criminal justice system with increasing failure to appear rates and increasing the likelihood of new criminal activity while defendants have pending cases. For a full cost-benefit analysis on arrest, many researchers study the impact of arrests on other key performance indicators in the criminal justice system, such as length of case processing time, number of "failure to appear" hearings, and sentence severity.

5.4 Recommendations to Marathon County

5.4.1 SAMHSA's Sequential Intercept Model. In the early 2000s, SAMHSA created a criminal justice system continuum model for jurisdictions to utilize and map out what resources are available under each "intercept".[21] It is recommended that Marathon County utilize this model to better understand what resources they have under each intercept and to determine where there are holes or an excess of resources. SAMHSA identifies intercept 0 as the most important intercept wherein individuals are kept out of the criminal justice system in totality. A vast amount of evidence-based programs exist at intercept 0 and may serve as new avenues of intervention for Marathon County in reducing arrests.

5.4.2 Key Performance Indicators (KPI) Dashboard. In Marathon County, the current practice is to request data and analysis as the thought arises. Pull-on-demand methods can lead to biases and the passing of ineffective policies. To monitor the criminal justice system as a whole,

[21] SAMHSA. "Data Collection Across the Sequential Intercept Model: Essential Measures". (Aug 2019).

key performance indicators should be set and an automated dashboard should be created. This dashboard should create regular reports for review by stakeholders and county board members to inform ongoing decision-making and future endeavors. The automation of pre-established key indicators creates an agreed-upon baseline for comparison and better controls for bias in interpretation.

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Appendix A. WIBRS Proportion Table: Overall, Before and After Tool Implement

		Overall				Before Actuarial Tool				After Actuarial Tool		
	N	Arrested New N = 2,539[1]	Summonsed/Cited N = 3,754[1]	Warrant/Other N = 1,397[1]	N	Arrested New N = 149[1]	Summonsed/Cited N = 144[1]	Warrant/Other N = 79[1]	N	Arrested New N = 866[1]	Summonsed/Cited N = 1,162[1]	Warrant/Other N = 526[1]
Arrested	7,690				371				2,554			
		2,539 (100%)	0 (0%)	1,397 (100%)		148 (100%)	0 (0%)	79 (100%)		866 (100%)	0 (0%)	526 (100%)
Chi-Squared Test[2]				<0.001				<0.001				<0.001
Agency	7,690				371				2,554			
Agency		163 (6.4%)	273 (7.3%)	140 (10%)		12 (8.1%)	1 (0.7%)	7 (8.9%)		69 (8.0%)	59 (5.1%)	60 (11%)
EMPD		354 (14%)	564 (15%)	191 (14%)		6 (4.1%)	15 (10%)	10 (13%)		116 (13%)	163 (14%)	71 (13%)
MNSO		448 (18%)	992 (26%)	256 (18%)		34 (23%)	32 (22%)	15 (19%)		184 (21%)	294 (25%)	121 (23%)
WPD		1,574 (62%)	1,925 (51%)	810 (58%)		96 (65%)	96 (67%)	47 (59%)		497 (57%)	646 (56%)	274 (52%)
Chi-Squared Test[2]				<0.001				<0.001				<0.001
Offense	7,690				371				2,554			
Drug		804 (32%)	1,480 (39%)	557 (40%)		73 (49%)	47 (33%)	39 (49%)		300 (35%)	410 (35%)	221 (42%)
Other		28 (1.1%)	69 (1.8%)	25 (1.8%)		3 (2.0%)	3 (2.1%)	2 (2.5%)		9 (1.0%)	15 (1.3%)	13 (2.5%)
Victim/Nonviolent		485 (19%)	1,417 (38%)	293 (21%)		31 (21%)	51 (35%)	16 (20%)		195 (23%)	432 (37%)	100 (19%)
Victim/Violent		1,222 (48%)	788 (21%)	522 (37%)		41 (28%)	43 (30%)	22 (28%)		362 (42%)	305 (26%)	192 (37%)
Chi-Squared Test[2]				<0.001				<0.001				<0.001
Race	7,690				371				2,554			
Asian		163 (6.4%)	164 (4.4%)	97 (6.9%)		12 (8.1%)	9 (6.2%)	3 (3.8%)		55 (6.4%)	40 (3.4%)	38 (7.2%)
Black		322 (13%)	486 (13%)	188 (13%)		18 (12%)	19 (13%)	11 (14%)		105 (12%)	179 (15%)	55 (10%)
Hispanic/LatinX		140 (5.5%)	147 (3.9%)	77 (5.5%)		7 (4.7%)	4 (2.8%)	4 (5.1%)		43 (5.0%)	59 (5.1%)	21 (4.0%)
Native American		75 (3.0%)	90 (2.4%)	42 (3.0%)		2 (1.4%)	4 (2.8%)	3 (3.8%)		25 (2.9%)	25 (2.2%)	19 (3.6%)
White		1,839 (72%)	2,867 (76%)	993 (71%)		109 (74%)	108 (75%)	58 (73%)		638 (74%)	859 (74%)	393 (75%)
Chi-Squared Test[2]				<0.001				0.8				<0.001
Sex	7,690				371				2,554			
Female		619 (24%)	1,290 (34%)	314 (22%)		50 (34%)	41 (28%)	23 (29%)		216 (25%)	400 (34%)	137 (26%)
Male		1,920 (76%)	2,464 (66%)	1,083 (78%)		99 (66%)	103 (72%)	56 (71%)		650 (75%)	762 (66%)	389 (74%)
Chi-Squared Test[2]				<0.001				0.6				<0.001
Age	7,690				371				2,554			
		33 (26, 40)	28 (19, 37)	32 (26, 39)		28 (21, 37)	24 (17, 34)	29 (24, 39)		32 (25, 39)	24 (17, 35)	31 (25, 38)
Chi-Squared Test[2]				<0.001				<0.001				<0.001

[1] n (%); Median (IQR)

[2] Pearson's Chi-squared test; Kruskal-Wallis rank sum test

Appendix B. WIBRS Proportion Table: Before and After COVID Restrictions

	N	COVID Arrested New N = 787[1]	 Summonsed/Cited N = 1,733[1]	 Warrant/Other N = 371[1]	N	After COVID Arrested New N = 738[1]	 Summonsed/Cited N = 715[1]	 Warrant/Other N = 421[1]
Arrested	2,891				1,874			
		787 (100%)	0 (0%)	371 (100%)		738 (100%)	0 (0%)	421 (100%)
Chi-Squared Test[2]				<0.001				<0.001
Agency	2,891				1,874			
Agency		54 (6.9%)	155 (8.9%)	53 (14%)		28 (3.8%)	58 (8.1%)	20 (4.8%)
EMPD		96 (12%)	245 (14%)	48 (13%)		136 (18%)	141 (20%)	62 (15%)
MNSO		127 (16%)	407 (23%)	68 (18%)		103 (14%)	259 (36%)	52 (12%)
WPD		510 (65%)	926 (53%)	202 (54%)		471 (64%)	257 (36%)	287 (68%)
Chi-Squared Test[2]				<0.001				<0.001
Offense	2,891				1,874			
Drug		187 (24%)	733 (42%)	107 (29%)		244 (33%)	290 (41%)	190 (45%)
Other		7 (0.9%)	28 (1.6%)	5 (1.3%)		9 (1.2%)	23 (3.2%)	5 (1.2%)
'ictim/Nonviolent		120 (15%)	663 (38%)	78 (21%)		139 (19%)	271 (38%)	99 (24%)
Victim/Violent		473 (60%)	309 (18%)	181 (49%)		346 (47%)	131 (18%)	127 (30%)
Chi-Squared Test[2]				<0.001				<0.001
Race	2,891				1,874			
Asian		52 (6.6%)	89 (5.1%)	24 (6.5%)		44 (6.0%)	26 (3.6%)	32 (7.6%)
Black		102 (13%)	197 (11%)	59 (16%)		97 (13%)	91 (13%)	63 (15%)
Hispanic/LatinX		47 (6.0%)	52 (3.0%)	27 (7.3%)		43 (5.8%)	32 (4.5%)	25 (5.9%)
Native American		25 (3.2%)	39 (2.3%)	7 (1.9%)		23 (3.1%)	22 (3.1%)	13 (3.1%)
White		561 (71%)	1,356 (78%)	254 (68%)		531 (72%)	544 (76%)	288 (68%)
Chi-Squared Test[2]				<0.001				0.11
Sex	2,891				1,874			
Female		162 (21%)	588 (34%)	61 (16%)		191 (26%)	261 (37%)	93 (22%)
Male		625 (79%)	1,145 (66%)	310 (84%)		547 (74%)	454 (63%)	328 (78%)
Chi-Squared Test[2]				<0.001				<0.001
Age	2,891				1,874			
		34 (27, 41)	30 (21, 38)	31 (26, 38)		34 (27, 41)	28 (19, 38)	34 (28, 41)
Chi-Squared Test[2]				<0.001				<0.001

[1]n (%); Median (IQR)
[2]Pearson's Chi-squared test; Kruskal-Wallis rank sum test

Appendix C. PROTECT Proportions Table

		Overall		Before Actuarial Tool		After Actuarial Tool		COVID		After COVID	
	N	Out-of-Custody N = 6,734	In Custody N = 6,646	Out-of-Custody N = 2,044	In Custody N = 1,993	Out Custody N = 1,593	In-Custody N = 1,694	Out-of-Custody N = 1,976	In Custody N = 1,345	Out-of-Custody N = 1,223	In Custody N = 1,699
PO_Hold	13,380										
PO_Hold		0 (0%)	622 (9.4%)	0 (0%)	226 (11%)	0 (0%)	144 (8.5%)	0 (0%)	121 (9.0%)	0 (0%)	136 (8.0%)
Chi-Squared			<0.001		<0.001		<0.001		<0.001		<0.001
Warrant	13,380										
Warrant		826 (12%)	773 (12%)	198 (9.7%)	201 (10%)	139 (8.7%)	144 (8.5%)	302 (15%)	140 (10%)	206 (17%)	298 (18%)
Chi-Squared			0.3		0.7		0.8		<0.001		0.6
Domestic	13,380										
Domestic		759 (11%)	899 (14%)	215 (11%)	252 (13%)	157 (9.9%)	171 (10%)	249 (13%)	276 (21%)	158 (13%)	216 (13%)
Chi-Squared			<0.001		0.035		0.8		<0.001		0.6
Agency	13,380										
Agency Other		1,098 (16%)	771 (12%)	363 (18%)	244 (12%)	288 (18%)	199 (12%)	298 (15%)	156 (12%)	161 (13%)	181 (11%)
EMPD		798 (12%)	727 (11%)	248 (12%)	211 (11%)	176 (11%)	149 (8.8%)	223 (11%)	158 (12%)	163 (13%)	222 (13%)
MNSO		1,141 (21%)	1,270 (19%)	401 (20%)	397 (20%)	336 (21%)	354 (21%)	412 (21%)	253 (19%)	289 (24%)	281 (17%)
State/Fed		359 (5.3%)	203 (3.1%)	126 (6.2%)	62 (3.1%)	111 (7.0%)	71 (4.2%)	81 (4.1%)	30 (2.2%)	48 (3.9%)	42 (2.5%)
WPD		3,068 (46%)	3,675 (55%)	906 (44%)	1,079 (54%)	682 (43%)	921 (54%)	962 (49%)	748 (56%)	562 (46%)	973 (57%)
Chi-Squared			<0.001		<0.001		<0.001		<0.001		<0.001
Race	13,380										
Asian		359 (5.3%)	455 (6.8%)	125 (6.1%)	155 (7.8%)	79 (5.0%)	110 (6.5%)	95 (4.8%)	88 (6.5%)	63 (5.2%)	109 (6.4%)
Black		656 (9.7%)	906 (14%)	181 (8.9%)	263 (13%)	140 (8.8%)	224 (13%)	212 (11%)	187 (14%)	129 (11%)	243 (14%)
Hispanic/LatinX		482 (7.2%)	222 (3.3%)	152 (7.4%)	54 (2.7%)	152 (9.5%)	59 (3.5%)	126 (6.4%)	59 (4.4%)	58 (4.7%)	54 (3.2%)
Native American		153 (2.3%)	233 (3.5%)	39 (1.9%)	65 (3.3%)	44 (2.8%)	54 (3.2%)	41 (2.1%)	52 (3.9%)	32 (2.6%)	65 (3.8%)
White		5,084 (75%)	4,830 (73%)	1,547 (76%)	1,456 (73%)	1,178 (74%)	1,247 (74%)	1,502 (76%)	959 (71%)	941 (77%)	1,228 (72%)
Chi-Squared			<0.001		<0.001		<0.001		<0.001		<0.001
Sex	13,380										
Female		2,204 (33%)	1,585 (24%)	661 (32%)	517 (26%)	535 (34%)	410 (24%)	647 (33%)	258 (19%)	400 (33%)	418 (25%)
Male		4,530 (67%)	5,061 (76%)	1,383 (68%)	1,476 (74%)	1,058 (66%)	1,284 (76%)	1,329 (67%)	1,087 (81%)	823 (67%)	1,281 (75%)
Chi-Squared			<0.001		<0.001		0.07		<0.001		0.002
Age	13,380										
17 to 25		1,732 (26%)	1,418 (21%)	621 (31%)	531 (27%)	390 (25%)	369 (22%)	485 (25%)	257 (19%)	260 (21%)	274 (16%)
26 to 35		2,322 (35%)	2,523 (38%)	705 (35%)	766 (39%)	577 (36%)	659 (39%)	678 (34%)	518 (39%)	389 (32%)	618 (36%)
36 to 45		1,501 (22%)	1,681 (25%)	377 (19%)	421 (21%)	340 (21%)	399 (24%)	477 (24%)	377 (28%)	343 (28%)	507 (30%)
46 to 55		767 (11%)	684 (10%)	223 (11%)	176 (8.8%)	192 (12%)	172 (10%)	213 (11%)	137 (10%)	148 (12%)	207 (12%)
56+		386 (5.8%)	328 (4.9%)	109 (5.4%)	95 (4.8%)	88 (5.5%)	91 (5.4%)	117 (5.9%)	54 (4.0%)	78 (6.4%)	91 (5.4%)
Chi-Squared			<0.001		0.001		<0.001		<0.001		0.002

Pearson's Chi-squared test; Wilcoxon rank sum test

Appendix D. WIBRS Dataset Regression Table

		Overall	Before Tool	After Tool	COVID	After COVID
(Intercept)		0.431 **	3.348 **	1.502 ***	-0.461 *	0.06
		(0.144)	(1.132)	(0.265)	(0.234)	(0.340)
Severity	VIF	1.02	1.02	1.05	1.01	1.02
Severity		0.520 ***	0.15	0.408 ***	0.778 ***	0.509 ***
		(0.025)	(0.112)	(0.044)	(0.045)	(0.054)
Agency	VIF	1.02	1.04	1.05	1.04	1.05
EMPD		-0.268 *	-2.815 *	-0.834 ***	-0.384 *	0.711 **
		(0.109)	(1.098)	(0.202)	(0.180)	(0.242)
MNSO		-0.594 ***	-2.497 *	-1.016 ***	-0.593 ***	-0.21
		(0.103)	(1.059)	(0.188)	(0.168)	(0.237)
WPD		-0.11	-2.631 *	-0.842 ***	-0.19	1.280 ***
		(0.095)	(1.042)	(0.177)	(0.149)	(0.225)
Race	VIF	1.06	1.05	1.07	1.07	1.09
Black		-0.571 ***	-0.21	-1.078 ***	-0.21	-0.762 **
		(0.125)	(0.527)	(0.229)	(0.205)	(0.290)
Hispanic/LatinX		0.03	0.68	-0.612 *	0.642 *	-0.19
		(0.155)	(0.743)	(0.274)	(0.261)	(0.341)
Native American		-0.14	-0.38	-0.24	-0.02	-0.49
		(0.183)	(0.813)	(0.327)	(0.316)	(0.398)
White		-0.484 ***	-0.26	-0.771 ***	-0.27	-0.620 *
		(0.109)	(0.450)	(0.202)	(0.177)	(0.257)
Sex	VIF	1.02	1.03	1.03	1.02	1.03
Male		0.409 ***	-0.19	0.394 ***	0.630 ***	0.462 ***
		(0.054)	(0.246)	(0.093)	(0.098)	(0.116)
Age	VIF	1.03	1.04	1.05	1.03	1.02
Age		0.410 ***	0.433 ***	0.534 ***	0.288 ***	0.456 ***
		(0.026)	(0.121)	(0.046)	(0.043)	(0.057)
N		7690.00	371.00	2554.00	2891.00	1874.00
AIC		9718.03	485.04	3241.79	3387.10	2121.77
BIC		9794.46	528.12	3306.09	3452.76	2182.66
Pseudo R2		0.16	0.11	0.15	0.23	0.26

All continuous predictors are mean-centered and scaled by 1 standard deviation. *** p < 0.001; ** p < 0

Appendix E. PROTECT Dataset Regression Table

		Overall	Before Tool	After Tool	COVID	After COVID
(Intercept)		-0.716 ***	-0.695 **	-0.419	-1.965 ***	0.055
		(0.139)	(0.243)	(0.300)	(0.294)	(0.316)
Severity Scale	VIF	1.02	1.03	1.06	1.06	1.03
Severity Scale		0.970 ***	1.108 ***	1.230 ***	1.041 ***	0.662 ***
		(0.021)	(0.040)	(0.047)	(0.049)	(0.043)
Domestic	VIF	1.02	1.02	1.02	1.11	1.04
Domestic		0.189 ***	0.025	-0.095	0.739 ***	0.141
		(0.057)	(0.109)	(0.130)	(0.108)	(0.126)
Race	VIF	1.08	1.09	1.09	1.03	1.09
Black		0.112	0.093	0.232	0.161	0.109
		(0.098)	(0.179)	(0.217)	(0.201)	(0.212)
Hispanic/LatinX		-0.455 ***	-0.687 **	-0.457	-0.044	-0.302
		(0.122)	(0.229)	(0.251)	(0.249)	(0.279)
Native American		0.425 **	0.294	0.129	1.016 ***	0.457
		(0.141)	(0.273)	(0.295)	(0.290)	(0.301)
White		-0.119	-0.189	-0.073	-0.011	-0.084
		(0.084)	(0.148)	(0.183)	(0.173)	(0.184)
Sex	VIF	1.03	1.03	1.03	1.03	1.04
Male		0.430 ***	0.369 ***	0.492 ***	0.647 ***	0.357 ***
		(0.044)	(0.081)	(0.092)	(0.094)	(0.093)
Warrant	VIF	1.02	1.02	1.02	1.02	1.03
Warrant		0.017	0.274 *	0.282	-0.359 **	0.167
		(0.061)	(0.124)	(0.149)	(0.123)	(0.112)
Age	VIF	14.64	15.19	14.81	13.95	14.94
26to35		0.278 ***	0.340 *	-0.079	0.653 ***	0.135
		(0.079)	(0.144)	(0.170)	(0.164)	(0.178)
36to45		0.304 *	0.446	-0.088	0.867 **	-0.04
		(0.134)	(0.255)	(0.284)	(0.274)	(0.288)
46to55		0.229	0.324	-0.434	1.121 **	-0.354
		(0.203)	(0.385)	(0.435)	(0.418)	(0.432)
56+		0.22	0.463	-0.353	1.047	-0.736
		(0.278)	(0.520)	(0.588)	(0.580)	(0.604)
Agency	VIF	1.05	1.03	1.08	1.06	1.06
EMPD		0.181 *	0.226	0.235	0.246	0.092
		(0.078)	(0.144)	(0.171)	(0.161)	(0.165)
MNSO		0.033	0.162	0.086	0.089	-0.287
		(0.068)	(0.127)	(0.143)	(0.143)	(0.151)
State/Federal		0.074	-0.01	0.31	-0.08	-0.016
		(0.116)	(0.207)	(0.220)	(0.274)	(0.276)
WPD		0.380 ***	0.423 ***	0.500 ***	0.319 *	0.338 *
		(0.060)	(0.110)	(0.126)	(0.125)	(0.134)
N		13337	4023	3276	3312	2726
AIC		15529.937	4500.802	3524.546	3723.271	3384.62
BIC		15664.906	4614.199	3634.245	3833.167	3491.011
Pseudo R2		0.268	0.322	0.366	0.285	0.158

All continuous predictors are mean-centered and scaled by 1 standard deviation. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Curriculum Vita

Ruth Heinzl was born and raised in central Wisconsin, moving to the Twin Cities in Minnesota to complete her Bachelor's Degree in Psychology as well as obtain her Substance Abuse Counseling license in 2008. For the next two years, Ruth worked in various residential and treatment facilities as a direct care employee and a Substance Abuse Counselor.

In 2010, Ruth began working in the criminal justice system as a case worker and later becoming the Prosecutor-led Diversion Program Supervisor in 2019. Over the last decade, Ruth has worked with various stakeholders and community partners on numerous initiatives to improve the effectiveness and efficiency of the criminal justice system through a person-centered mindset. Through these initiatives, Ruth gained a passion for data analysis and a determination to understand Marathon County's criminal justice data at its core.

In the Spring of 2021, Ruth began her Masters in Data Analytics and Policy program at Johns Hopkins University to further develop her data analytics skills. Ruth graduated from Johns Hopkins in the fall of 2022 with a determination to provide more informative, relevant, and accurate data visualizations. Her goal is to make data meaningful and provide actionable solutions.