BUREAU OF BUSINESS
& ECONOMIC RESEARCH

New Mexico Prisoner Forecast (FY2027–FY2037)

Prepared for the New Mexico Sentencing Commission (NMSC)

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Introduction

1.1. Background

For Fiscal Years (FY) 2026–2036, UNM's Bureau of Business & Economic Research (UNM BBER) developed an Autoregressive Integrated Moving Average (ARIMA) model to forecast male and female prison populations in the State of New Mexico. In response to a request from the New Mexico Sentencing Commission (NMSC), BBER proposes to develop updated ARIMA models for the FY2027–2037 male and female prison population forecasts.

Accordingly, this report presents updated short- and long-term projections for male and female prisoners in New Mexico, covering one and ten fiscal years, respectively. [1] The assumptions, limitations, and methodology that inform these forecasts are explained in the following section.

1.2. Assumptions, Limitations, and Methodology

1.2.1. Assumptions and Limitations

Given that models cannot fully capture every nuance that may arise in the future with certainty, certain assumptions have been made to enhance the model's reliability and usefulness:

- No new legislative or policy measures that alter sentencing guidelines will be enacted.
- Admission and sentencing patterns will remain static.
- Seasonal variations observed in historical data will continue into the future.
- External factors like age, race/ethnicity, sentence length, years served, and the type of crime are not factored into the forecast; instead, the models are based solely on historical prison population data by gender.

It is also important to note that this report is not intended to serve as a definitive prediction of the prison population in New Mexico. Instead, it is intended to provide guidance on how the prison population is likely to evolve under the existing framework of laws, policies, and procedures. As adjustments to these components occur, different outcomes – which may not be immediately observable – may be possible.

1.2.2. Methodology

Data cleaning is a critical step of the analysis process and should always be completed before working with the data to ensure optimal results. This subsection describes how the data were cleaned and the justification behind each decision.

NMSC maintains a database that tracks daily totals for male and female prisoners in the State. From this data, we calculated monthly averages, aggregating the daily totals to create a time series that spans from January 2014 to December 2025. For some months, complete data were not available, resulting in averages that may have been either slightly lower, slightly higher, or the same as those recorded. Additionally, because missing data were coded as "zero," we excluded these entries from our analysis. This was done to maintain the integrity of the dataset and to avoid the misleading impact of these non-representative data entries, thereby ensuring true population estimates.

[1] This report was inspired by Athanasopoulos and Weatherburn (2018), Bassey (2019).

Analyzing the Behavior of Time Series Data

Time series analysis involves studying a sequence of data points collected at regular intervals, like prisoner data. By breaking down the components of a time series, we can uncover trends and patterns.

Three main elements make up a time series dataset, each of which will be discussed in more detail below:[2]

- Trends
- Seasonality
- Noise

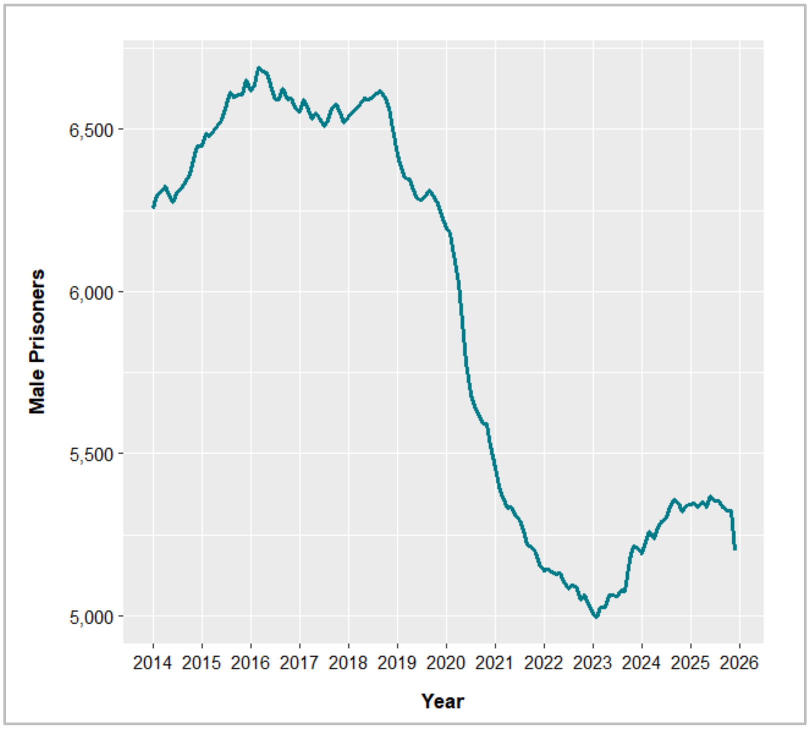
2.1. Trends for Inmates in New Mexico

Trends show the consistent, long-term movement and direction of the data over a long period of time. Consecutive observations are plotted against time to determine whether the data are increasing, decreasing, or stationary.[3]

Figure 1 presents a general overview of the monthly average number of male prisoners in New Mexico from January 2014 to December 2025. Over this period, the data reveal several distinct trends. From January 2014 to March 2016, the number of male prisoners steadily increased. However, starting in April 2016, the trend shifted as the average number of prisoners began to decline, continuing this downward trend through September 2018. The decline then accelerated between October 2018 and February 2023, as marked by significant dips and sharp decreases. In March 2023, the trend reversed, with data rising steadily through November 2025 before plunging again in December 2025.

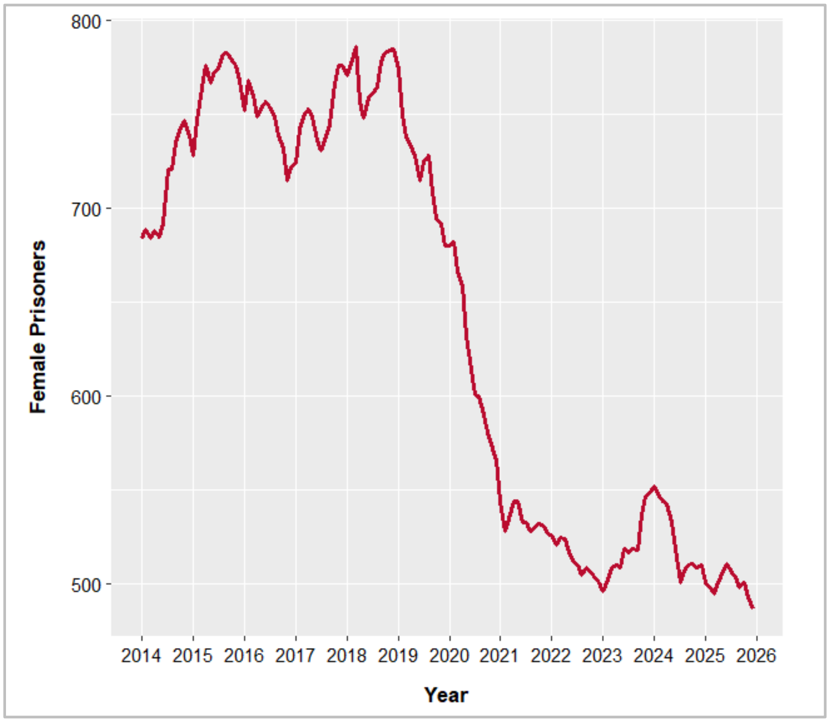
[2] Cyclicality is also an important metric. However, since our analysis focuses solely on the number of inmates incarcerated at a given time without accounting for other factors like age, crime type, sentencing, and/or policy changes, it can be challenging to assess whether any of these variables have contributed to cyclical patterns. This is because cyclical patterns do not follow a fixed frequency and typically last longer than seasonal ones.
[3] Stationary means that the data have no obvious pattern, i.e., trends and/or seasonality are not present.

Figure 1: Monthly Average Number of Male Prisoners in NM (2014–2025)



Similarly, female prisoner data also showed various trends from January 2014 to December 2025. While there was some fluctuation from January 2014 to December 2018, the numbers overall displayed a positive trend. However, beginning in January 2019, there was a significant decline in the number of female prisoners that continued through January 2023. Although occasional upticks occurred between February 2023 and December 2025, figures have remained below pre-December 2018 levels and have continued on a downward trajectory (see Figure 2).

Figure 2: Monthly Average Number of Female Prisoners in NM (2014–2025)



2.2. Seasonality for Inmates in New Mexico

Seasonality refers to recurring, predictable patterns that repeat at fixed intervals. A seasonal plot, which can help identify seasonality, resembles a time plot but is structured differently. Instead of displaying the data in a single, continuous line, the data are presented for individual years. In this form, each line represents a separate year of data, therefore allowing us to compare values for the same month across different years.

2.2.1. Seasonal Plots

Figure 3, which is a seasonal plot of male prisoners in New Mexico, illustrates the monthly averages for each year. As seen in the graph, there is a significant overall decrease in the number of male prisoners, starting in March 2020 and continuing through December 2025. Prior to March 2020, male prisoners fluctuated between 6,200 and 6,700, whereas from 2021 to 2025 (dashed lines), they ranged between 5,000 and 5,500.

Table 1, which complements Figure 3, presents the seasonal data in tabular form. In this table, a value of 1 indicates the month with the highest number of male prisoners recorded that year, while 12 represents the month with the lowest. A month-by-month analysis reveals mild seasonality, with slightly lower incarceration rates in January, December, and the summer months.

Figure 3: Seasonal Plot - Male Prisoners in NM (2014–2025)

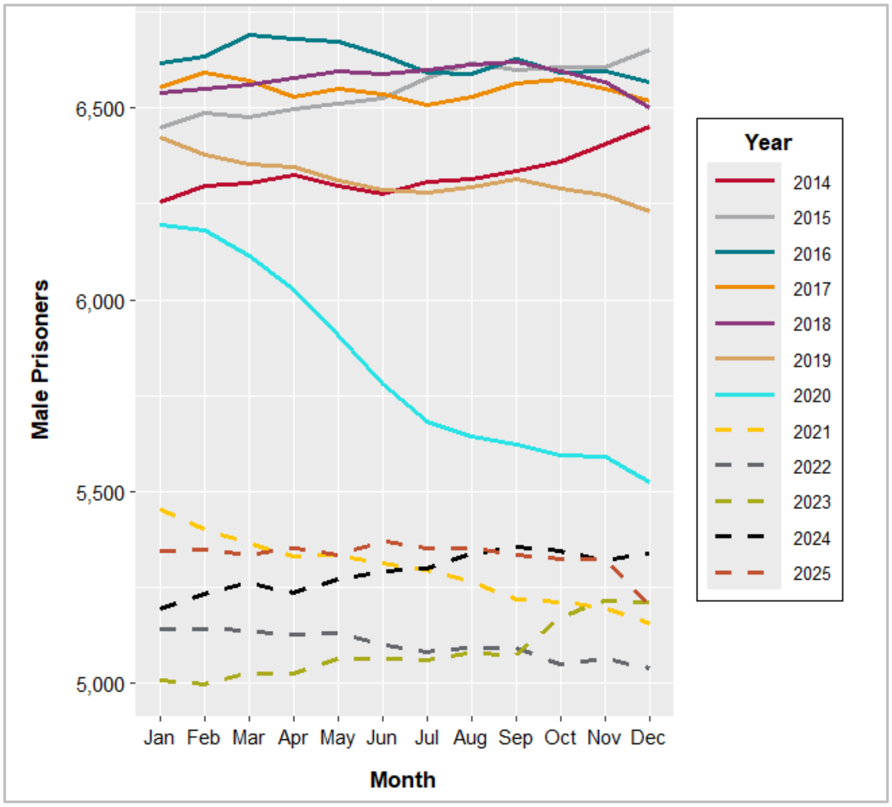


Table 1: New Mexico Male Prisoner Rankings (2014–2025)

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
2014	12	9	8	5	10	11	7	6	4	3	2	1
2015	12	10	11	9	8	7	6	2	5	4	3	1
2016	7	5	1	2	3	4	10	11	6	9	8	12
2017	5	1	3	9	7	8	12	10	4	2	6	11
2018	11	10	9	7	4	6	3	2	1	5	8	12
2019	1	2	3	4	6	9	10	7	5	8	11	12
2020	1	2	3	4	5	6	7	8	9	10	11	12
2021	1	2	3	5	4	6	7	8	9	10	11	12
2022	2	1	3	5	4	6	9	7	8	11	10	12
2023	11	12	10	9	6	7	8	4	5	3	1	2
2024	12	11	9	10	8	7	6	4	1	2	5	3
2025	6	5	7	4	8	1	2	3	9	10	11	12

From 2014 to 2019, incarceration rates for female prisoners remained relatively high, with monthly totals fluctuating between 680 and 800. However, this trend shifted in March 2020 and continued through 2025, with numbers declining to a range of 500 to 550 between 2021 and 2025 (dashed lines), as shown in Figure 4. Similar to that for males, a monthly breakdown suggests modest seasonal variation, with incarceration rates dipping slightly in January, December, and the summer months (see Table 2).

Figure 4: Seasonal Plot - Female Prisoners in NM (2014–2025)

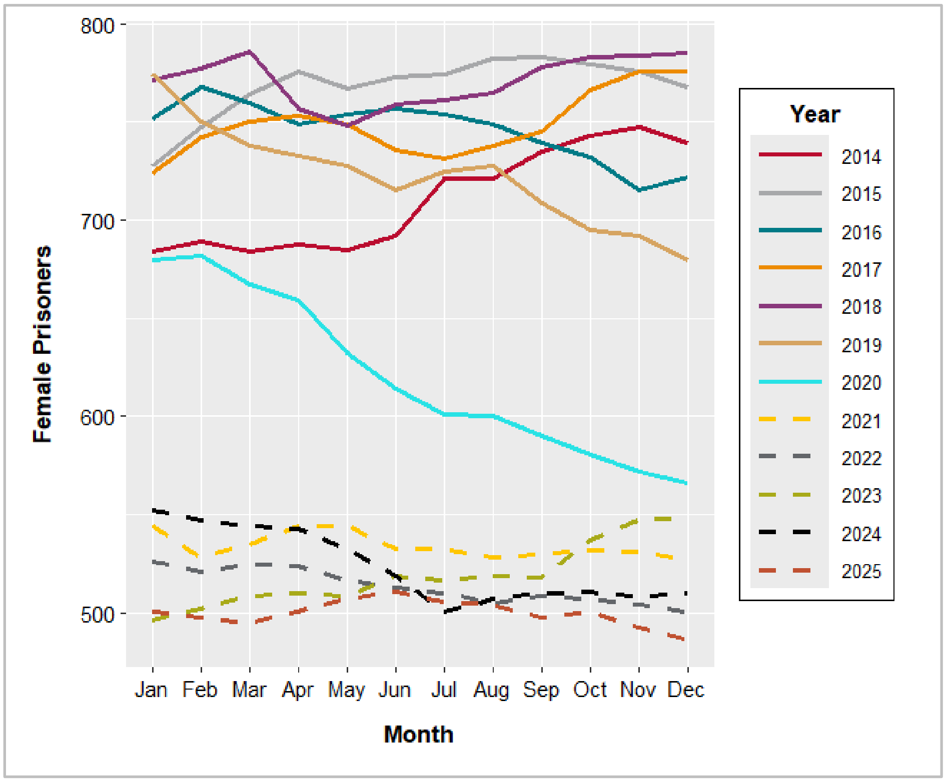


Table 2: New Mexico Female Prisoner Rankings (2014–2025)

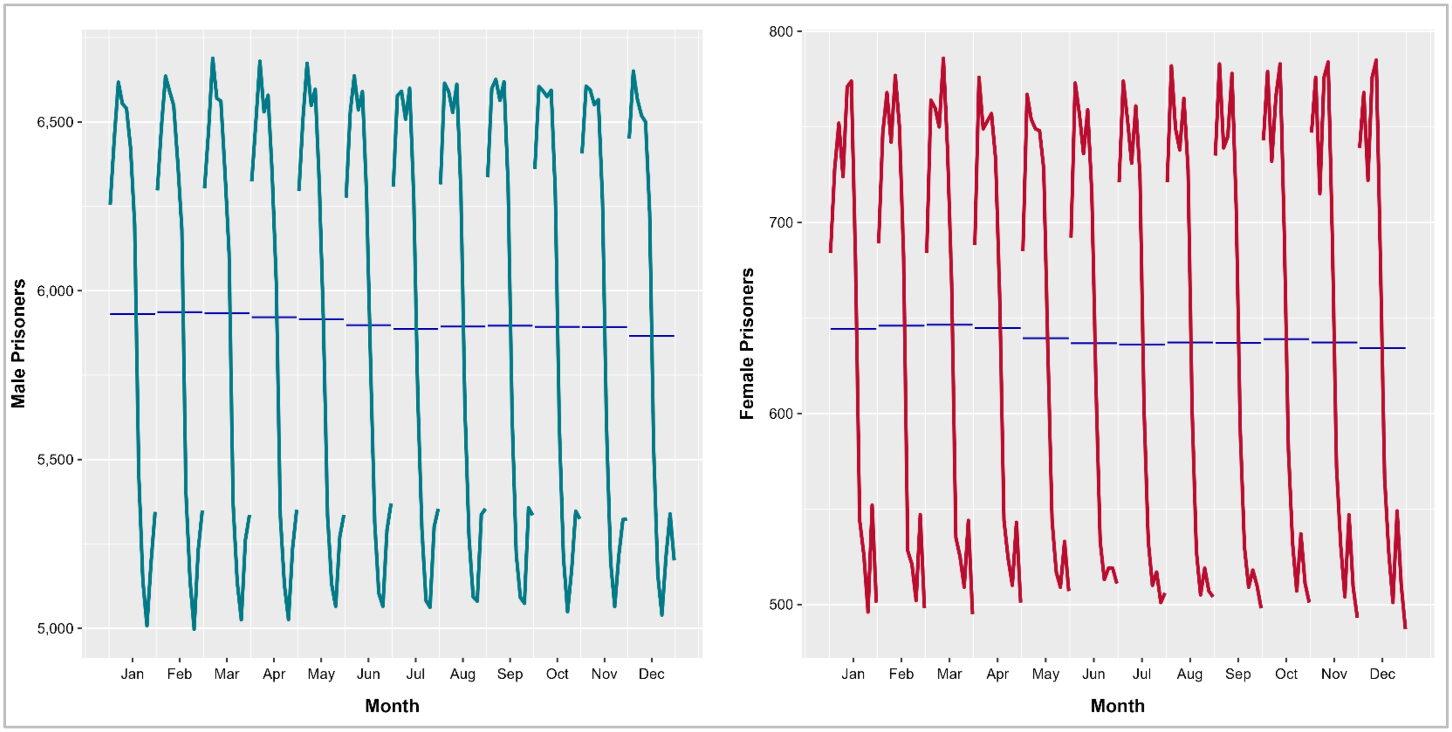
	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
2014	11	8	12	9	10	7	5	6	4	2	1	3
2015	12	11	10	4	9	7	6	2	1	3	5	8
2016	6	1	2	7	4	3	5	8	9	10	12	11
2017	12	8	5	4	6	10	11	9	7	3	1	2
2018	7	6	1	11	12	10	9	8	5	4	3	2
2019	1	2	3	4	5	8	7	6	9	10	11	12
2020	2	1	3	4	5	6	7	8	9	10	11	12
2021	1	10	4	2	3	5	6	11	9	7	8	12
2022	1	4	2	3	5	6	7	10	8	9	11	12
2023	12	11	9	8	10	4	7	5	6	3	2	1
2024	1	2	3	4	5	6	12	11	8	7	10	9
2025	5	8	10	6	2	1	3	4	9	7	11	12

2.2.2. Seasonal Subseries Plots

This subsection aims to analyze seasonality using subseries plots. Seasonal subseries plots gather and display the data by season (e.g., months). Thus, the first line plots all the incarceration numbers for January from 2014 to 2025, the second line shows February data, and so on for the remaining months. The dark blue horizontal line represents the average number of incarcerated individuals for each month from 2014 to 2025.

Just like what we observed in Section 2.1 and Section 2.2.1, the plots in Figure 5 indicate a clear downward trend in incarceration rates, with higher levels observed in earlier years followed by a pronounced decline beginning in 2020. The seasonal component, on the other hand, is relatively weak, with limited variability for both male and female populations. The only notable pattern is modestly lower averages in January, December, and the summer months.

Figure 5: Seasonal Subseries Plot - Male (Left) and Female (Right) Prisoners in NM (2014–2025)



2.3. Assessing White Noise Using the ACF for Inmates in New Mexico

Autocorrelation functions (ACF) and partial autocorrelation functions (PACF) are tools used in time series analysis that enable us to understand the relationships between observations at different time lags. ACF measures the correlation between a time series and its past values. PACF, on the other hand, measures the direct correlation between a time series and its past values, removing the influence at intermediate lags. This can also be shown visually as:

$$ACF: S_{t-2} \rightarrow S_{t-1} \rightarrow S_t$$

$$PACF: S_{t-2} \rightarrow S_t$$

As seen in the equations above, the ACF considers the intermediate lag at S_{t-1}, whereas the PACF does not.

ACF plots, in particular, are important because they can help us identify seasonality and trends. When trends are present, autocorrelations at small lags tend to be large and positive because nearby observations are also similar in value. So, the ACF of a trended time series tends to have positive values that slowly decrease as the lags increase. When seasonality is present, the autocorrelations will be larger at seasonal lags (at multiple times of the seasonal period) than for other lags. In cases where data exhibit both trends and seasonality, the ACF plot will reflect a combination of these effects.[4]

ACF plots also use 95% confidence intervals to visually indicate whether autocorrelations at different lags are statistically significant. The standard error, which represents the lower and upper bounds of the 95% confidence interval, is calculated as the sample standard deviation divided by the square root of the sample size. This can also be represented mathematically as

$$SE = \pm \frac{s}{\sqrt{n}}$$

Where s is the sample standard deviation and n is the sample size.

In a two-tailed hypothesis test with a 95% confidence interval (0.05 significance level), the critical value or sample standard deviation is 1.96. Moreover, for both male and female prisoners, the sample size is 144, as there are 144 monthly observations from January 2014 to December 2025. Thus, our upper and lower bounds are:

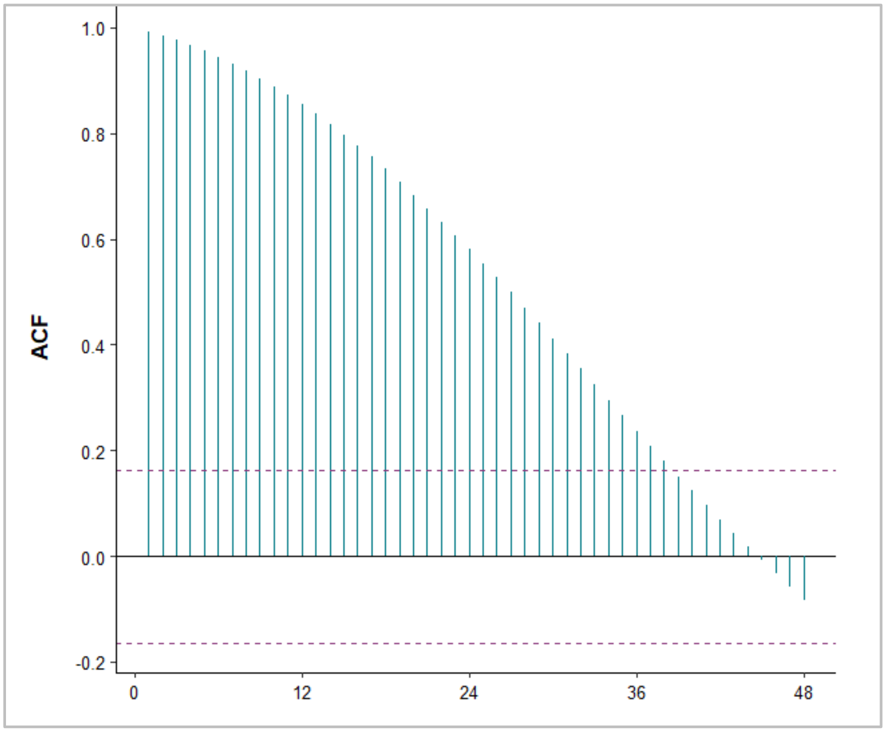
$$SE = \pm \frac{s}{\sqrt{n}} = \pm \frac{1.96}{\sqrt{144}} \approx \pm 0.1633$$

2.3.1. ACF for Male and Female Prisoners

Figure 6 plots the autocorrelation coefficients of the autocorrelation function (ACF) for male prisoners in what is called a correlogram. As the plot shows, the data have a trend as indicated by the presence of positive, large values that gradually decrease with increasing lags. Additionally, the ACF reveals mild annual seasonality, with somewhat noticeable spikes occurring at lags 12, 24, 36, and 48. This confirms what was observed in Section 2.1 and Section 2.2.

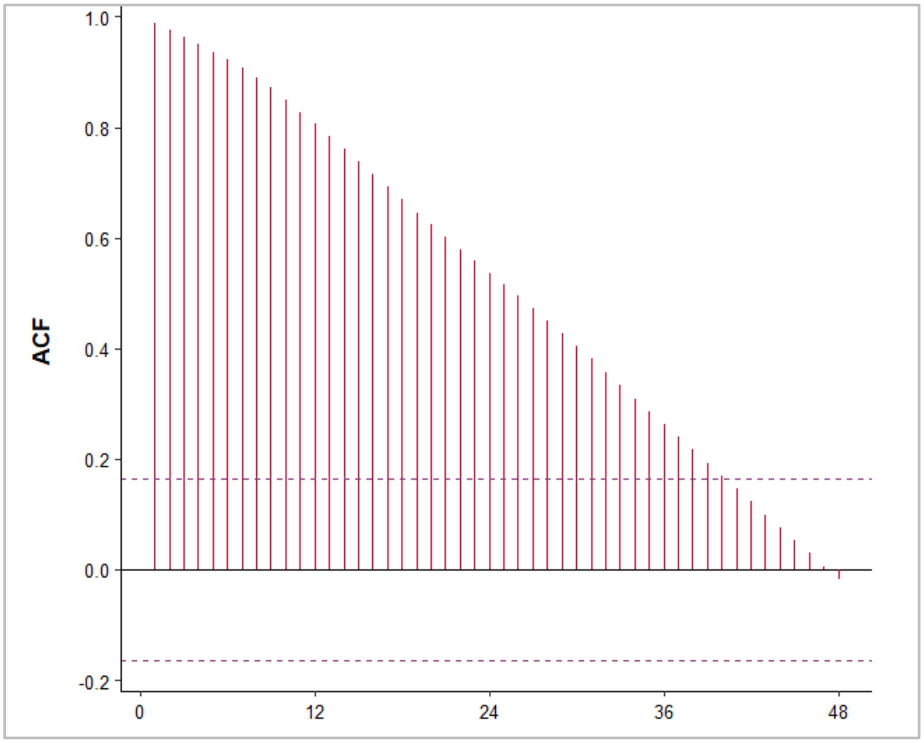
[4] See Section 2.8 (Autocorrelation) for more details.

Figure 6: Autocorrelation Function (ACF) Plot of Monthly Male Prisoners in NM



A similar pattern can be observed for female prisoners. As seen in Figure 7 below, the series shows a trend since the ACF has positive values that slowly decrease as the lags increase. There is also a slight seasonal component, with spikes occurring at lags 12, 24, 36, and 48, thus indicating a yearly seasonal pattern. This again confirms what was observed in Section 2.1 and Section 2.2.

Figure 7: Autocorrelation Function (ACF) Plot of Monthly Female Prisoners in NM



2.4. KPSS Test

Another way to determine whether the data display trends or seasonality is to use a statistical test like the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. In this test, the null hypothesis is that the data are stationary, and we look for evidence that the null hypothesis is false. The KPSS test provides a p-value that ranges from 0.01 to 0.1. If the actual p-value is less than 0.01, it is reported as 0.01, while values exceeding 0.1 are capped at 0.1. Small p-values (less than 0.05) suggest that differencing is required.

For male prisoners, because the reported p-value is 0.01, we reject the null hypothesis, thereby concluding that the data are not stationary and thus we must difference the data.

Similarly, for female prisoners, because the reported p-value is 0.01, we reject the null hypothesis, thereby concluding that the data are not stationary and thus we must difference the data.

2.5. Conclusion

This chapter has shown how both male and female prisoner data exhibited trends. The time plots were not horizontal, the ACFs did not decrease to zero quickly, and the KPSS test yielded p-values of 0.01. These indicators suggest that both the male and female series are non-stationary, which means that the mean and variance of the series change over time.

Since stationary data is required for ARIMA modeling – as will be discussed in the next chapter – the data must be transformed by computing the differences between consecutive observations.

ARIMA Modeling

ARIMA, which stands for Autoregressive Integrated Moving Average, is a common statistical method used in time series forecasting that predicts future values based on historical patterns. ARIMA models consist of three components:[5]

1. Autoregressive (AR): This component relates the current values to its past values through a regression equation and is denoted by the parameter p.
2. Integrated (I): This component involves differencing the time series to make it stationary, ensuring that the mean and variance remain constant over time. It is denoted by the parameter d.
3. Moving Average (MA): This component uses the dependency between an observation and a residual error. It is denoted by the parameter q.

Hence, the formula for an ARIMA model is expressed as $ARIMA(p, d, q)$, where:

- p = order of autoregression/number of autoregressive terms,
- d = order of differencing/number of differences needed to make the series stationary,
- q = order of moving average/number of lagged forecasting errors.

To estimate the parameters p, d, and q, an analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots – which were introduced in Section 2.3 – will need to be conducted. Specifically, the ACF plot will help determine the MA order (q), whereas the PACF plot will help determine the AR order (p).

The rest of this chapter will be dedicated to developing ARIMA models for both male and female prisoners.

3.1. ARIMA Model for Male Prisoners

3.1.1. Differencing Time Series by Identifying d for Male Prisoners

Recall the ACF plot for male prisoners in Figure 8, in which large values gradually decrease with increasing lags. Because there are many significant lags (bars exceeding the confidence intervals or dashed lines), differencing is required to eliminate trends and seasonality.

[5] See Section 8.5 (Non-Seasonal ARIMA Models) for more details.

Figure 8: ACF Plot of Monthly Male Prisoners in NM

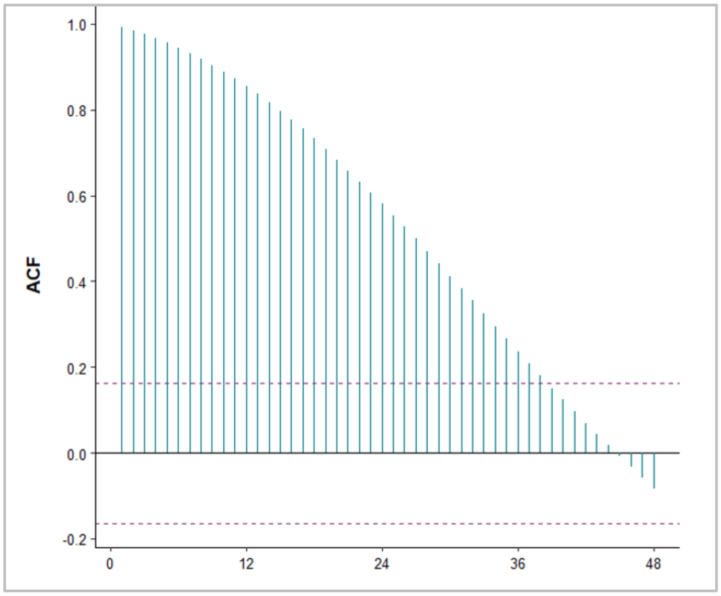
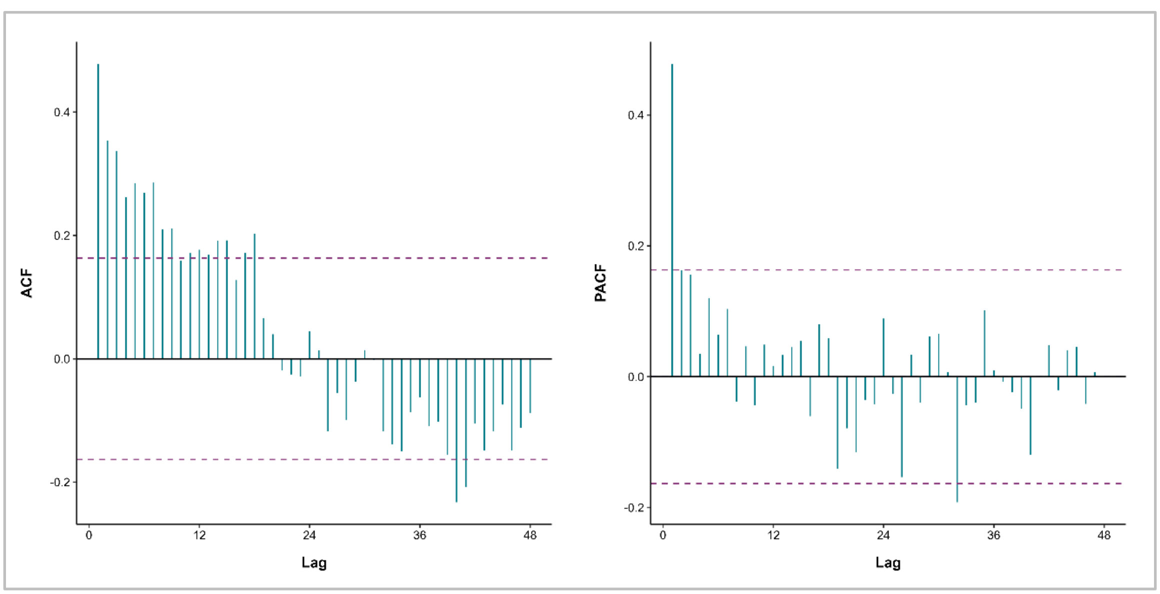


Figure 9 shows the ACF and PACF plots of the first-order differenced monthly male prisoner series. Although the ACF plot may suggest differencing the series again since there are several lags that are outside of the confidence intervals, the plot exhibits a gradual decay over many lags. In contrast, the PACF has a large spike at lag 1 before converging to values near zero. Together, these plots suggest that the remaining dependence is better accounted for by adding an additional AR term as opposed to differencing again.

We can also confirm this using the KPSS test. When computing the KPSS test, a p-value of 0.07 is calculated. Given that this p-value is greater than 0.05, we fail to reject the null hypothesis, concluding that the data are stationary. Thus, because the data are now stationary ($d = 1$), we can identify the values for p and q.

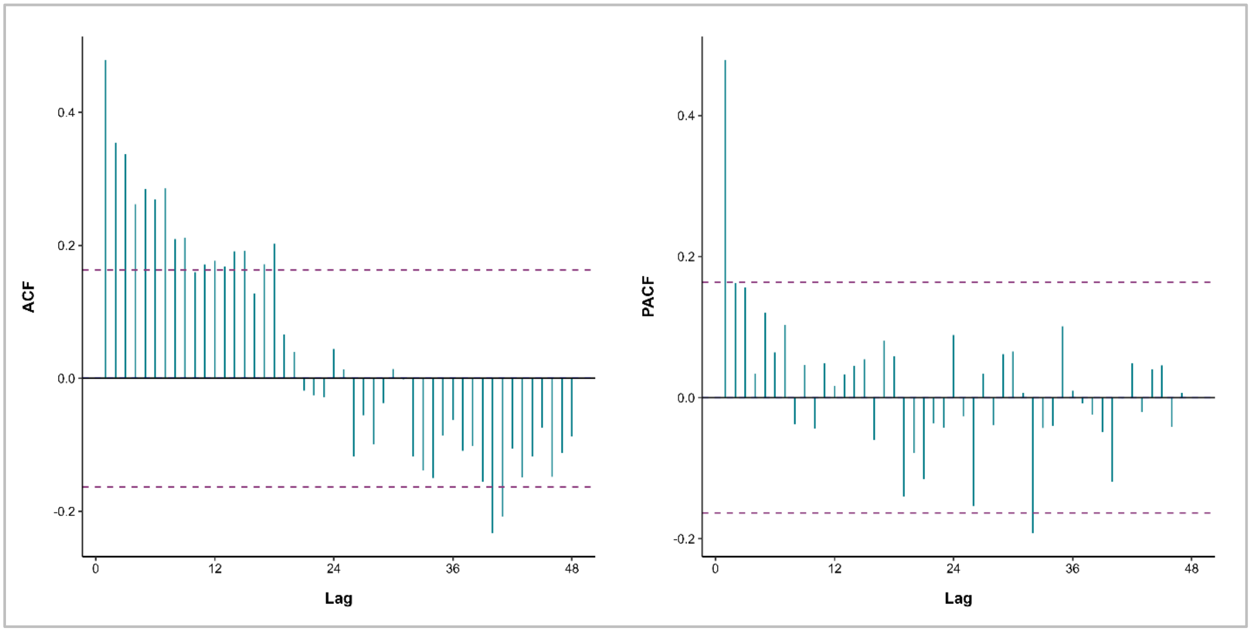
Figure 9: 1st-Order Differencing ACF and PACF Plots of Monthly Male Prisoners in NM



3.1.2. Identifying p and q for Male Prisoners

Recall the first-order differenced ACF and PACF plots for male prisoners:

Figure 10: 1st-Order Differencing ACF and PACF Plots of Monthly Male Prisoners in NM



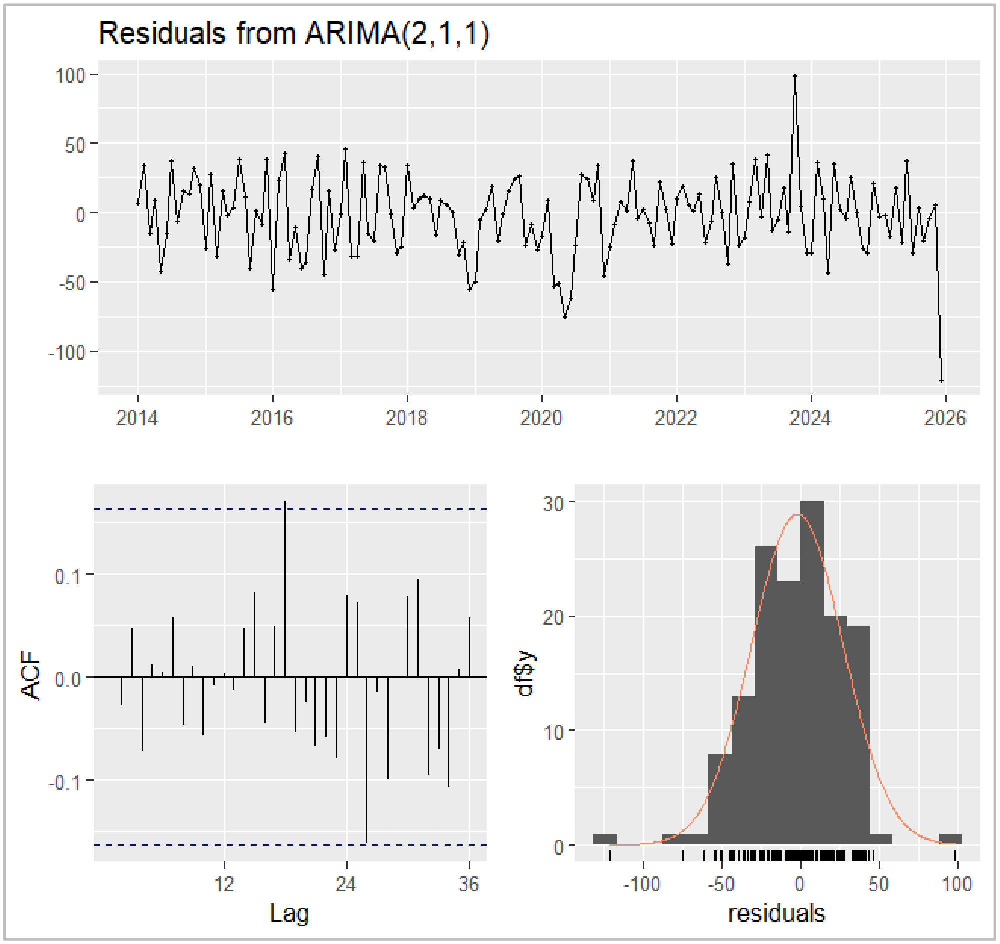
Given the significant spike at lag 1 in the PACF plot, an MA(1) component ($q = 1$) is appropriate. The ACF plot also displays several significant spikes that slowly decrease over time, indicating that an additional AR term is needed, hence $p = 2$. As discussed in Section 3.1.1, the original series was differenced once, so $d = 1$. Taken together, the appropriate ARIMA model for the male prisoner data is $ARIMA(2,1,1)$.

3.1.3. Plotting the Residuals and Testing for Normality for Male Prisoners

The ACF plot of the residuals from the $ARIMA(2,1,1)$ model shows that all autocorrelations fall within the threshold limits, indicating that the residuals are behaving like white noise. A portmanteau test yields a large p-value of 0.8723, also suggesting that the residuals are white noise and that autocorrelation is no longer present. Furthermore, the residuals seem to follow a normal distribution, verifying that the male prisoner series is now stationary. Overall, these three tests in Figure 11 confirm that the $ARIMA(2,1,1)$ model is the most suitable model for analyzing male prisoners in New Mexico.[6]

[6] We could have also used an $ARIMA(1,2,1)$ model, in which the series was differenced twice. However, when it came to forecasting, the $ARIMA(2,1,1)$ model did much better relative to the $ARIMA(1,2,1)$ model, even though the $ARIMA(1,2,1)$ model performed slightly better with the historical data.

Figure 11: Residuals from the $ARIMA(2,1,1)$ Model



3.2. ARIMA Model for Female Prisoners

3.2.1. Differencing Time Series by Identifying d for Female Prisoners

Recall the ACF plot for female prisoners in Figure 12, in which large values gradually decrease with increasing lags. Because there are many significant lags (bars exceeding the confidence intervals or dashed lines), differencing is required to eliminate trends and seasonality.

Figure 12: ACF Plot of Monthly Female Prisoners in NM

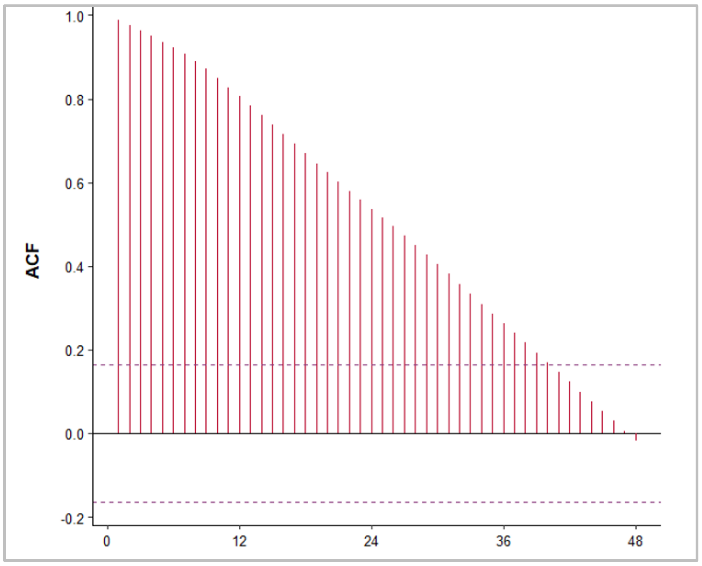
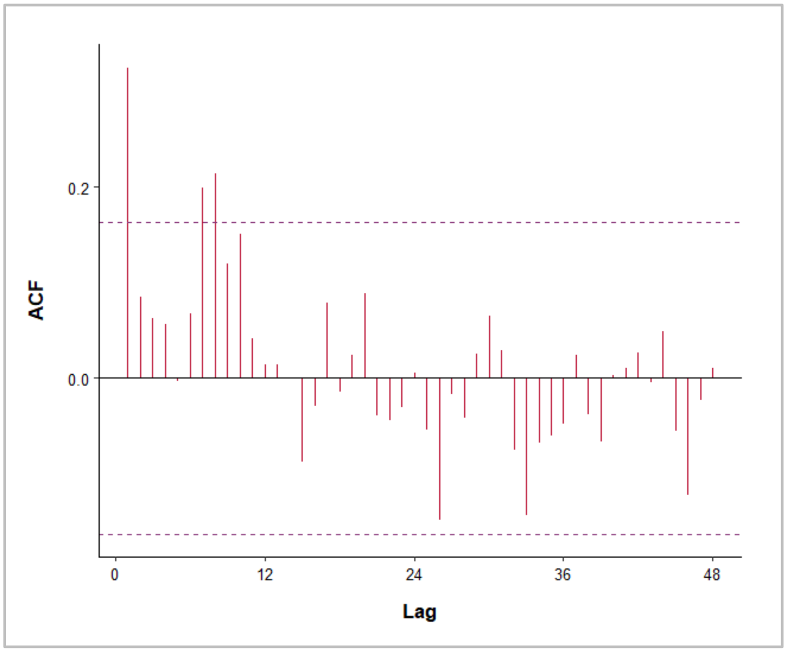


Figure 13 below shows the ACF plot of the first-order differenced monthly female prisoner series. The ACF plot has a significant lag at 1 (the first red bar is above the purple upper confidence interval of +0.1633), which suggests that first-order differencing has successfully eliminated (or reduced) trend and seasonality.

We can also confirm this using the KPSS test. When computing the KPSS test, a p-value of 0.1 is calculated. Given that this p-value is greater than 0.05, we fail to reject the null hypothesis, concluding that the data are stationary. Thus, because the data are now stationary ($d = 1$), we can identify the values for p and q.

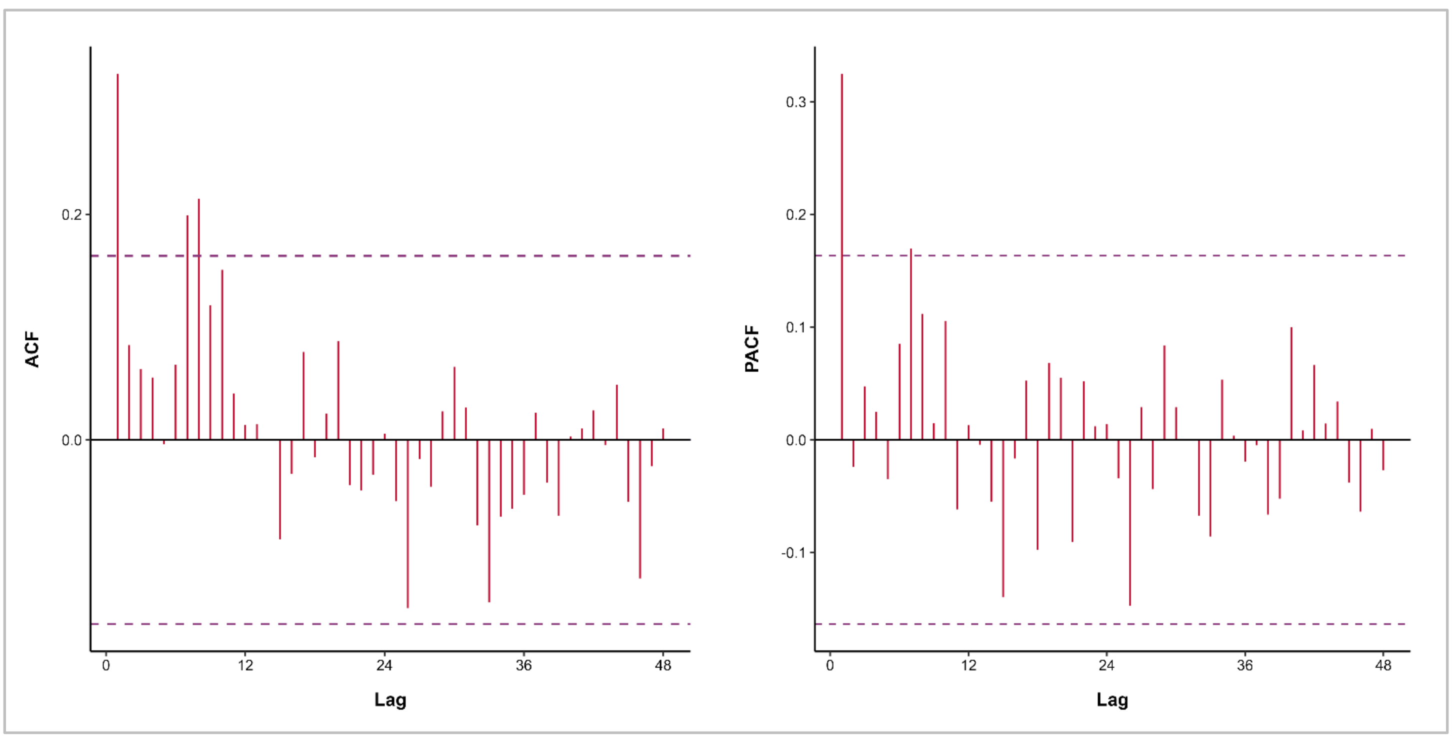
Figure 13: 1st-Order Differencing ACF Plot of Monthly Female Prisoners in NM



3.2.2. Identifying p and q for Female Prisoners

Recall the first-order differenced ACF and PACF plots for female prisoners:

Figure 14: 1st-Order Differencing ACF and PACF Plots of Monthly Female Prisoners in NM



As Figure 14 displays, the ACF and PACF plots of the differenced data show the following patterns:

- The ACF plot is exponentially decaying;
- There is a significant spike at lag 1 in the PACF plot, and no spikes are observed beyond lag 1. In other words, the bar at lag 1 exceeds the upper confidence interval bound, and there are no additional spikes beyond that point.

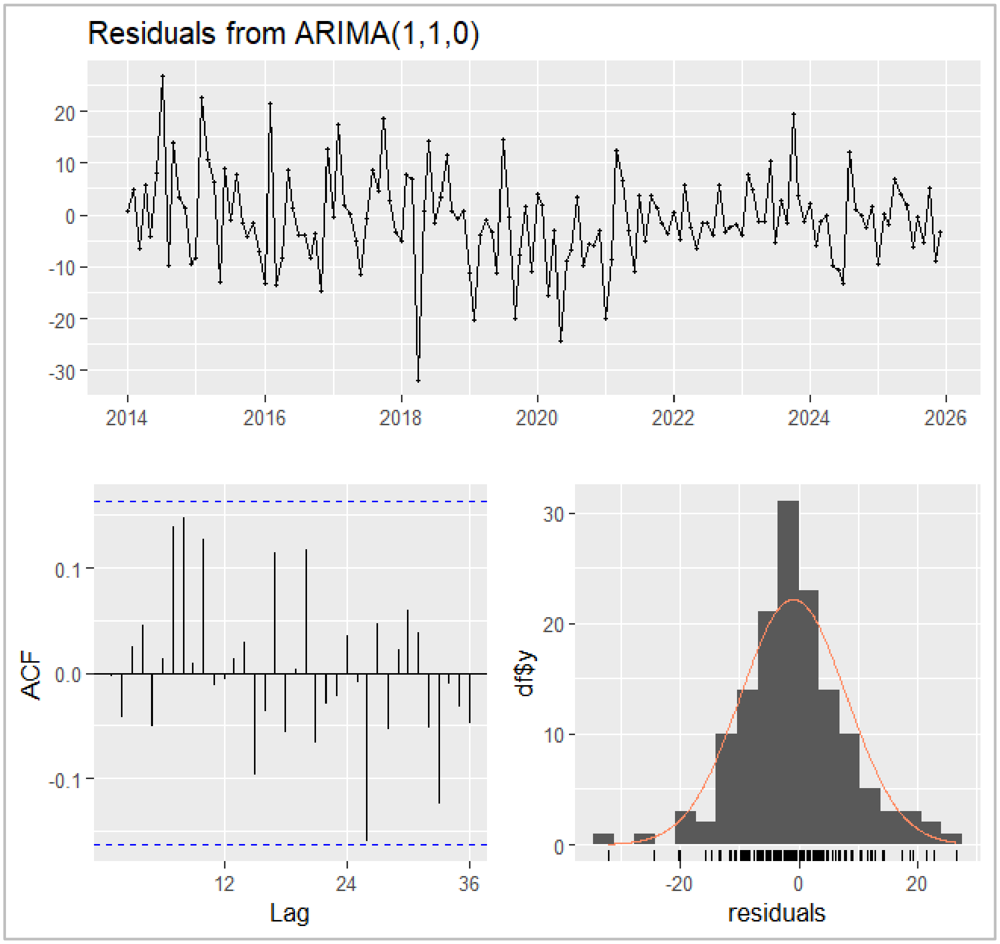
These two conditions satisfy an $ARIMA(p, d, 0)$ model.[7] In this notation, p represents the lag in the PACF plot where the spike occurs (in this case, at lag 1); d indicates the degree of differencing (d is 1, as explained in Section 3.2.1), and q is 0. Therefore, the ARIMA model for female prisoners is $ARIMA(1,1,0)$.

3.2.3. Plotting the Residuals and Testing for Normality for Female Prisoners

The ACF plot of the residuals from the $ARIMA(1,1,0)$ model shows that all autocorrelations fall within the threshold limits, indicating that the residuals are behaving like white noise. A portmanteau test yields a large p-value of 0.7455, also suggesting that the residuals are white noise and that autocorrelation is no longer present. Furthermore, the residuals follow a normal distribution, verifying that the female prisoner series is now stationary. Overall, these three tests in Figure 15 confirm that the $ARIMA(1,1,0)$ model is the most suitable model for analyzing female prisoners in New Mexico.

[7] See Section 8.5 (Non-Seasonal ARIMA Models) for more details.

Figure 15: Residuals from the ARIMA(1,1,0) Model



Forecasting Male and Female Prisoners using ARIMA Models

This chapter forecasts male and female prison populations by integrating the ARIMA models that were developed in Chapter 3. Forecast results are presented through figures and tables that include both point forecasts (a single predicted value) and interval forecasts (range of values within a certain confidence interval). Both 80% and 95% prediction intervals have been generated, which means that the actual values are expected to fall within these ranges 80% and 95% of the time, respectively. Additionally, for model training, longer training windows have been used for the 10-year forecasts, whereas shorter windows have been employed for the 1-year forecasts to better account for recent changes.[8]

4.1. Forecasting Male Prisoners

4.1.1. 1-Year (FY2027) Male Prisoner Forecast

Figure 16 shows the 1-year forecast for Fiscal Year 2027 (FY2027) using the $ARIMA(2,1,1)$ model, which was trained on data from June 2021 to December 2025. This training period was chosen because it better captures recent trends and shifts in dynamics. In contrast, data from January 2014 to September 2018 are significantly higher than those observed from June 2021 onward, while October 2018 to mid-2021 captures a large structural decline that is no longer present in recent years.

To assess the model's performance, the forecast also includes data from January 2026 to May 2026, even though FY2027 runs from July 1, 2026, to June 30, 2027. This was done to compare the model's predictions with actual male prisoner data already released by NMSC.

In addition to the data and forecast lines, 80% (represented in lighter blue) and 95% (represented in darker blue) prediction intervals are also included in the plot. The values have also been recorded in Table 3.

[8] Training windows refer to the range of historic values that are used to predict current and future values.

Figure 16: Plot of 1-Year Forecast using the ARIMA(2,1,1) Model. Trained on June 2021–Dec. 2025 Data

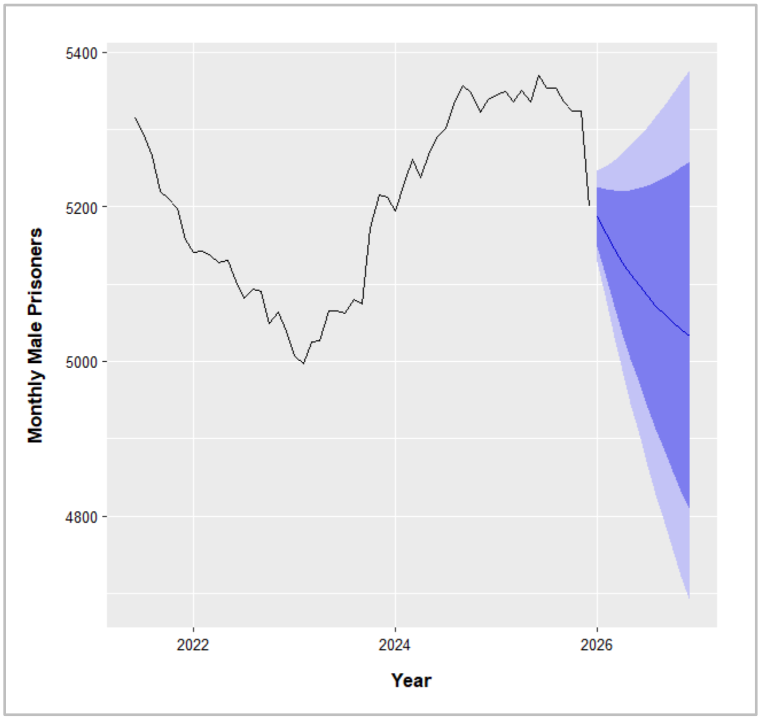


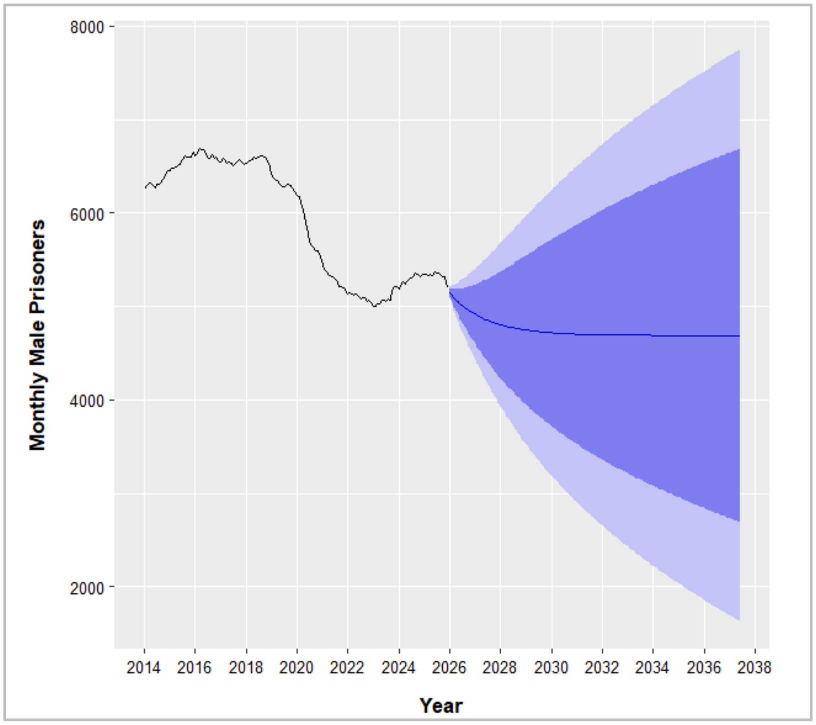
Table 3: Table of 1-Year Forecast using the ARIMA(2,1,1) Model. Trained on June 2021–Dec. 2025 Data

	Actual Value	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
January 2026	5,116	5,187	5,149	5,226	5,129	5,246
February 2026	5,097	5,165	5,108	5,222	5,078	5,252
March 2026	5,092	5,146	5,071	5,221	5,032	5,260
April 2026	5,083	5,128	5,036	5,220	4,988	5,269
May 2026	5,102	5,112	5,003	5,221	4,945	5,279
June 2026	-	5,097	4,971	5,224	4,905	5,290
July 2026	-	5,084	4,941	5,227	4,865	5,303
August 2026	-	5,072	4,912	5,232	4,828	5,316
September 2026	-	5,061	4,884	5,237	4,791	5,330
October 2026	-	5,051	4,858	5,243	4,756	5,345
November 2026	-	5,041	4,833	5,250	4,722	5,361
December 2026	-	5,033	4,808	5,258	4,689	5,377
January 2027	-	5,025	4,785	5,266	4,657	5,393
February 2027	-	5,018	4,762	5,275	4,627	5,410
March 2027	-	5,012	4,741	5,283	4,597	5,427
April 2027	-	5,006	4,720	5,293	4,568	5,444
May 2027	-	5,001	4,700	5,302	4,540	5,462
June 2027	-	4,996	4,681	5,312	4,513	5,479

4.1.2. 10-Year (FY2027-FY2037) Male Prisoner Forecast

Similar to the 1-year forecast, Figure 17 and Table 4 present the 10-year (FY2027–FY2037) forecast utilizing the $ARIMA(2,1,1)$ model. Since we are forecasting a decade into the future, the training window includes all available historical data. This approach is justified because having a larger dataset allows for better estimation of the model parameters, which is particularly important given the increased uncertainty associated with longer time periods. In addition, the monthly averages have been grouped into yearly averages based on the fiscal year (FY), which runs from July 1st to June 30th of the next year. For example, FY2027 includes data from July 1, 2026, to June 30, 2027.[9]

Figure 17: Plot of 10-Year Forecast using the $ARIMA(2,1,1)$ Model. Trained on Jan. 2014–Dec. 2025 Data



[9] To view the 10-Year (FY2027–FY2037) forecast on a month-by-month basis, please refer to Appendix A.

Table 4: Table of 10-Year Forecast using the $ARIMA(2,1,1)$ Model. Trained on Jan. 2014–Dec. 2025 Data

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2027	4,932	4,630	5,233	4,470	5,393
FY2028	4,812	4,256	5,368	3,962	5,662
FY2029	4,752	3,967	5,536	3,552	5,952
FY2030	4,722	3,735	5,708	3,213	6,230
FY2031	4,706	3,541	5,871	2,925	6,487
Fy2032	4,698	3,373	6,023	2,672	6,724
FY2033	4,694	3,225	6,164	2,446	6,942
FY2034	4,692	3,089	6,295	2,241	7,144
FY2035	4,691	2,965	6,418	2,051	7,332
FY2036	4,691	2,849	6,533	1,874	7,508
Fy2037	4,691	2,740	6,641	1,707	7,674

4.2. Forecasting Female Prisoners

4.2.1. 1-Year (FY2027) Female Prisoner Forecast

Figure 18 presents a plot of the 1-year forecast generated using the $ARIMA(1,1,0)$ model, which was trained on data from January 2021 to December 2025. This training window was chosen because it reflects the dynamics of the post-2020 period, during which values remained below those observed from 2014 to 2020 following the substantial decline between 2020 and 2021.

To assess the model's performance, the forecast also includes data from January 2026 to May 2026, even though FY2027 runs from July 1, 2026, to June 30, 2027. This was done to compare the model's predictions with actual female prisoner data already released by NMSC.

The plot also includes 80% (lighter blue) and 95% (darker blue) prediction intervals. The values have also been recorded in Table 5.

Figure 18: Plot of 1-Year Forecast using the ARIMA(1,1,0) Model. Trained on Jan. 2021–Dec. 2025 Data

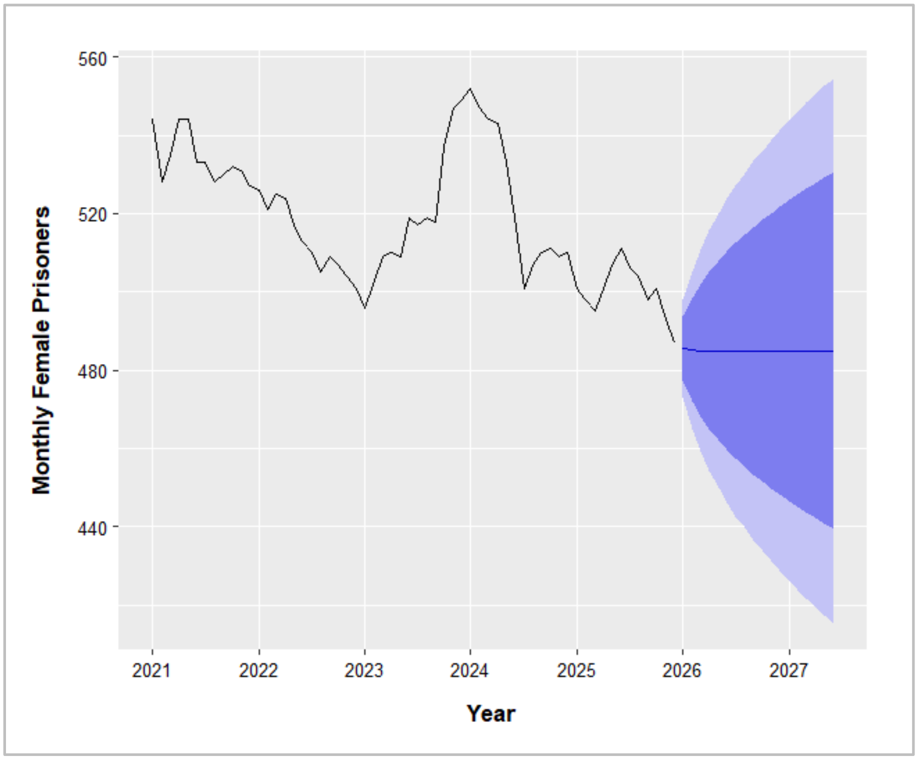


Table 5: Table of 1-Year Forecast using the ARIMA(1,1,0) Model. Trained on Jan. 2021–Dec. 2025 Data

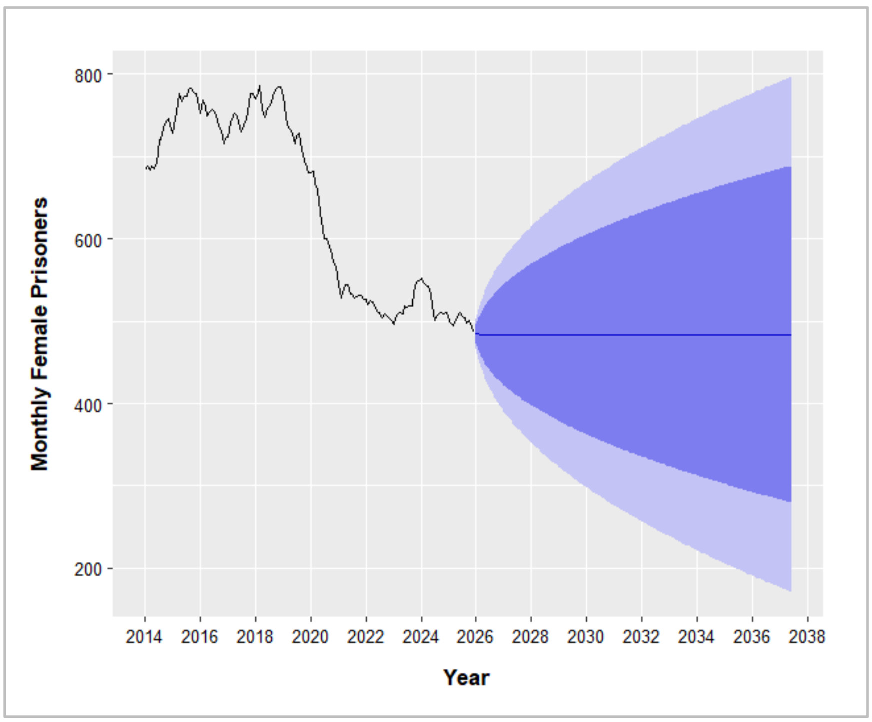
	Actual Value	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
January 2026	491	485	477	494	473	498
February 2026	493	485	472	498	465	505
March 2026	495	485	468	502	459	511
April 2026	498	485	465	505	454	516
May 2026	501	485	462	508	450	520
June 2026	-	485	460	510	446	524
July 2026	-	485	457	513	443	527
August 2026	-	485	455	515	440	530
September 2026	-	485	453	517	437	533
October 2026	-	485	452	518	434	536
November 2026	-	485	450	520	431	539
December 2026	-	485	448	522	429	541
January 2027	-	485	447	523	426	544
February 2027	-	485	445	525	424	546
March 2027	-	485	444	526	422	548
April 2027	-	485	442	528	420	550
May 2027	-	485	441	529	417	553
June 2027	-	485	439	530	415	555

As seen in the table above, the model projects the female prison population to level off. Although the most recent observations indicate a slight increase, there are insufficient post-2026 observations for the ARIMA model to identify this as an ongoing trend. Instead, the $ARIMA(1,1,0)$ model reflects the historical behavior of the series, which was generally stable over the sample period, aside from the steep decline between January 2019 and January 2021 and the unusual drop from May 2024 to December 2025. As such, the historical data do not provide sufficient statistical evidence of an increase or decrease in the female prison population, and adding more AR/MA terms does not improve model fit. Therefore, the prediction intervals should also be considered when interpreting the forecasts.

4.2.2. 10-Year (FY2027-FY2037) Female Prisoner Forecast

Similar to the 1-year forecast, Figure 19 and Table 6 present the 10-year (FY2027–FY2037) forecast using the $ARIMA(1,1,0)$ model. Since this forecast spans a decade, the training window includes all historical data. This approach is justified, as a larger dataset allows for better estimation of the model parameters (this is vital given the increased uncertainty associated with longer time periods). In addition, the monthly averages have been grouped into yearly averages based on the fiscal year (FY), which runs from July 1st to June 30th of the next year. For example, FY2027 includes data from July 1, 2026, to June 30, 2027.[10]

Figure 19: Plot of 10-Year Forecast using the $ARIMA(1,1,0)$ Model. Trained on Jan. 2014–Dec. 2025 Data



[10] To view the 10-Year (FY2027–FY2037) forecast on a month-by-month basis, please refer to Appendix B.

Table 6: Table of 10-Year Forecast using the $ARIMA(1,1,0)$ Model. Trained on Jan. 2014–Dec. 2025 Data

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2027	484	425	543	394	574
FY2028	484	399	569	354	614
FY2029	484	380	588	325	643
Fy2030	484	364	604	300	668
FY2031	484	349	619	278	690
FY2032	484	337	632	258	710
Fy2033	484	325	644	240	728
FY2034	484	313	655	223	745
FY2035	484	303	665	207	761
FY2036	484	293	675	192	776
Fy2037	484	284	684	178	790

Similar to the 1-year forecast, the model projects the female prison population to level off over the next ten fiscal years for the same reasons mentioned earlier. The historical data do not provide sufficient statistical evidence of an increase or decrease in the female prison population, and adding more AR/MA terms does not improve model fit. Therefore, the prediction intervals should also be considered when interpreting the forecasts.

4.3. Conclusion

This chapter has presented 1-year and 10-year projections for both male and female prisoners in New Mexico using ARIMA models. Although the 1-year forecasts deviate slightly from the observed values, the models are driven by the historical behavior of the series, and recent observations have not yet provided sufficient evidence of a steady trend, even after changing the sample period. Therefore, the forecasts should be interpreted alongside their prediction intervals to account for forecast uncertainty.

With regards to the long-term (10-year) forecasts, assessing the performance of these forecasts will be more difficult as ARIMA models are better suited for short-term forecasts; nonetheless, these projections can still offer valuable directional insights. Moreover, while ARIMA is not the only available or recommended forecasting technique – alternatives such as exponential smoothing and regression analysis are also viable options – it remains one of the most widely used methods due to its balance of stability and reliability, especially when taking context into account.

Appendix A: 10-Year (FY2027–FY2037) Male Prisoner Forecast on a Month-by-Month Basis

FY2027–FY2029

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2027					
July 2026	5,014	4,834	5,194	4,739	5,289
August 2026	4,996	4,794	5,198	4,687	5,305
September 2026	4,979	4,754	5,204	4,636	5,323
October 2026	4,963	4,716	5,210	4,586	5,341
November 2026	4,948	4,679	5,217	4,537	5,359
December 2026	4,934	4,643	5,225	4,488	5,379
January 2027	4,920	4,607	5,233	4,441	5,399
February 2027	4,908	4,572	5,243	4,395	5,420
March 2027	4,896	4,539	5,253	4,350	5,441
April 2027	4,884	4,505	5,263	4,305	5,463
May 2027	4,873	4,473	5,274	4,261	5,486
June 2027	4,863	4,442	5,285	4,218	5,508
FY2028					
July 2027	4,854	4,411	5,297	4,176	5,531
August 2027	4,845	4,381	5,309	4,135	5,555
September 2027	4,836	4,351	5,321	4,094	5,578
October 2027	4,828	4,322	5,334	4,054	5,602
November 2027	4,820	4,294	5,347	4,015	5,626
December 2027	4,813	4,266	5,360	3,977	5,650
January 2028	4,806	4,239	5,374	3,939	5,674
February 2028	4,800	4,213	5,387	3,902	5,698
March 2028	4,794	4,187	5,401	3,866	5,722
April 2028	4,788	4,162	5,415	3,830	5,747
May 2028	4,783	4,137	5,429	3,795	5,771
June 2028	4,778	4,112	5,443	3,760	5,795
FY2029					
July 2028	4,773	4,089	5,457	3,726	5,819
August 2028	4,768	4,065	5,471	3,693	5,844
September 2028	4,764	4,042	5,486	3,660	5,868
October 2028	4,760	4,020	5,500	3,628	5,892
November 2028	4,756	3,997	5,515	3,596	5,916
December 2028	4,752	3,976	5,529	3,565	5,940
January 2029	4,749	3,954	5,543	3,534	5,964
February 2029	4,746	3,934	5,558	3,504	5,988
March 2029	4,743	3,913	5,572	3,474	6,012
April 2029	4,740	3,893	5,587	3,444	6,035
May 2029	4,737	3,873	5,601	3,415	6,059
June 2029	4,734	3,853	5,616	3,387	6,082

FY2030–FY2032

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2030					
July 2029	4,732	3,834	5,630	3,359	6,105
August 2029	4,730	3,815	5,644	3,331	6,128
September 2029	4,728	3,797	5,658	3,304	6,151
October 2029	4,725	3,778	5,673	3,277	6,174
November 2029	4,724	3,760	5,687	3,250	6,197
December 2029	4,722	3,742	5,701	3,224	6,219
January 2030	4,720	3,725	5,715	3,198	6,242
February 2030	4,718	3,708	5,729	3,173	6,264
March 2030	4,717	3,691	5,743	3,148	6,286
April 2030	4,715	3,674	5,757	3,123	6,308
May 2030	4,714	3,657	5,770	3,098	6,330
June 2030	4,713	3,641	5,784	3,074	6,351
FY2031					
July 2030	4,711	3,625	5,798	3,050	6,373
August 2030	4,710	3,609	5,811	3,026	6,394
September 2030	4,709	3,593	5,825	3,003	6,415
October 2030	4,708	3,578	5,838	2,980	6,436
November 2030	4,707	3,563	5,851	2,957	6,457
December 2030	4,706	3,548	5,865	2,934	6,478
January 2031	4,705	3,533	5,878	2,912	6,499
February 2031	4,704	3,518	5,891	2,890	6,519
March 2031	4,704	3,503	5,904	2,868	6,539
April 2031	4,703	3,489	5,917	2,846	6,559
May 2031	4,702	3,475	5,930	2,825	6,579
June 2031	4,702	3,461	5,942	2,804	6,599
FY2032					
July 2031	4,701	3,447	5,955	2,783	6,619
August 2031	4,700	3,433	5,968	2,762	6,639
September 2031	4,700	3,419	5,980	2,742	6,658
October 2031	4,699	3,406	5,993	2,721	6,677
November 2031	4,699	3,392	6,005	2,701	6,697
December 2031	4,698	3,379	6,017	2,681	6,716
January 2032	4,698	3,366	6,030	2,661	6,735
February 2032	4,697	3,353	6,042	2,642	6,753
March 2032	4,697	3,340	6,054	2,622	6,772
April 2032	4,697	3,328	6,066	2,603	6,790
May 2032	4,696	3,315	6,078	2,584	6,809
June 2032	4,696	3,302	6,089	2,565	6,827

FY2033–FY2035

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2033					
July 2032	4,696	3,290	6,101	2,546	6,845
August 2032	4,695	3,278	6,113	2,527	6,863
September 2032	4,695	3,266	6,125	2,509	6,881
October 2032	4,695	3,254	6,136	2,491	6,899
November 2032	4,695	3,242	6,148	2,472	6,917
December 2032	4,694	3,230	6,159	2,454	6,934
January 2033	4,694	3,218	6,170	2,437	6,952
February 2033	4,694	3,206	6,182	2,419	6,969
March 2033	4,694	3,195	6,193	2,401	6,986
April 2033	4,694	3,183	6,204	2,384	7,003
May 2033	4,693	3,172	6,215	2,366	7,020
June 2033	4,693	3,160	6,226	2,349	7,037
FY2034					
July 2033	4,693	3,149	6,237	2,332	7,054
August 2033	4,693	3,138	6,248	2,315	7,071
September 2033	4,693	3,127	6,258	2,298	7,087
October 2033	4,693	3,116	6,269	2,281	7,104
November 2033	4,692	3,105	6,280	2,265	7,120
December 2033	4,692	3,094	6,290	2,248	7,136
January 2034	4,692	3,083	6,301	2,232	7,153
February 2034	4,692	3,073	6,311	2,216	7,169
March 2034	4,692	3,062	6,322	2,199	7,185
April 2034	4,692	3,052	6,332	2,183	7,201
May 2034	4,692	3,041	6,343	2,167	7,216
June 2034	4,692	3,031	6,353	2,151	7,232
FY2035					
July 2034	4,692	3,020	6,363	2,136	7,248
August 2034	4,692	3,010	6,373	2,120	7,263
September 2034	4,692	3,000	6,383	2,104	7,279
October 2034	4,691	2,990	6,393	2,089	7,294
November 2034	4,691	2,980	6,403	2,073	7,309
December 2034	4,691	2,970	6,413	2,058	7,325
January 2035	4,691	2,960	6,423	2,043	7,340
February 2035	4,691	2,950	6,433	2,028	7,355
March 2035	4,691	2,940	6,443	2,013	7,370
April 2035	4,691	2,930	6,452	1,998	7,385
May 2035	4,691	2,920	6,462	1,983	7,399
Jun 2035	4,691	2,910	6,472	1,968	7,414

FY2036–FY2037

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2036					
July 2035	4,691	2,901	6,481	1,953	7,429
August 2035	4,691	2,891	6,491	1,938	7,443
September 2035	4,691	2,882	6,500	1,924	7,458
October 2035	4,691	2,872	6,510	1,909	7,472
November 2035	4,691	2,863	6,519	1,895	7,487
December 2035	4,691	2,853	6,528	1,881	7,501
January 2036	4,691	2,844	6,538	1,866	7,515
February 2036	4,691	2,835	6,547	1,852	7,529
March 2036	4,691	2,825	6,556	1,838	7,543
April 2036	4,691	2,816	6,565	1,824	7,558
May 2036	4,691	2,807	6,574	1,810	7,571
June 2036	4,691	2,798	6,583	1,796	7,585
FY2037					
July 2036	4,691	2,789	6,592	1,782	7,599
August 2036	4,691	2,780	6,601	1,768	7,613
September 2036	4,691	2,771	6,610	1,755	7,627
October 2036	4,691	2,762	6,619	1,741	7,640
November 2036	4,691	2,753	6,628	1,727	7,654
December 2036	4,691	2,744	6,637	1,714	7,667
January 2037	4,691	2,735	6,646	1,700	7,681
February 2037	4,691	2,727	6,655	1,687	7,694
March 2037	4,691	2,718	6,663	1,673	7,708
April 2037	4,691	2,709	6,672	1,660	7,721
May 2037	4,690	2,700	6,681	1,647	7,734
June 2037	4,690	2,692	6,689	1,634	7,747

Appendix B: 10-Year (FY2027–FY2037) Female Prisoner Forecast on a Month-by-Month Basis

FY2027–FY2029

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2027					
July 2026	484	441	527	418	550
August 2026	484	437	531	413	555
September 2026	484	434	534	408	560
October 2026	484	431	537	403	565
November 2026	484	428	539	399	569
December 2026	484	426	542	395	573
January 2027	484	423	545	391	577
February 2027	484	421	547	387	581
March 2027	484	418	550	384	584
April 2027	484	416	552	380	588
May 2027	484	414	554	377	591
June 2027	484	412	556	373	594
FY2028					
July 2027	484	410	558	370	598
August 2027	484	408	560	367	601
September 2027	484	406	562	364	604
October 2027	484	404	564	361	607
November 2027	484	402	566	358	610
December 2027	484	400	568	356	612
January 2028	484	398	570	353	615
February 2028	484	396	571	350	618
March 2028	484	395	573	347	620
April 2028	484	393	575	345	623
May 2028	484	391	577	342	626
June 2028	484	390	578	340	628
FY2029					
July 2028	484	388	580	337	631
August 2028	484	387	581	335	633
September 2028	484	385	583	333	635
October 2028	484	383	584	330	638
November 2028	484	382	586	328	640
December 2028	484	380	587	326	642
January 2029	484	379	589	323	644
February 2029	484	378	590	321	647
March 2029	484	376	592	319	649
April 2029	484	375	593	317	651
May 2029	484	373	595	315	653
June 2029	484	372	596	313	655

FY2030–FY2032

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2030					
July 2029	484	371	597	311	657
August 2029	484	369	599	309	659
September 2029	484	368	600	307	661
October 2029	484	367	601	305	663
November 2029	484	365	603	303	665
December 2029	484	364	604	301	667
January 2030	484	363	605	299	669
February 2030	484	362	606	297	671
March 2030	484	360	608	295	673
April 2030	484	359	609	293	675
May 2030	484	358	610	291	677
June 2030	484	357	611	289	679
FY2031					
July 2030	484	355	612	287	680
August 2030	484	354	614	286	682
September 2030	484	353	615	284	684
October 2030	484	352	616	282	686
November 2030	484	351	617	280	688
December 2030	484	350	618	279	689
January 2031	484	349	619	277	691
February 2031	484	347	620	275	693
March 2031	484	346	622	273	694
April 2031	484	345	623	272	696
May 2031	484	344	624	270	698
June 2031	484	343	625	268	700
FY2032					
July 2031	484	342	626	267	701
August 2031	484	341	627	265	703
September 2031	484	340	628	263	704
October 2031	484	339	629	262	706
November 2031	484	338	630	260	708
December 2031	484	337	631	259	709
January 2032	484	336	632	257	711
February 2032	484	335	633	256	712
March 2032	484	334	634	254	714
April 2032	484	333	635	252	715
May 2032	484	332	636	251	717
June 2032	484	331	637	249	719

FY2033–FY2035

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2033					
July 2032	484	330	638	248	720
August 2032	484	329	639	246	722
September 2032	484	328	640	245	723
October 2032	484	327	641	243	725
November 2032	484	326	642	242	726
December 2032	484	325	643	240	727
January 2033	484	324	644	239	729
February 2033	484	323	645	237	730
March 2033	484	322	646	236	732
April 2033	484	321	647	235	733
May 2033	484	320	648	233	735
June 2033	484	319	649	232	736
FY2034					
July 2033	484	318	650	230	738
August 2033	484	317	651	229	739
September 2033	484	316	652	228	740
October 2033	484	315	652	226	742
November 2033	484	314	653	225	743
December 2033	484	314	654	223	744
January 2034	484	313	655	222	746
February 2034	484	312	656	221	747
March 2034	484	311	657	219	749
April 2034	484	310	658	218	750
May 2034	484	309	659	217	751
June 2034	484	308	660	215	753
FY2035					
July 2034	484	307	660	214	754
August 2034	484	307	661	213	755
September 2034	484	306	662	211	757
October 2034	484	305	663	210	758
November 2034	484	304	664	209	759
December 2034	484	303	665	207	760
January 2035	484	302	666	206	762
February 2035	484	301	666	205	763
March 2035	484	301	667	204	764
April 2035	484	300	668	202	766
May 2035	484	299	669	201	767
June 2035	484	298	670	200	768

FY2036–FY2037

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
FY2036					
July 2035	484	297	671	199	769
August 2035	484	297	671	197	771
September 2035	484	296	672	196	772
October 2035	484	295	673	195	773
November 2035	484	294	674	194	774
December 2035	484	293	675	192	775
January 2036	484	292	675	191	777
February 2036	484	292	676	190	778
March 2036	484	291	677	189	779
April 2036	484	290	678	188	780
May 2036	484	289	679	186	782
June 2036	484	289	679	185	783
FY2037					
July 2036	484	288	680	184	784
August 2036	484	287	681	183	785
September 2036	484	286	682	182	786
October 2036	484	285	682	180	787
November 2036	484	285	683	179	789
December 2036	484	284	684	178	790
January 2037	484	283	685	177	791
February 2037	484	282	685	176	792
March 2037	484	282	686	175	793
April 2037	484	281	687	173	794
May 2037	484	280	688	172	796
June 2037	484	279	688	171	797

Appendix C: References

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