Unemployment in Pennsylvania (1995–2025): A Time-Series Study of Economic Trends and the Steel Industry's Role

Introduction

In the 1980s, steel mills and manufacturing factories surrounded Pittsburgh's Golden Triangle, symbolizing the economic prosperity of Pennsylvania. Two years ago, a visit to Mount Washington in Pittsburgh told me a different story. Looking down from above, the modern skyline of the Golden Triangle, with skyscrapers reflecting light across the rivers, vividly showed how Pittsburgh had transformed from the "steel city" into a hub for finance, education, and technology. This major industrial shift led to the core question of this report: how has the decline of the steel industry shaped unemployment in Pennsylvania over the past thirty years?

To address this question, first, a background section will introduce Pennsylvania's economic features which includes the makeup of different employment sectors, the significant events that influenced Pennsylvania's labor market, and the demographic characteristics that shape employment dynamics. These elements provide context for the role of the steel industry and elaborate my research motivation. Then, a data section will mainly depend on the seasonally adjusted unemployment data for Pennsylvania from July 1995 to June 2025, obtained from the FRED. Next, a method section will follow the Box–Jenkins framework in R studio into 3 parts, identification, estimation, and diagnostics.

This econometrics part begins with seasonal decomposition to separate trend, seasonal, and irregular components. It then applies ADF and KPSS test to check stationarity and determine a need for differencing of 1. ACF and PACF plots guide the selection of autoregressive and moving average terms, and ARIMA models are estimated on the adjusted series. The Ljung–Box test checks the adequacy of the chosen model, while AIC and BIC criteria help compare alternative specifications. Finally, the study uses ARIMA forecasting to project short-term unemployment dynamics beyond 2025. The report concludes by summarizing key findings, drawing broader economic implications, and reflecting on possible limitations. Finally, an appendix will provide the figures and tables that support the results and illustrate the research process.

Background on Pennsylvania's Economy

Pennsylvania offers a distinctive case for the study of unemployment because of its diverse economic makeup, significant events, and demographic profile. A long record of structural change defines the diversity of Pennsylvania's economic makeup, and the state's top 3 industries by real GDP 1995 verses 2025 can explain the structural shift: In 1995, manufacturing ranked first, followed by finance, insurance, and real estate, and retail trade. By 2025, the leading sectors are expected to be real estate and rental services, educational services and healthcare, and professional and business services. Each of these service-oriented industries now contributes over $100 billion in GDP, marking a decisive move away from heavy industry toward a service-dominated economy.

Major shocks also highlight the state's unemployment fluctuations. The 2008 financial crisis triggered steep job losses in construction and manufacturing, and the COVID-19 pandemic pushed unemployment close to 16 percent in April 2020. Demographic conditions further shape labor outcomes: rural counties with aging populations experience slower labor-force recovery, while urban centers benefit from the resilience of universities and research institutions. These factors help explain why Pennsylvania's unemployment rate does not simply mirror the national average. Together, these characteristics make Pennsylvania an especially instructive state for time-series analysis of unemployment.

Manufactural sector leading by steel industry then offers another distinctive case for the unemployment study. The state contains two other major sectors of employment. First, agriculture remains an important but stable contributor: Pennsylvania consistently ranks among the top producers of dairy, mushrooms, and apples, sustaining rural communities with relatively steady jobs. Second, the modern service sector has grown into the largest employer, anchored by healthcare, higher education, and finance in cities such as Philadelphia and Pittsburgh. However, these sectors show steadier employment patterns when they are compared to the manufactural one. The steel sector has undergone sharp contraction since the late twentieth century. Plant closures, layoffs, and the collapse of integrated mills in Pittsburgh and the Monongahela Valley created persistent regional distress and made unemployment more cyclical. This cyclical behavior constitutes a trend suitable for time-series analysis. The sharp contractions during deindustrialization, the spike in 2008, and the sudden surge during COVID-19 all appear as distinct shocks in the data. Such events explain why Pennsylvania's unemployment series is non-stationary and why differencing and ARIMA modeling are appropriate tools. By applying these methods, the analysis can capture both the structural decline rooted in steel deindustrialization and the recurring cyclical fluctuations amplified by major economic crises. As a result, my research topic is unemployment in Pennsylvania (1995–2025): a time-series study of economic trends and the steel Industry's role.

Data

The dataset for this study is the seasonally adjusted unemployment rate for Pennsylvania (PAUR), obtained from FRED. The frequency of the data is monthly which covers the span from July 1995 through June 2025 which produces approximately 360 observations. A choice of seasonally adjusted unemployment data rather than non-seasonally adjusted is crucial because the focus of this project is on structural shifts in Pennsylvania's labor market, especially the decline of the steel industry and its sensitivity to economic recessions. Seasonal fluctuations such as agricultural harvest cycles or temporary holiday employment are less relevant to this project. Adjusting for seasonality makes it easier to remove those seasonal fluctuations and that better reflect the state's industrial history relativeness to the unemployment situation.

From ***Figure1.0***, we can see that many historically significant events we've mentioned above manifest as dramatic rises in unemployment. First, the 2008 global financial crisis produced a sharp increase in unemployment that peaked above 8 percent in 2010. At the same time period, manufacturing sectors decreased severely and Pennsylvania's remaining steel-related industries were among the hardest hit. This period highlights the cyclical sensitivity of steel employment: demand for durable goods and construction materials collapses during recessions which leads to a major job loss. Second, The COVID-19 pandemic in 2020 produced the most dramatic increase in the entire series, with unemployment surging to nearly 16 percent in April. Unlike the slow build of the 2008 crisis, this was an abrupt collapse across both services and manufacturing. While the rate fell quickly in the following months, the shock emphasizes how exposed Pennsylvania remains to sudden disruptions. Service-based urban areas rebounded faster, but counties tied to industry and older workforces continued to lag behind.

However, we cannot tie any direct evidence from the general unemployment fluctuations to the steel industry. Because there is no dramatic rise or fall in any given periods reflect clear trend reflect the relativeness. So, we conduct a literature review to see if there any sector information can reveals hint about the relativeness. Haller, William in his article "Industrial Restructuring and Urban Change in the Pittsburgh Region: Developmental, Ecological, and Socioeconomic Tradeoffs." Point out the urbanization has made the major jobs type change from factory based to service based. This is because more people relocate their home into cities like Pittsburgh, the demand for services increased, and the shutdown of many steel factories force more people participate into the service sector. An increase in service sector and decrease in manufacturing one might contribute to the rise and fall pattern of unemployment rate the late 1990s and early 2000s. Also, even when the national economy improved in the late 1990s, unemployment in Pennsylvania remained structurally higher. This mean that a signal of the regional dislocation caused by the decline of steel. However, how deindustrialization contribute to unemployment rate changes is not clear as the above shocks, and that is the reason we need econometrics techniques to research about it.

So, these data patterns show why Pennsylvania's unemployment is expected to be non-stationary before we actually test with KPSS/ADF. This combination produces visible breaks in the data, making ARIMA and related time-series methods especially appropriate. Differencing helps filter out persistence from structural shifts, and forecasting can capture how new shocks may influence future unemployment in the next 2 years. These methods will elaborate in the next section.

Methodology

In general, this project gives classical times series research frame using the three steps of Box–Jenkins along with a forecasting. Each step will follow a basic logic: the prior result from the figures that shown in the Appendix part at the end of the report and from the tests will decide the next step's method type. For example, if the KPSS/ADF test gives a non-stationary label for the original data, then we must add a process of differencing. This is to avoid a misleading of a "predictable structure" drift from directly using AR/MA terms.

-Box–Jenkins Identification

STL decomposition

The first methods I apply to this project is the STL decomposition. I already describe the reason for skipping seasonality, so the initial factors I consider only include Tt (trend component) and Rt (irregular or random remainder). However, from ***figure 1.1***, the STL output figure still has a clear annual pattern for the seasonal component part. I consider the reason of this unexpected outcome as the relatively tiny scale for the y-axis (+/-0.2), so it can still be skipped for the moment. From the trend part, we can tell a long run movement of unemployment rate. The spike on 2008 and 2020 corresponds to the 2008 crisis and COVID-19.

Stationary test and AR/MA selection

Next, I use ADF and KPSS determine whether the dataset is nonstationary as I expected earlier. With the output from R that

KPSS:

KPSS Level = 0.5119, Truncation lag parameter= 5, p-value = 0.03899

ADF:

Dickey-Fuller = -2.7191, Lag order = 7, p-value =0.2734; alternative hypothesis: stationary

We can tell that the KPSS test rejects the null of stationarity at the 5% level, while the ADF test fails to reject the null of a unit root. So, the results indicate that the series is non-stationary in levels and requires differencing before model estimation. I apply value of 1 difference to the dataset and recheck the stationarity, I got the below that which indicates that unemployment series becomes stationary

KPSS:

KPSS Level = 0.031539, Truncation lag parameter= 5, p-value = 0.1

ADF:

Dickey-Fuller = -7.6778, Lag order = 7, p-value =0.01; alternative hypothesis: stationary

Then, I generate ACF and PACF ***figure 1.2***: form that figure, we can tell that ACF displays a gradual tailing off, while the PACF shows a sharp cutoff after lag one. This pattern is consistent with an AR-type process, most likely AR (1).

After differencing the unemployment series once, the data became stationary. With stationarity confirmed, the next step involved identifying the potential orders for the ARIMA model. Because the series is already seasonally adjusted, I set the seasonal orders P=Q=D=0. This choice reflects the fact that seasonal variation has already been removed by FRED and avoids adding unnecessary seasonal terms. The nonseasonal difference order was fixed at d=1, since the first difference was enough to achieve stationarity. The focus of the model selection turned to the autoregressive and moving-average components. Inspection of the ACF and PACF plots provided important cues. The autocorrelation function tailed off slowly, while the partial autocorrelation function displayed a strong spike at lag one and then cut off. This pattern is consistent with autoregressive behavior rather than moving-average behavior. Based on this evidence, I placed emphasis on AR terms and fixed the moving-average order at q=0.

To avoid relying on a single guess, I considered a small set of candidate autoregressive orders. The PACF suggested that only low lags were relevant, so I limited the range of AR orders to p=0,1,2,3. This produced a manageable group of models, ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (2,1,0), and ARIMA (3,1,0). Among these, the ARIMA (0,1,0) served as a baseline or random walk with drift, while the higher-order models allowed me to check whether additional lag terms improved fit.

The goal in this stage was not to fit the most complicated model but rather to balance explanatory power with simplicity. A parsimonious model is easier to interpret, reduces the risk of overfitting, and provides forecasts that generalize better. By fixing q=0q=0 and by restricting p to a small set of values, I followed the principle of starting from the simplest specifications and only moving to more complex ones if the data required it.

The identification process therefore produced a clear set of next steps. I confirmed the period at m=12m=12, though no seasonal terms were necessary. I set d=1and D=0, constrained the nonseasonal parameters to p ∈ {0,1,2,3}and q=0. This provided a grid of plausible ARIMA models that I could take forward into estimation. Each of these candidates would then be compared based on information criteria, residual diagnostics, and forecast performance to determine the most appropriate specification for Pennsylvania unemployment.

- Box–Jenkins Estimation

Model Selection by AICc

The unemployment data set includes around 360 monthly observations, which makes the sample medium in size. To choose the best-fitting ARIMA model, I compared several candidate specifications based on their AICc and BIC values. AICc is the most common selection criterion in practice because it balances fit and complexity. It avoids the risk of overfitting while still capturing important dynamics in the series.

Among the models tested, ARIMA (2,1,0) with drift gave the lowest AICc value of 695.22. Other candidates such as ARIMA (2,1,1) or ARIMA (4,3,1) had slightly higher AICc values and higher BIC scores, which means they either fit less well or were more complex without enough improvement in accuracy. Based on this evidence, ARIMA (2,1,0) with drift was chosen as the preferred model for the analysis.

Parameter Estimation

After selecting ARIMA (2,1,0) with drift, I estimated the parameters. The first autoregressive term (AR1) is significant at the 1% level ($p = 0.0017$). This result confirms that unemployment in Pennsylvania shows strong short-run persistence: changes in one period are highly related to changes in the next. The second autoregressive term (AR2) has a weaker effect, with a p-value of 0.138, so it is not statistically significant. This suggests that while there may be some influence from two-month lags, it is not stable or strong enough to drive the model.

The drift term has a very high p-value (0.83), which means it is not significant. In practical terms, this tells us that there is no clear long-run deterministic trend in the series once we difference the data. Instead, the unemployment rate is better described as a process shaped by short-run dynamics and cyclical shocks rather than by a steady upward or downward drift.

Model Summary

The chosen specification for this study is an ARIMA (2,1,0) model with drift. The coefficient estimates show that the first autoregressive term (AR1 = –0.1659) is significant, which indicates that unemployment changes in one month strongly affect the following month. The second autoregressive term (AR2 = –0.0781) is weaker and not significant, suggesting that any influence at a two-month lag is limited. The drift parameter is very small (–0.0056) and not statistically meaningful, so the series does not display a long-run deterministic trend once it has been differenced.

The variance of the residuals is low ($\sigma^2 \approx 0.40$), which means the model explains a large share of the variation in Pennsylvania's unemployment data. The log-likelihood is –343.55, and the information criteria values are AIC = 695.1, AICc = 695.22, and BIC = 710.64. These values are reasonably close, which suggests that the model is parsimonious: it fits the data without adding unnecessary complexity. Taken together, the evidence shows that ARIMA (2,1,0) with drift balances both accuracy and simplicity, making it a solid choice for forecasting.

Model Fitting and In-Sample Accuracy

To evaluate how well the model fits the historical data, several accuracy measures were calculated. The mean absolute error (MAE) is only 0.1257, and the mean absolute percentage error (MAPE) is 1.75%. Both values are very small, which shows that the model tracks actual unemployment movements closely on average. The root mean square error (RMSE) is higher, at 0.6291, because it gives more weight to large outliers. This difference reflects the extreme shock from the COVID-19 pandemic in 2020, when unemployment briefly spiked to nearly 16 percent. That unusual event created a much larger error for the model than during normal periods.

Despite this outlier, the overall fit is strong. The fitted series closely follows the actual unemployment line across the 30-year sample, and the residuals look like white noise with no clear patterns left unexplained. This means the model captures both the structural trend and the cyclical fluctuations of Pennsylvania's unemployment fairly well. In short, the ARIMA (2,1,0) model with drift not only matches the historical data with high accuracy but also provides a reliable base for producing short-term forecasts. ***Figure2.1*** can give us a visual illustration there.

- *Box–Jenkins Diagnostics*

Residual analysis

The residuals fluctuate around zero with no long-term drift, aside from the clear spike during COVID. The histogram shows most values close to zero, which supports the idea that errors behave like white noise. The residual ACF and PACF contain no strong spikes outside the confidence bands. This means the ARIMA model has removed the main structure from the data and left only random noise. ***Figure3.1*** can give us a visual illustration there.

Ljung Box Tests

I tested for autocorrelation with Ljung–Box statistics at multiple lags. At lag 12 the test statistic was 3.68 with a p-value of 0.96. At lag 24 the statistic was 4.96 with a p-value close to 1. At lag 36 the statistic was 5.37 with a p-value of 1.00. All p-values are very high, so I cannot reject the null hypothesis of no autocorrelation.

Ljung-Box-Combines check

A combined Ljung–Box test produced Q = 4.96 with a p-value of 0.9999. This result confirms the same conclusion as the separate lag tests. The residuals act like white noise with no hidden structure. The ARIMA (2,1,0) with drift therefore gives a reliable and adequate specification for Pennsylvania unemployment. ***Figure3.2*** can give us a visual illustration there.

-Forecasting

The goal for this part is to predict short-term unemployment dynamics, particularly in 2 years. (H=24) After estimating candidate models, the ARIMA (2,1,0) with drift produced the best fit for Pennsylvania's seasonally adjusted unemployment series. The model generated forecasts that remain close to four percent during the projection period from mid-2025 through 2027. For example, the point forecast for July 2025 equals 3.97 percent, and the point forecast for December 2025 equals 3.94 percent. These numbers suggest a stable path, with unemployment holding just under four percent in the near future.

The forecast intervals widen as the horizon extends. At an 80 percent confidence level, the interval ranges from roughly 2.83 to 5.61 percent. At a 95 percent level, the interval broadens further, ranging from about 1.41 to 6.54 percent. These intervals emphasize that uncertainty grows the further out the projection extends. The presence of wide bands signals that the state's unemployment rate remains vulnerable to external shocks, even though the central forecast projects stability.

The interpretation of these forecasts connects directly to Pennsylvania's economic history. A small negative drift in the ARIMA (2,1,0) specification reflects gradual structural improvements in the labor market. The model suggests that the unemployment rate does not rise sharply once temporary disruptions fade, which is consistent with the slow recovery pattern in the state's industrial economy. In other words, the labor market shows resilience, but the forecasts also remind us that any strong negative shock could push the actual path outside of the projected bands. ***Figure4.1*** can give us a visual illustration there.

To evaluate the reliability of the model, I divided the sample into training and test sets. The training set produced low error values, with RMSE equal to 0.65 and MAPE equal to 1.8 percent, indicating that the model tracked historical unemployment well. The test set, which held out the last 18 months of the series, produced modest errors, with RMSE equal to 0.317 and MAPE equal to 3.5 percent. These error levels are acceptable for macroeconomic forecasting, especially given the volatility in the COVID-19 period. The model slightly underestimated the height of the COVID spike, which explains part of the higher test errors, but overall, the forecasts stayed within reasonable limits. ***Figure 4.2*** can give us a visual illustration there.

I also carried out a holdout backtest to compare actual unemployment against the model's out-of-sample predictions. In this exercise, the model forecasted the last 18 months while the actual observations were hidden. The predicted series, shown in blue, aligned well with the actual red series. The mean absolute percentage error of about 3.5 percent confirmed that ARIMA (2,1,0) with drift delivered a solid performance. Importantly, the backtest showed that the model captured the overall direction of unemployment and kept its forecasts inside the official confidence intervals. ***Figure 4.3*** can give us a visual illustration there.

So, the evidence demonstrates that ARIMA (2,1,0) with drift provides a useful tool for short-term unemployment forecasting in Pennsylvania. The model fits the data well, produces interpretable forecasts, and performs reasonably under backtesting. The stable forecast near four percent reflects both structural diversification in the state's economy and the absence of obvious new shocks in the training data. At the same time, the widening confidence intervals highlight the risks that remain. This combination of stability and caution is central to understanding how Pennsylvania's labor market may evolve in the near term.

Conclusion

This report examines the unemployment dynamics of Pennsylvania between 1995 and 2025 and develops forecasts through 2027. The econometrics part applies an ARIMA (2,1,0) with drift to the series after confirming stationarity through differencing. Residual diagnostics and Ljung–Box tests confirm that the specification fits the data in a consistent way. The forecasts suggest that Pennsylvania's unemployment will settle near 4 percent in the next two years. The wide confidence intervals around the projections remind us that labor market outcomes remain uncertain and subject to external influences.

The analysis produces several clear insights. First, the state still carries the long-term consequences of deindustrialization. The collapse of the steel industry and the erosion of related manufacturing jobs have left a permanent mark on the labor market. Many regions in Pennsylvania continue to experience limited opportunities because of this historical decline. The trend component of unemployment reflects this structural scar. Second, the state exhibits strong cyclical sensitivity. During the 2008 financial crisis unemployment surged, and during the COVID-19 pandemic unemployment spiked at unprecedented levels. These episodes demonstrate that Pennsylvania remains exposed to national and global downturns. Third, the state has diversified into healthcare, education, and services. These sectors have provided stability and have absorbed some of the workforce that lost jobs in manufacturing. This diversification has not eliminated vulnerability, but it has reduced the volatility of unemployment in recent years.

The study also recognizes important limitations. The model does not include exogenous variables such as steel production, energy prices, or fiscal and monetary policy shocks. These factors influence the labor market in Pennsylvania, and their exclusion restricts the scope of the analysis. The extreme shock of COVID-19 also presents difficulties. A univariate ARIMA model cannot fully capture such a rare and disruptive event. These limitations mean that the forecasts must be interpreted with caution and supplemented with economic reasoning.

The research also opens for further research. One direction involves the use of vector autoregression to compare Pennsylvania with the United States as a whole or with neighboring states such as Ohio or New York. Such a comparison would highlight whether Pennsylvania responds more strongly or weakly to national shocks. Another extension would involve ARIMAX or SARIMAX models that add predictors such as steel output or energy prices. These models would allow researchers to study how specific drivers shape unemployment in Pennsylvania. A third direction involves the study of sector-level unemployment. Manufacturing, agriculture, and services each respond to shocks in distinct ways, and disaggregated analysis would show which sectors carry greater risks for the state's workforce.

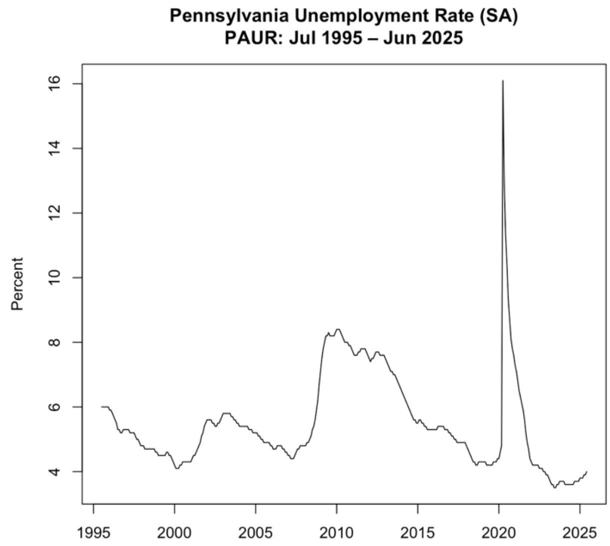
The results of this study offer both quantitative forecasts and broader interpretations. The ARIMA model points to a near-term stabilization of unemployment around four percent. The historical context explains why the state continues to show sensitivity to shocks. The deindustrialization of the late twentieth century created a structural weakness. The global financial crisis and the COVID-19 pandemic revealed that weakness once again. At the same time, the growth of services, healthcare, and education demonstrates the potential of new sectors to support employment and reduce instability.

Additionally, there are some signals for the policymakers. Pennsylvania cannot rely on its past industrial base to provide stable jobs. The state must continue to invest in new sectors and to encourage workforce adaptation. Structural diversification has already reduced volatility, but resilience requires ongoing effort. Future shocks will test the labor market again. A strong service sector and a flexible labor force will determine whether Pennsylvania can withstand those shocks without repeating the severe unemployment spikes of the past.

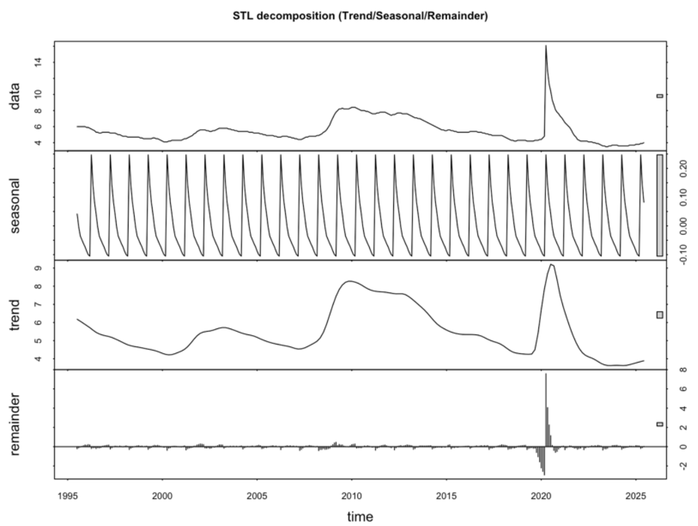
In conclusion, the study shows that time-series methods can clarify both the statistical properties of unemployment and the economic forces that shape them. Pennsylvania has made progress, but the scars of deindustrialization remain, the risks of cyclical downturns persist, and the possibility of unexpected shocks continues to hang over the labor market. The forecasts suggest stability but also caution. The future of employment in Pennsylvania depends not only on macroeconomic conditions but also on the state's ability to sustain diversification and to prepare its workforce for a changing economy.

Appendix from R studio

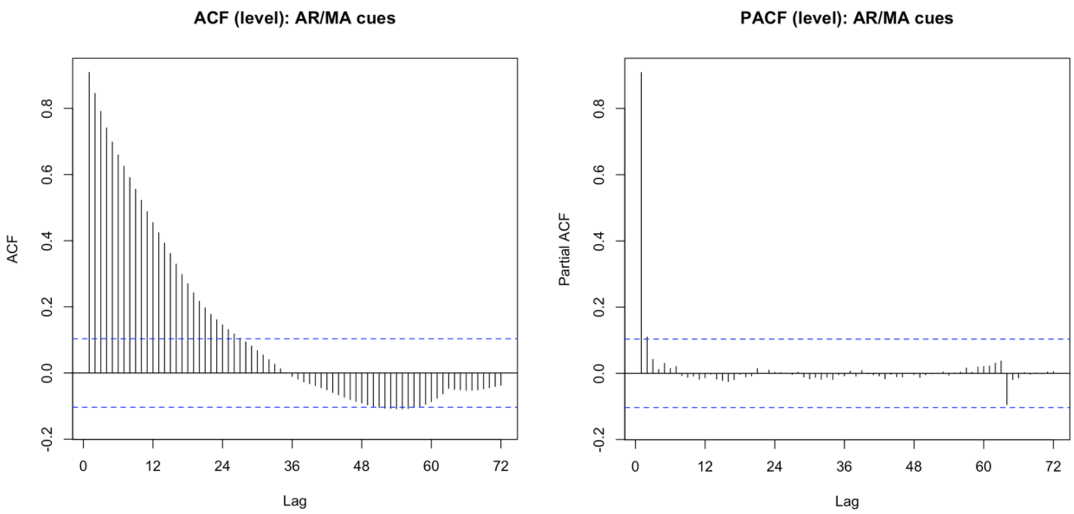
1. Box–Jenkins Identification



PAUR 1.0

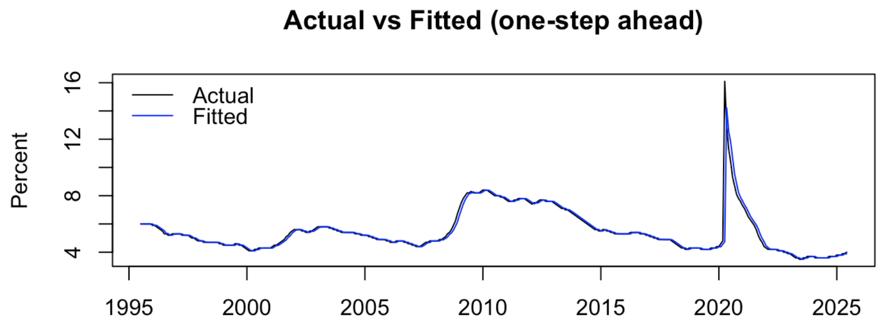


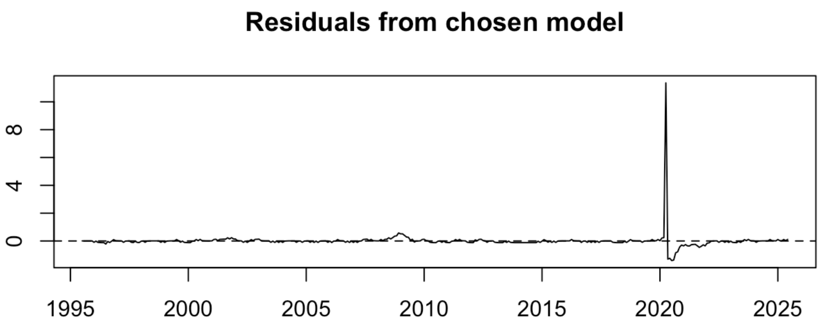
STL Decomposition 1.1



MA/AR cues from ACF/PACF 1.2

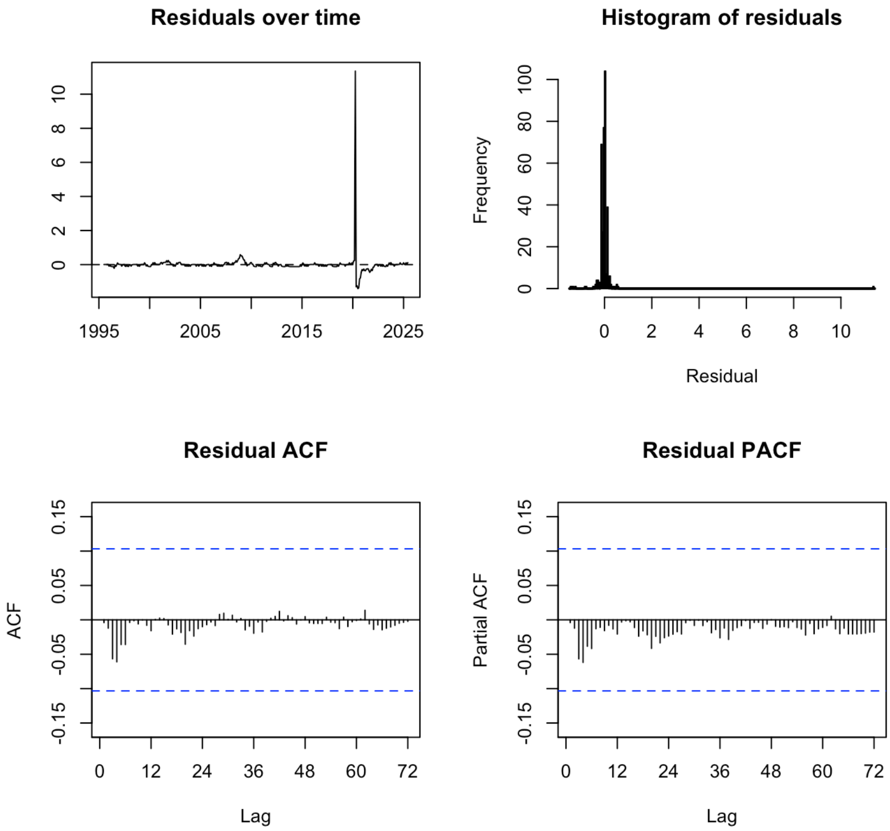
2. Box–Jenkins Estimation



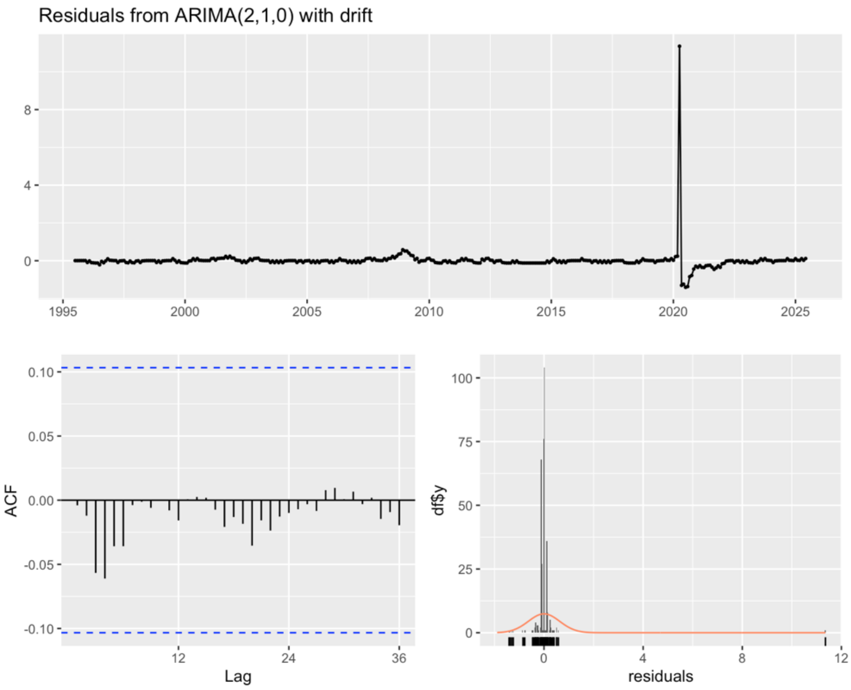


In-sample accuracy 2.1

3. Box–Jenkins Diagnostics

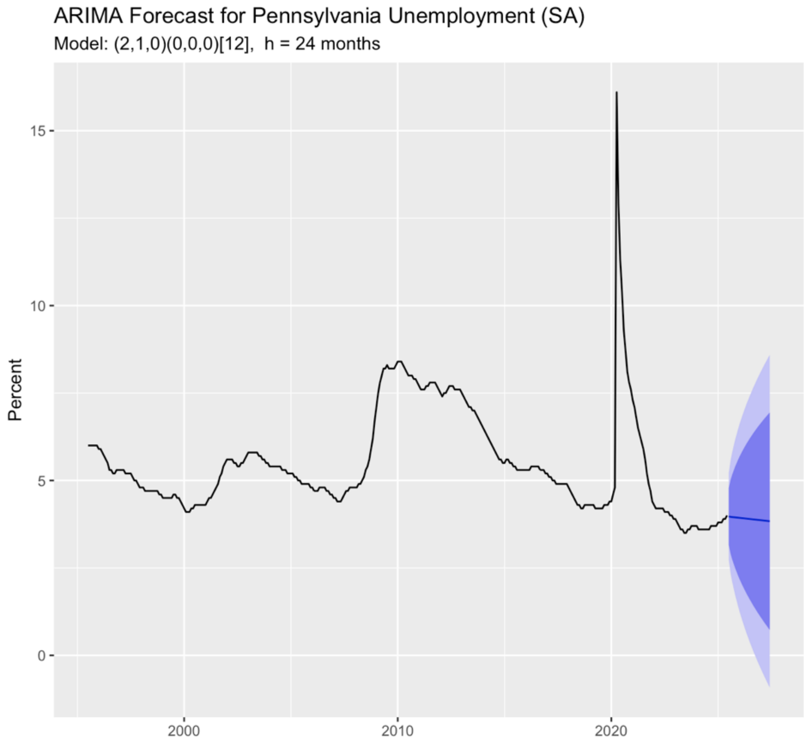


Residual Analysis 3.1

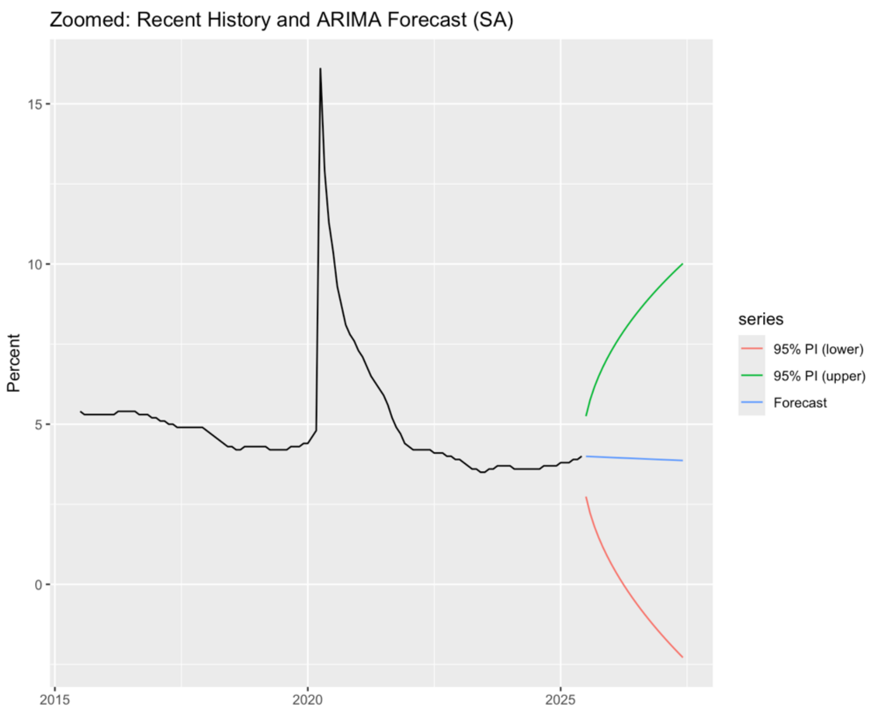


Residuals from ARIMA (2,1,0) with drift 3.2

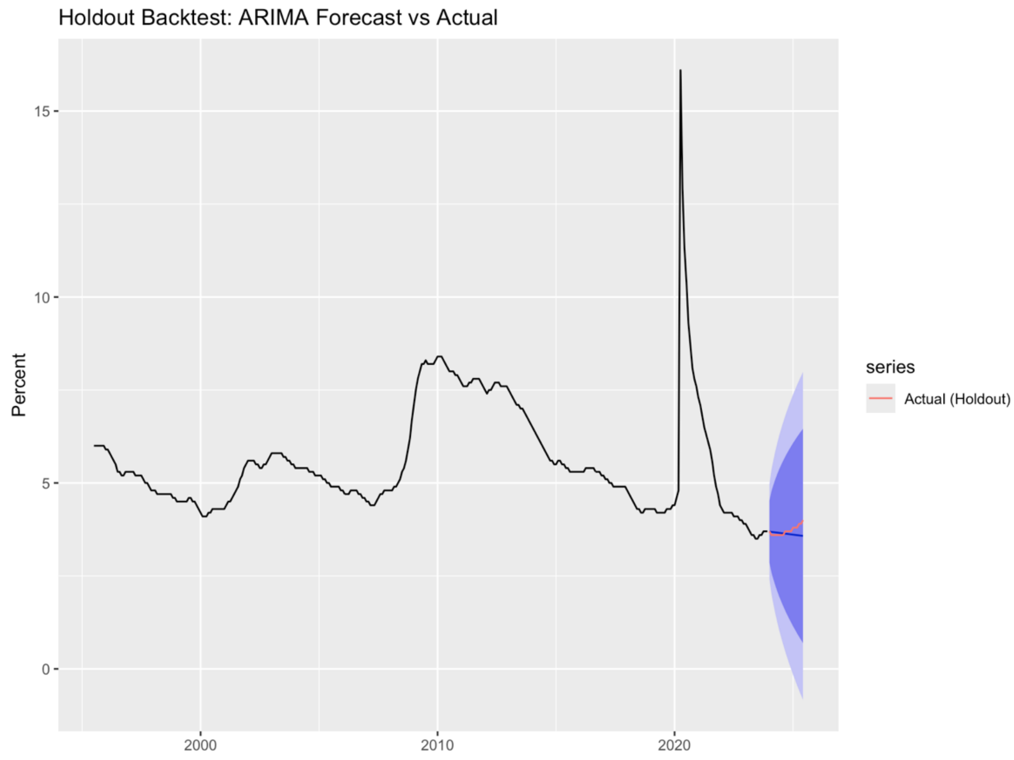
4. Forecasting



ARIMA Forecast for PA Unemployment SA 4.1



Recent History and ARIMA Forecast SA 4.2



Holdout Backtest: Forecast vs Actual 4.3

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