

Forecasting US Employment With Time Series Models

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1 Introduction and Motivation

Understanding employment trends is crucial for policymakers, economists, and businesses to make informed decisions about resource allocation, economic planning, and workforce strategies. The Leisure and Hospitality sector, in particular, plays a vital role in the U.S. economy, contributing significantly to employment and consumer spending. Analyzing historical employment data and forecasting future trends in this sector can provide valuable insights into its growth trajectory and resilience to disruptions.

This report explores employment trends in the Leisure and Hospitality sector using time series modeling. By leveraging data from 1990 to 2024, it examines seasonality, long-term trends, and the impact of unprecedented shocks such as the COVID-19 pandemic. The analysis compares the performance of various ARIMA models on both seasonally adjusted and non-seasonally adjusted data, with the goal of identifying the most reliable forecasting approach. The findings aim to inform future research and decision-making in this dynamic and economically significant sector.

2 Data Preprocessing and Exploratory Data Analysis

The original U.S. employment data from 1990-2019 is sourced from the `fpp3` package. This report focuses on the employment time series for Leisure and Hospitality. The dataset is split into a training set (1990-2017), and a validation set (2017-2019). Additionally, the latest data from 2020 to 2024 is obtained from FRED economic data for further forecasting and analysis. We first look at the time series and seasonality plots for the training set below.

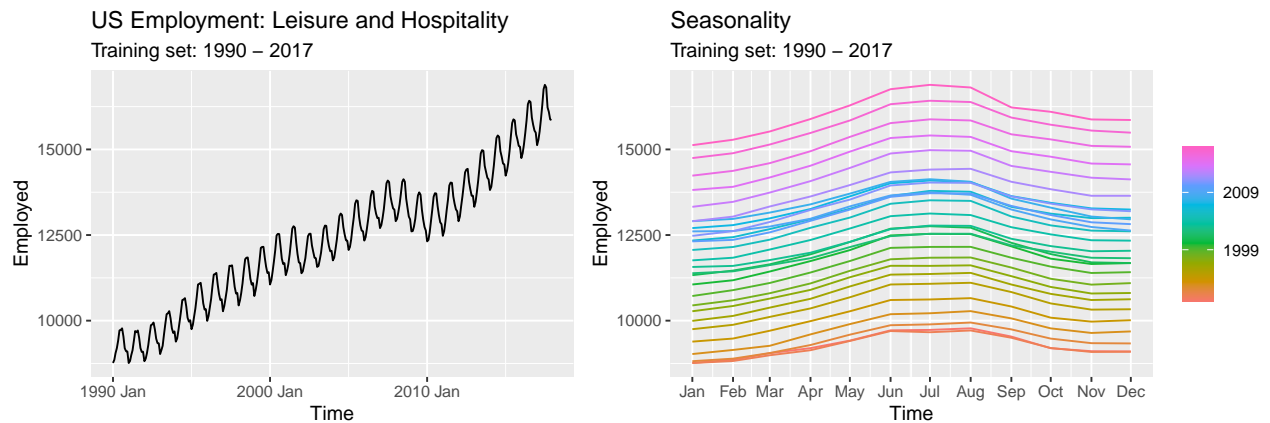


Figure 1: Clear persistent trend and seasonality in leisure and hospitality

The time series plot on the left reveals a clear persistent upward trend, while the seasonality plot on the right highlights annual patterns. Leisure and Hospitality employment peaks in the summer months, and dips in the winter. This behavior aligns with industry expectations, as tourism often peaks in the summer months, leading to increased hiring in this sector.

To better understand the underlying structure of the time series, STL decomposition is applied to break down the time series into its components, namely the trend, the yearly seasonality, and remainder. The resulting plot is below.

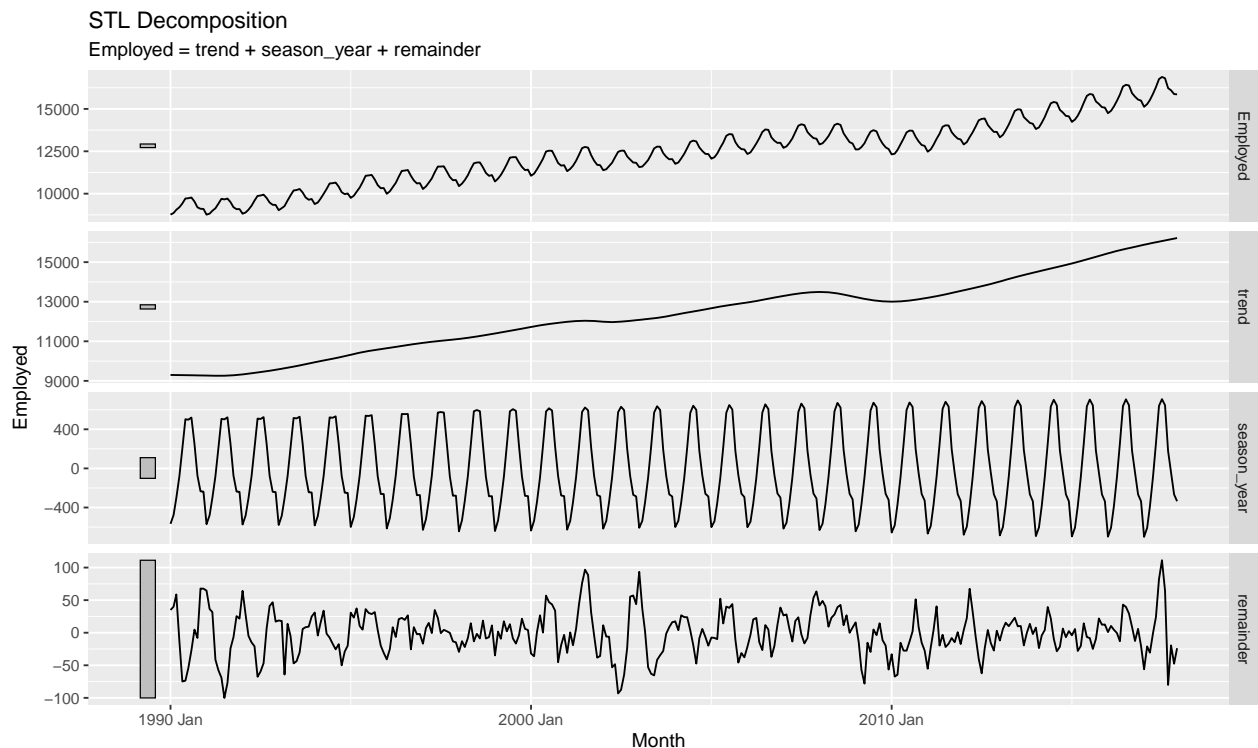


Figure 2: Note the increasing variance in seasonality as the year increases

The decomposition plot shows a long-term upward trend, indicative of overall economic growth. There is also increasing variance in the seasonality over time. To stabilize the variance, we will transform the variable using a logarithm.

The Augmented Dickey-Fuller (ADF) test is used to check for stationarity. As expected from the persistent trend in the time series plot, the initial test yields a p-value of 0.2385, indicating insufficient evidence to reject the null hypothesis of non-stationarity. To address this, we apply both first differencing to remove the upward trend, and seasonal differencing (12) to address the yearly seasonality. After these transformations, the ADF test is repeated on the transformed data. The p-value of 0.01 provides sufficient evidence to reject the null hypothesis, confirming that the time series is now stationary in the mean.

We can now plot the ACF and PACFs of the transformed series to observe if they give us any insight into how we should build our model.

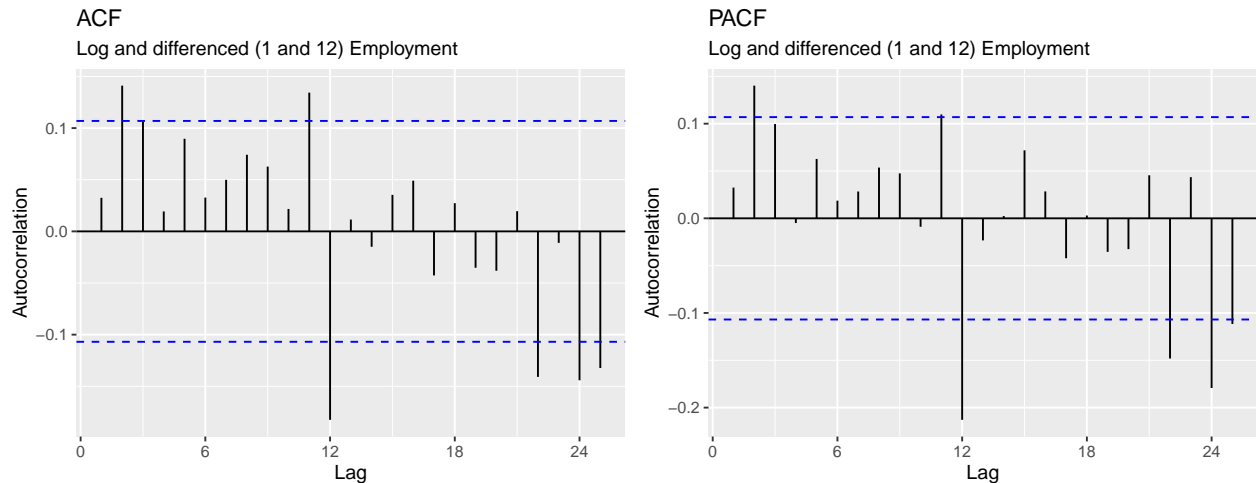


Figure 3: ACF and PACF

The ACF and PACFs of the transformed series taper off quickly, suggesting the presence of both MA and AR components. Additionally, the sudden spikes at lags 12 and 24 suggest that there is a seasonal MA term. Based on these observations, we propose an $\text{ARIMA}(2,1,2)(0,1,1)[12]$ model.

To ensure model parsimony, we also use the `ARIMA` function to automatically select a model based on the Bayesian Information Criterion (BIC), which is better suited for avoiding overfitting due to its stronger penalty for model complexity compared to AIC.

3 Model Development: Non-Seasonally Adjusted Employment

Table 1: Model Comparison: BIC and Log-Likelihood

Model	BIC	Log-Likelihood
auto: $\text{ARIMA}(2,0,1)(0,1,2)[12]$ w/ drift	-2807.491	1423.978
$\text{ARIMA}(2,1,2)(0,1,1)[12]$	-2788.233	1411.450

The `ARIMA` function selected $\text{ARIMA}(2,0,1)(0,1,2)[12]$ w/ drift, which slightly outperformed our proposed $\text{ARIMA}(2,1,2)(0,1,1)[12]$ in terms of maximizing log-likelihood and minimizing BIC. However, since the BIC and log-likelihoods values for both models are very close, we further evaluate their performance by examining the residuals to assess the quality of their training fits to decide which model to pick for forecasting. The residual diagnostics plots are below; the first row is for the model the `ARIMA` function picked, and the second row is for our proposed model.

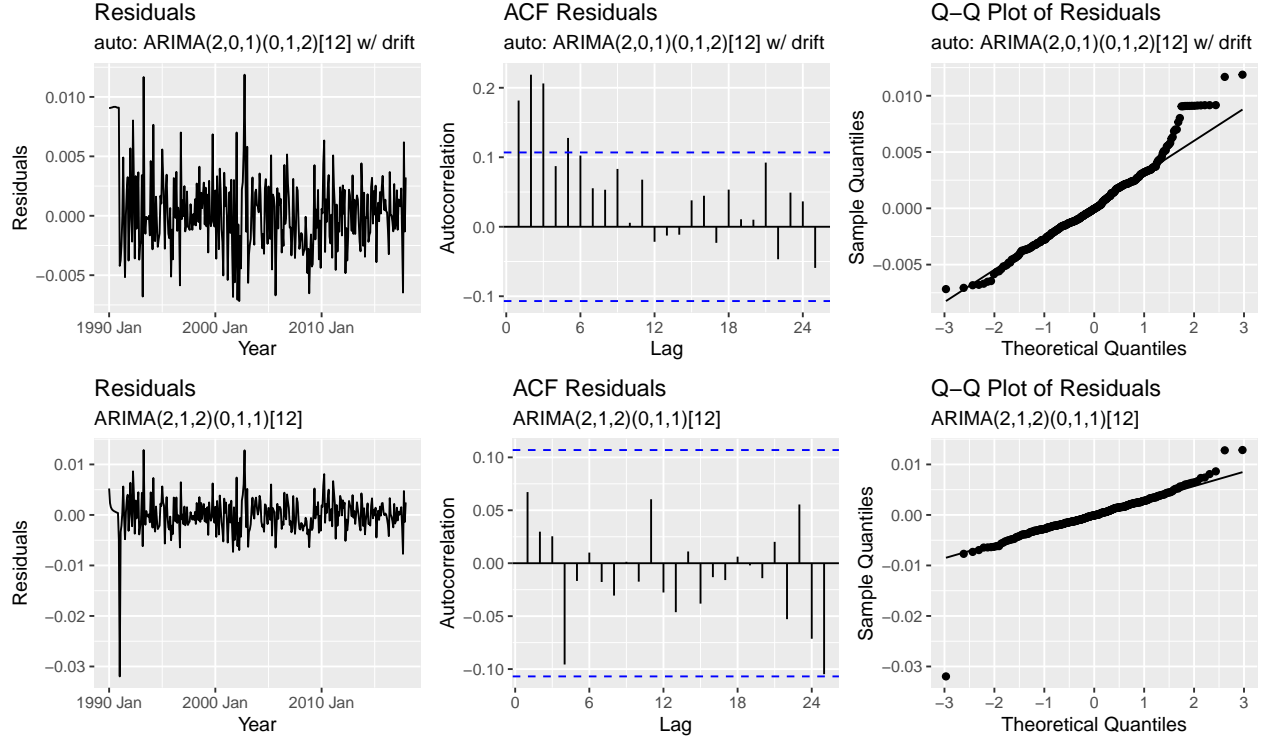


Figure 4: $\text{ARIMA}(2,1,2)(0,1,1)[12]$ residuals look more like white noise

Upon comparing the residuals, the ACF plot for our chosen model, $\text{ARIMA}(2,1,2)(0,1,1)[12]$, exhibits patterns that are much closer to white noise. This finding is supported by the results of the Ljung-Box tests:

- For the ARIMA auto-selected model ($\text{ARIMA}(2,0,1)(0,1,2)[12]$ w/ drift), the test produced a p-value of $4.609\text{e-}06$, indicating strong evidence of correlation in the residuals.
- For our chosen model ($\text{ARIMA}(2,1,2)(0,1,1)[12]$), the test yielded a p-value of 0.9649 , suggesting insufficient evidence to reject the null hypothesis of uncorrelated residuals.

4 Model Development: Seasonally Adjusted Employment

To enhance our analysis, we construct an additional model based on seasonally adjusted employment. Seasonal adjustment is performed by subtracting the seasonal component from the original values, as derived from the STL decomposition shown in Figure 2. The resulting plot of seasonally adjusted employment is presented below.



Figure 5: Seasonally adjusted employment

We proceed to build a model for the seasonally adjusted employment data, allowing the ARIMA function to select the optimal model based on the lowest BIC. This process results in the model $ARIMA(2,1,1)(2,0,1)[12]$ w/ drift. We now conduct model diagnostics by analyzing the residuals.

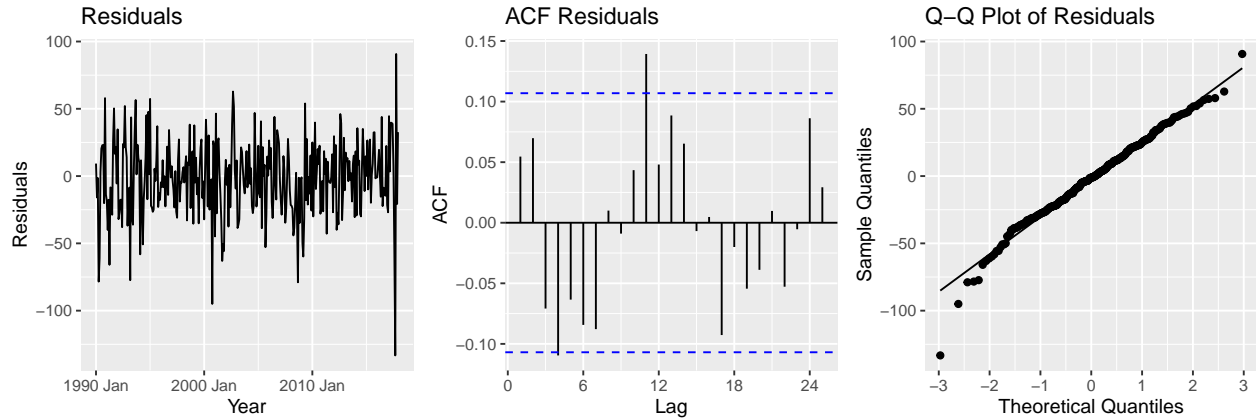


Figure 6: $ARIMA(2,1,1)(2,0,1)[12]$ w/ drift on seasonally adjusted values does not have white noise residuals

Although the Q-Q plot shows close adherence to a normal distribution, the ACF of the residuals does not entirely resemble white noise, particularly due to the spike at lag 11. This observation suggests that the model may not fully capture the underlying structure of the time series. The Ljung-Box test yielded a p-value of 0.05326, which is close to the 0.05 threshold. While this result provides weak evidence against the null hypothesis of uncorrelated residuals, it does not strongly support rejecting the null.

Given the marginal Ljung-Box test result and the availability of a validated model for non-seasonally adjusted data, we will proceed with forecasting using both models. This dual approach enables us to compare their practical forecasting accuracy while accounting for the limitations of the seasonally adjusted model.

5 Validation and Model Performance (Forecasting up to 2019)

The non-seasonally adjusted (NSA) model appears to forecast more accurately on the validation set, with predictions aligning closely with the observed values and falling well within the middle of the 80% confidence

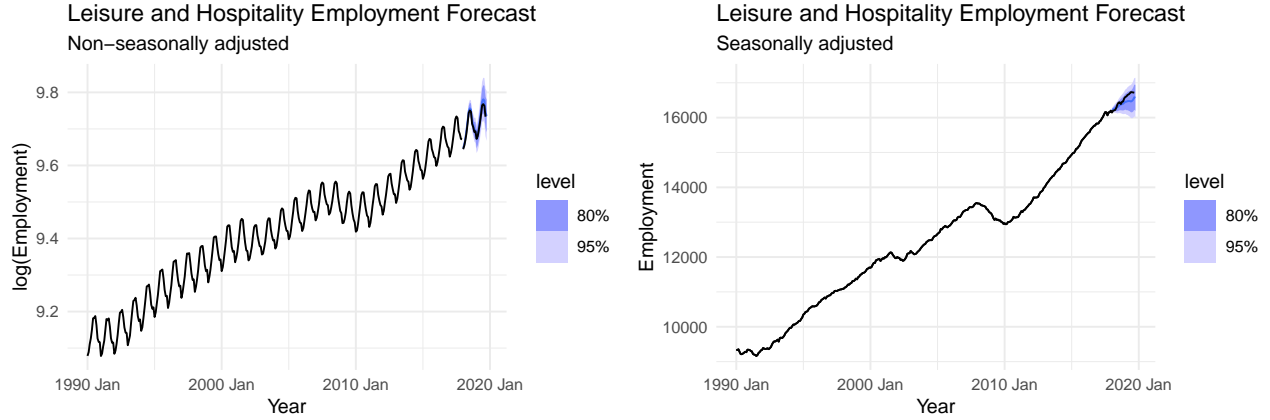


Figure 7: Model for non-seasonally adjusted values seems to forecast better

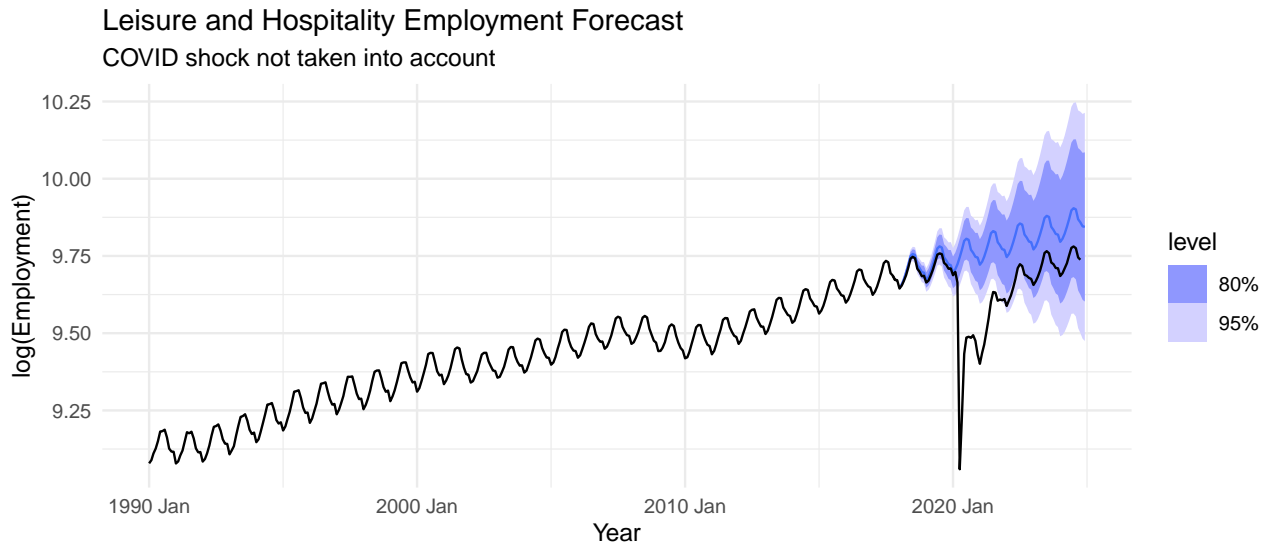
interval. In contrast, the seasonally adjusted (SA) model forecasts lower growth, with actual values nearing the 95% confidence interval. To further evaluate performance, we compare the RMSE of the two models on the validation data, ensuring that the NSA data was transformed back from its logarithmic scale before calculating RMSE.

Table 2: RMSE Comparison Between NSA and SA Models

Model	RMSE
Non-Seasonally Adjusted	335.6922
Seasonally Adjusted	604.8099

As expected, the NSA model ($ARIMA(2,1,2)(0,1,1)[12]$) achieves a lower RMSE, indicating better performance. Based on this result, we proceed to use the NSA model for forecasting from 2020 to the present and discuss the role of exogenous variables.

6 Extended Forecasting and Implications (2020 Onwards)



The forecast generated by the $ARIMA(2,1,2)(0,1,1)[12]$ model projects leisure and hospitality employment from 2020 onward, under the assumption that historical trends and seasonal patterns persist. However, the

plot reveals that the forecast fails to account for the unprecedented shock of the COVID-19 pandemic, which caused a dramatic decline in employment in 2020. This stark deviation underscores the profound impact of the pandemic on the sector.

By comparing actual employment values to the forecasted trend, we gain insights into whether current employment levels have recovered to their pre-pandemic trajectory. While employment in the leisure and hospitality sector has shown signs of recovery, the persistent gap between actual and forecasted values serves as an indicator of the pandemic's long-term effects.

This analysis highlights the limitations of relying solely on historical data for forecasting, particularly when faced with unexpected, exogenous shocks. Incorporating exogenous variables—such as pandemic metrics, government interventions, or economic recovery indicators—could provide valuable context to improve model performance. Future work could explore advanced approaches like SARIMAX or machine learning models to better account for such disruptions and deliver more robust projections.