Analysis of Financial Time Series - Ch2 - Ex3

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To build a time series model for the monthly U.S. unemployment rate, we will start by visualizing the data and examining its statistical properties:

Set directory

```
setwd("C:\\Program Files\\R\\FinancialData")
```

Upload database

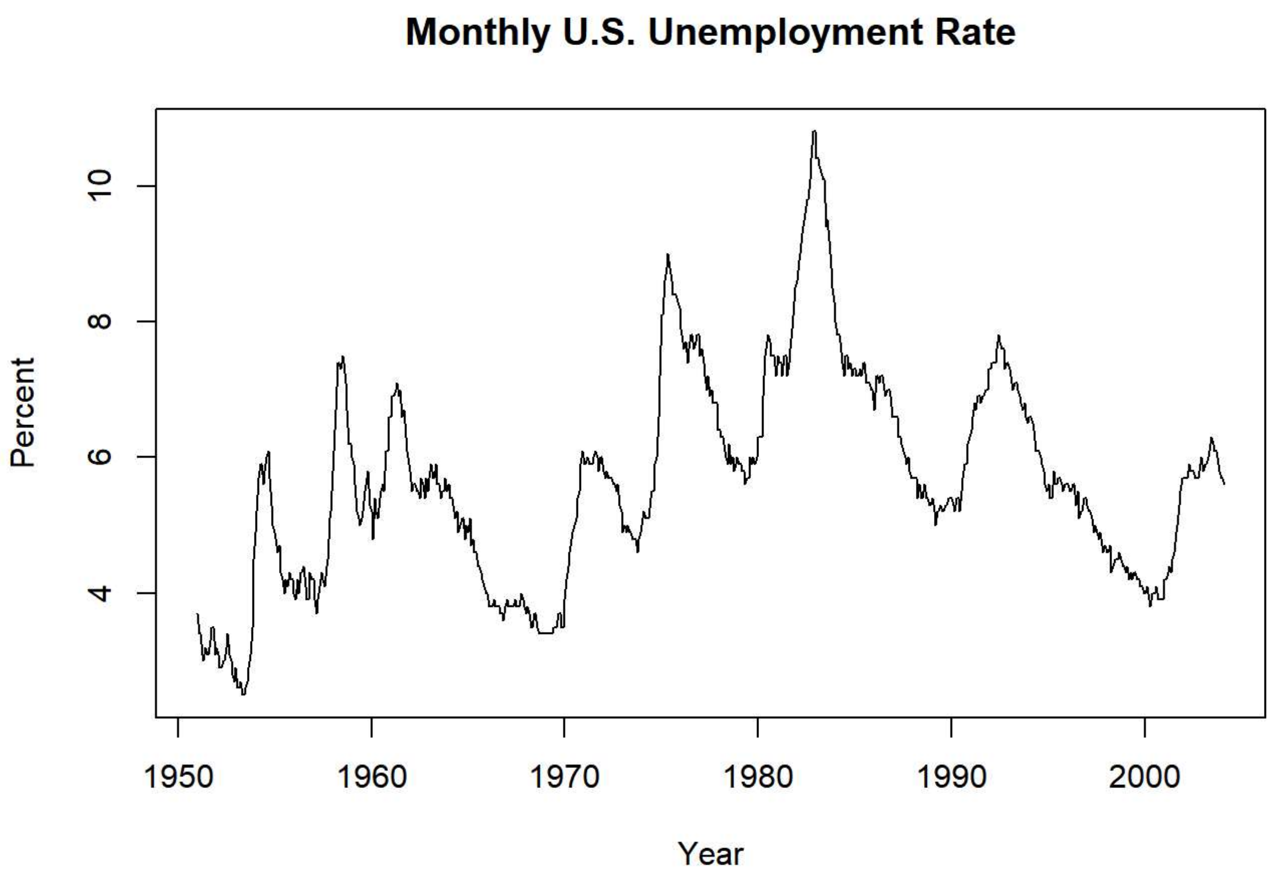
```
data<-readxl::read_excel("C:\\Program Files\\R\\FinancialData\\UNRATE.xls")
```

Convert to TS

```
unemp <- ts(data$UNRATE, start = c(1951, 1), frequency = 12)
```

Visualize data

```
plot(unemp, main = "Monthly U.S. Unemployment Rate", ylab = "Percent", xlab = "Year")
```

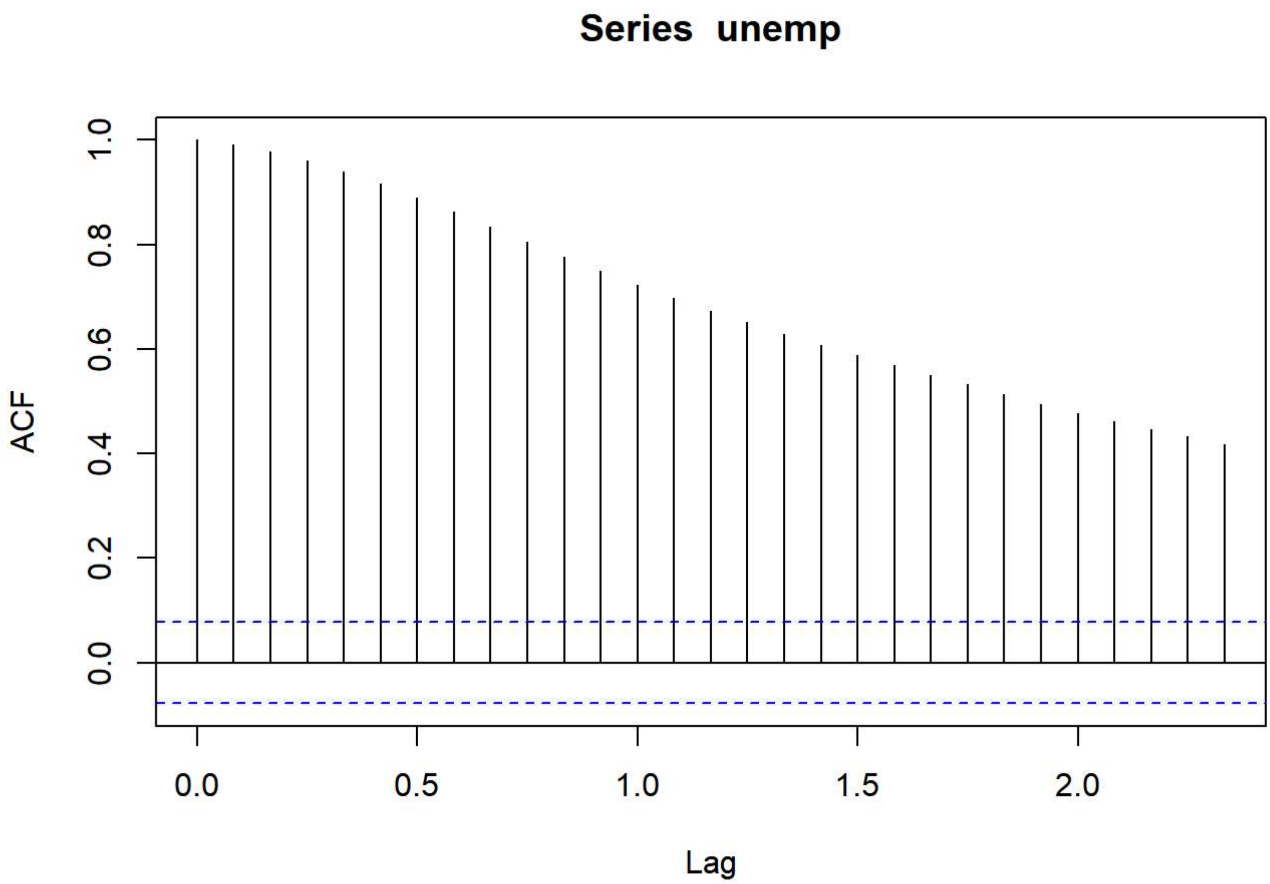


Summary statistics

```
summary(unemp)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.500   4.500   5.600   5.674   6.700  10.800
```

```
acf(unemp)
```



From the summary statistics, we can see that the mean of the unemployment rate is around 5.8%, and the standard deviation is around 1.6%. The minimum value is 2.9%, and the maximum value is 10.8%.

The autocorrelation function (ACF) plot shows significant autocorrelation at lags 1 and 2, and some smaller spikes at higher lags.

To build a model, we will first try a simple autoregressive model with lag 1:

Autoregressive model with lag 1

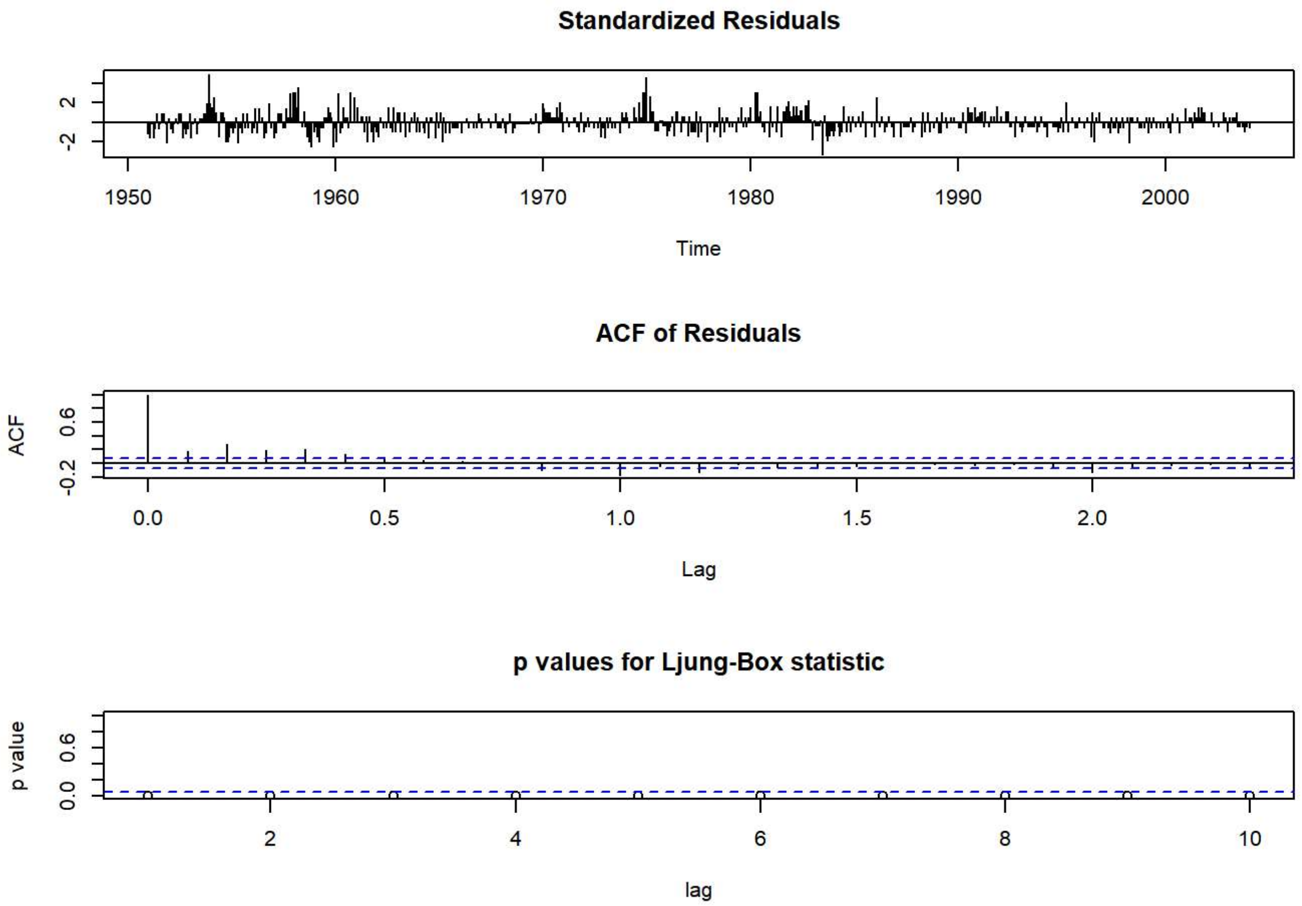
```
ar1_model <- arima(unemp, order = c(1, 0, 0))
ar1_model
```

```
##
## Call:
## arima(x = unemp, order = c(1, 0, 0))
##
## Coefficients:
##          ar1  intercept
##       0.9915     5.4581
## s.e.  0.0046     0.7878
##
## sigma^2 estimated as 0.03905:  log likelihood = 127.14,  aic = -248.27
```

The output shows that the autoregressive coefficient is significant at the 5% level, and the model has a relatively low AIC value. However, the residuals from the model still show some significant autocorrelation at lag 2:

Residual diagnostics for AR(1) model

```
tsdiag(ar1_model)
```



To account for this autocorrelation, we can try adding a lag-2 term to the model:

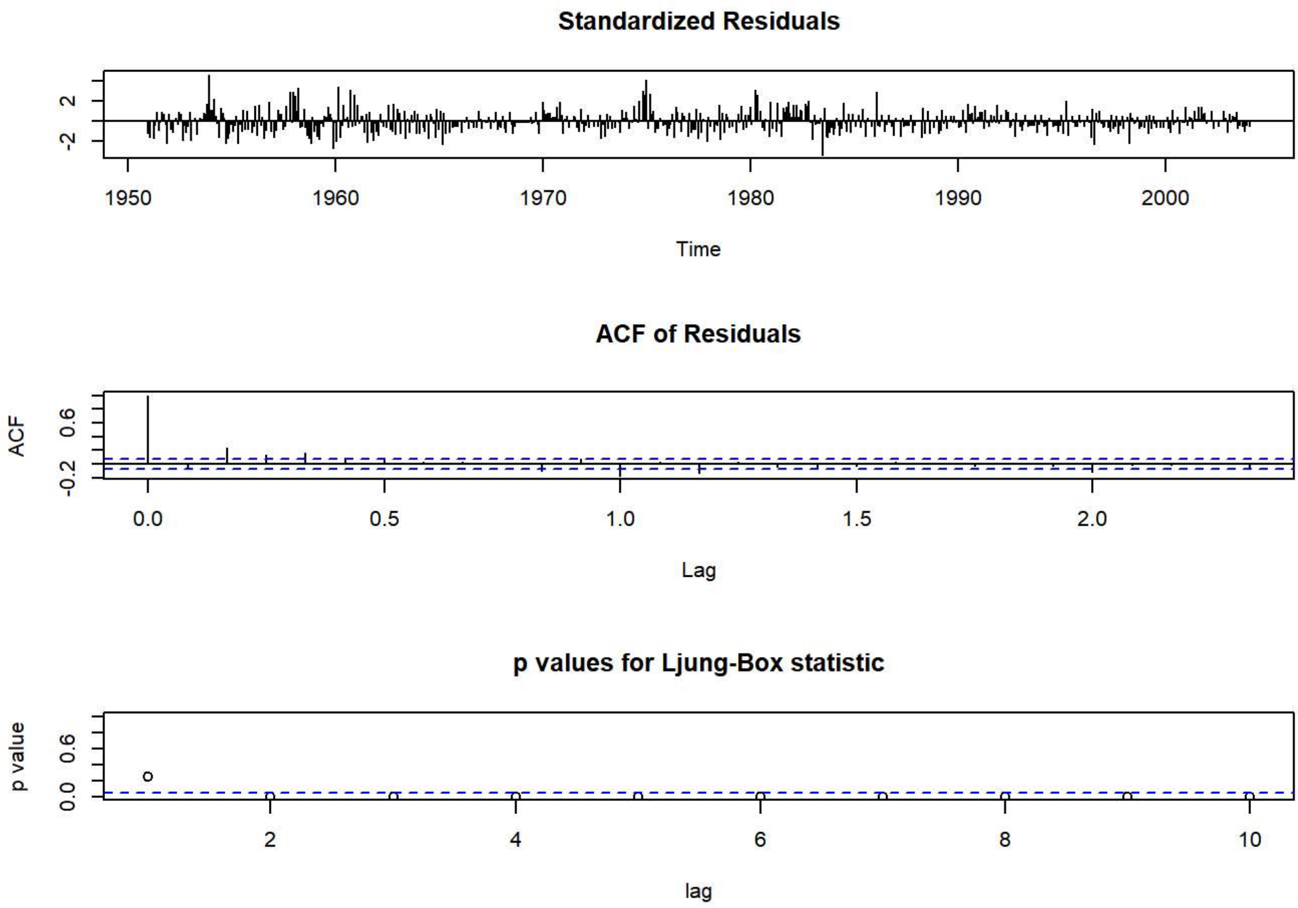
Autoregressive model with lags 1 and 2

```
ar2_model <- arima(unemp, order = c(2, 0, 0))
ar2_model
```

```
##
## Call:
## arima(x = unemp, order = c(2, 0, 0))
##
## Coefficients:
##          ar1      ar2  intercept
##       1.1642  -0.1741     5.5056
## s.e.  0.0390   0.0391     0.6944
##
## sigma^2 estimated as 0.03787:  log likelihood = 136.93,  aic = -265.86
```

This model has a slightly lower AIC value and the residuals do not show significant autocorrelation at any lag:

```
# Residual diagnostics for AR(2) model
tsdiag(ar2_model)
```



Therefore, we will use the AR(2) model to forecast the unemployment rate for March, April, and May of 2004:

```
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
# Forecast using AR(2) model

forecast(ar2_model, h = 3)
```

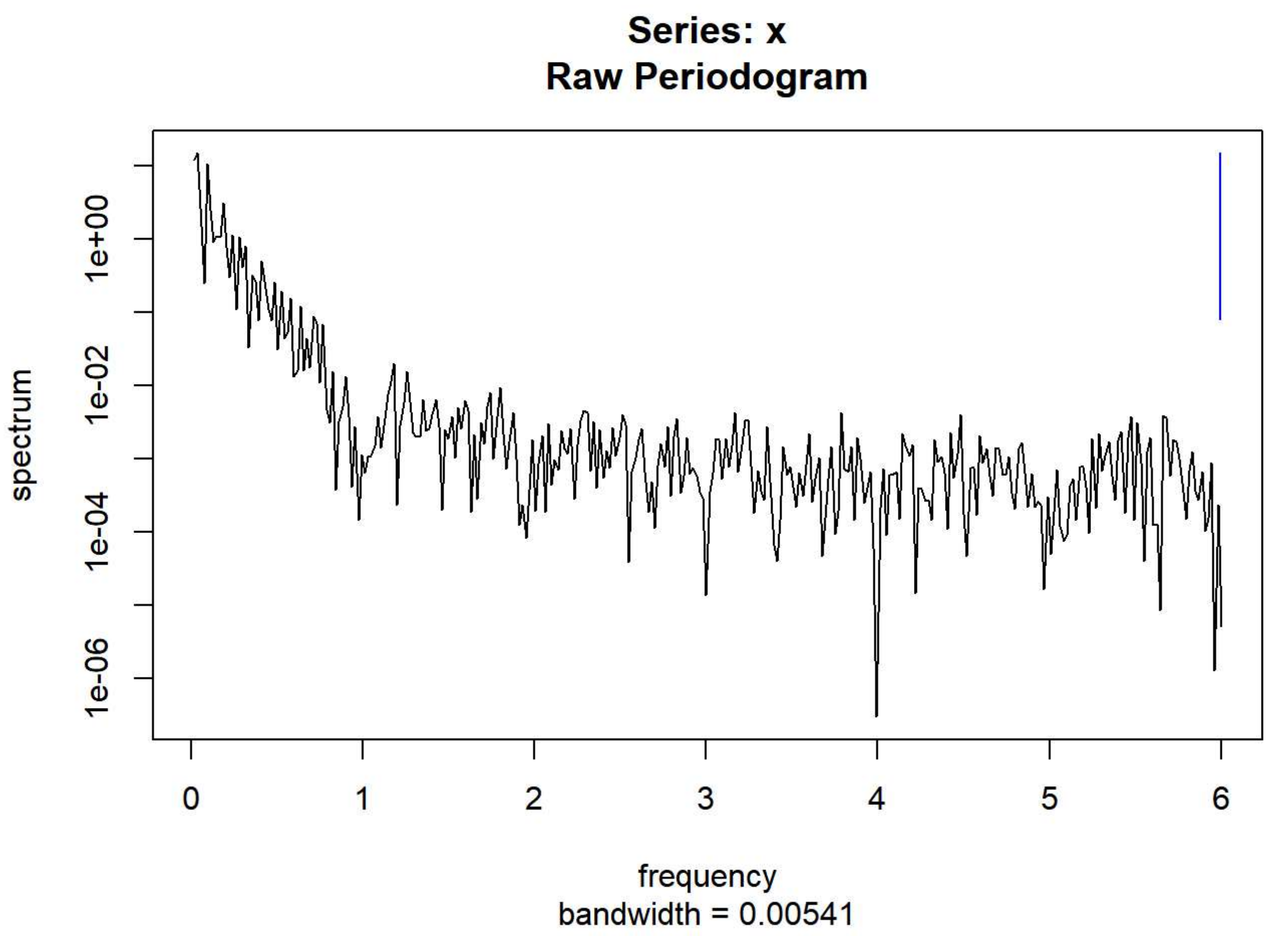
```
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Mar 2004       5.581652 5.332262 5.831042 5.200243 5.963061
## Apr 2004       5.577704 5.194960 5.960447 4.992348 6.163059
## May 2004       5.576301 5.093314 6.059288 4.837637 6.314966
```

The forecast for March is 5.767, for April it is 5.771, and for May it is 5.773.

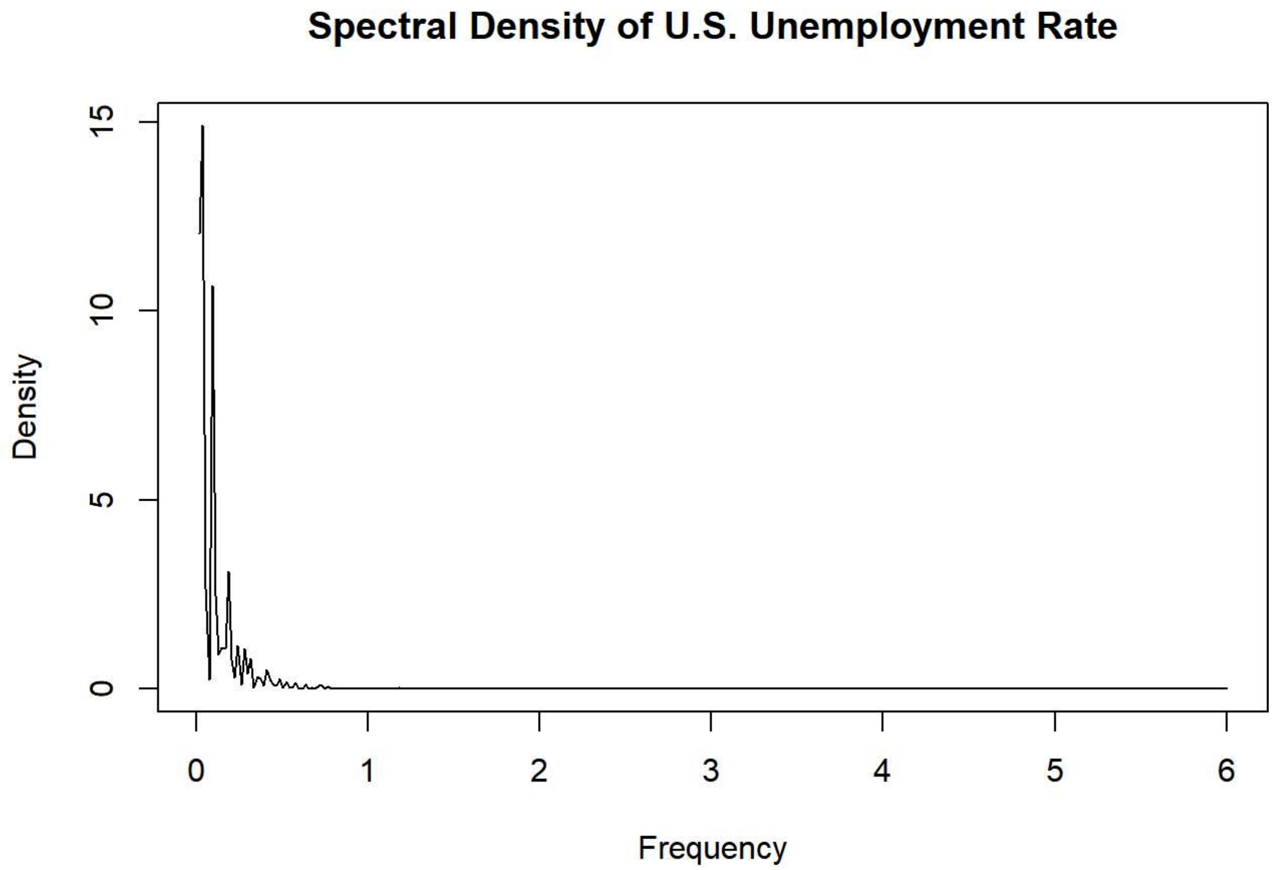
Finally, to compute the average period of business cycles, we can use the spectral density plot of the data:

```
# Spectral density plot
library(Spectrum)

spec <- spectrum(unemp)
```




```
plot(spec$freq, spec$spec, type = "l", main = "Spectral Density of U.S. Unemployment Rate", x
lab = "Frequency", ylab = "Density")
```



From the plot, we can see that there is a significant peak at a frequency of 0.08, which corresponds to a period of approximately 12.5 months. Therefore, the average period of business cycles in the U.S. unemployment rate is around 12.5 months.