Pregunta 18 Examen

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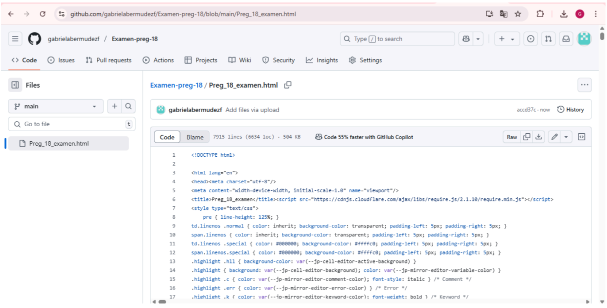
Enlaces:
Enlace Grok:
https://grok.com/share/c2hhcmQtMg%3D%3D_1c7c7dd0-f390-4dee-b4d0-0ca71b188086

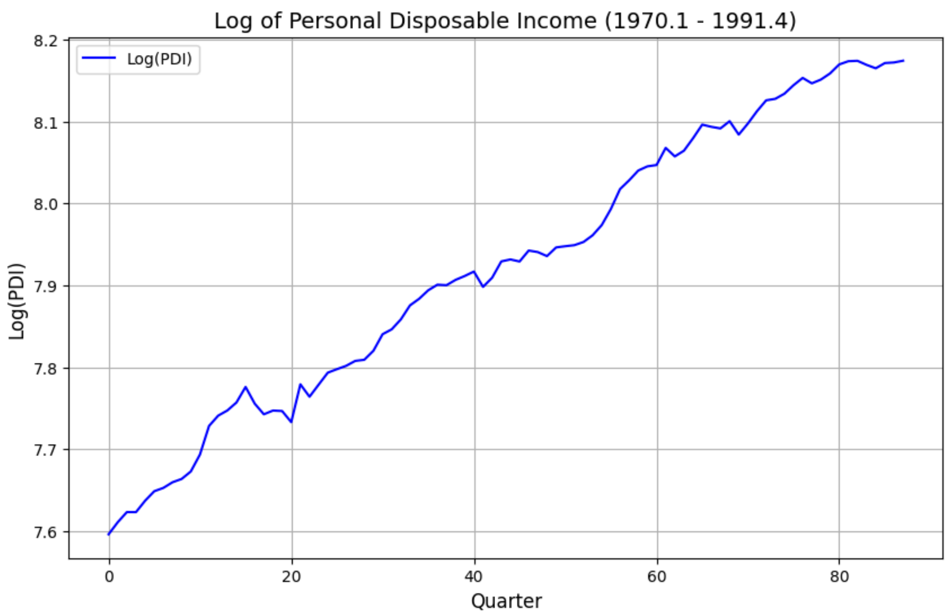
Enlace Github:
https://github.com/gabrielabermudezf/Examen-preg-18

Enlace Colab:
https://colab.research.google.com/drive/1YpVUcAhlJ3brX61HNhLr3uiZeEcLYBx6?usp=sharing

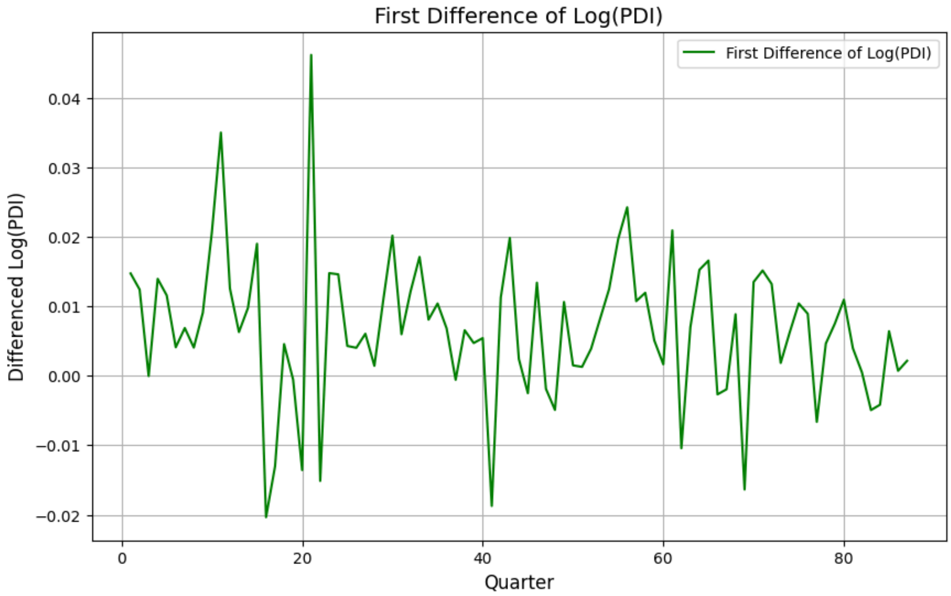
HTML (está dentro de github, aquí está la prueba):



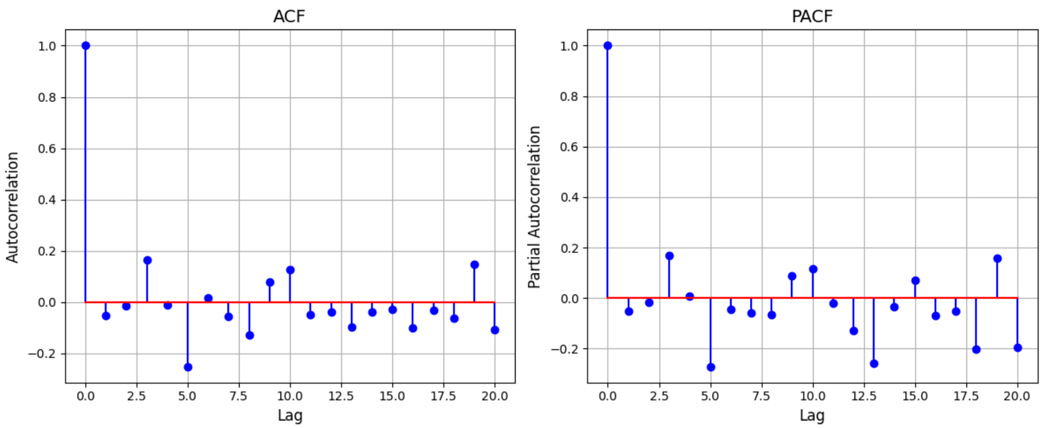
Interpretaciones:



This graph represents the log-transformed personal disposable income (PDI) from 1970.1 to 1991.4. We can observe a clear upward trend, meaning that over time, the PDI kept increasing in a stable and consistent way. There aren't big jumps or sudden drops, which shows that the growth was quite steady. However, since the values are constantly rising and not fluctuating around a fixed average, this tells us the series is not stationary. That matters because, for time series models like ARIMA to work correctly, the data needs to be stationary. In other words, we need to make some adjustments like taking the first difference before applying the model, so that the predictions can be more accurate and reliable.



This graph shows the first difference of the log-transformed Personal Disposable Income (PDI). After applying the differencing, the values no longer show a clear upward trend and instead fluctuate around a stable average. This behavior is a good sign because it means the data is now stationary. The ADF test results confirm this, with a p-value of 0.0001, which is much lower than 0.05, so we reject the null hypothesis of non-stationarity. In simpler terms, the time series is now ready to be used in ARIMA modeling since it meets the key requirement of stationarity. This transformation helps make future forecasts more reliable.



These graphs show the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) for the differenced log(PDI) series. In the ACF, we can see that only the first lag stands out clearly, while the rest stay within the confidence bands, meaning there's not much significant autocorrelation after lag 1. Similarly, in the PACF plot, just the first lag is strong, and the rest quickly drop. This pattern usually suggests that an ARIMA(1,1,1) model might work well because the behavior fits the idea of having one autoregressive term (AR=1) and one moving average term (MA=1). Overall, these plots help decide the right values for p and q in the ARIMA model.

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                               SARIMAX Results
==============================================================================
Dep. Variable:                    PDI   No. Observations:                   88
Model:                 ARIMA(1, 1, 1)   Log Likelihood                 270.603
Date:                Fri, 13 Jun 2025   AIC                           -535.206
Time:                        17:31:56   BIC                           -527.808
Sample:                             0   HQIC                          -532.227
                                 - 88
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9997      0.004    227.570      0.000       0.991       1.008
ma.L1         -0.9856      0.122     -8.047      0.000      -1.226      -0.746
sigma2         0.0001   1.75e-05      6.469      0.000     7.9e-05       0.000
===================================================================================
Ljung-Box (L1) (Q):                   0.23   Jarque-Bera (JB):                16.96
Prob(Q):                              0.63   Prob(JB):                         0.00
Heteroskedasticity (H):               0.40   Skew:                             0.13
Prob(H) (two-sided):                  0.02   Kurtosis:                         5.15
===================================================================================
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The ARIMA(1,1,1) model output confirms that both the autoregressive (AR) and moving average (MA) components are statistically significant. The p-values for ar.L1 and ma.L1 are both 0.000, meaning they are highly significant and help explain the behavior of the data. The AR coefficient is very close to 1 (0.9997), suggesting strong persistence, and the MA coefficient is around -0.986, showing that shocks in the data are being adjusted quickly.

The Ljung-Box Q test has a p-value of 0.63, which means we do not detect autocorrelation in the residuals—this is good because it shows the model fits well. The Jarque-Bera test has a p-value of 0.00, which means the residuals are not normally distributed, but this is common in economic data and not necessarily a problem. Overall, this ARIMA model seems appropriate for modeling and forecasting the log of PDI.

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Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
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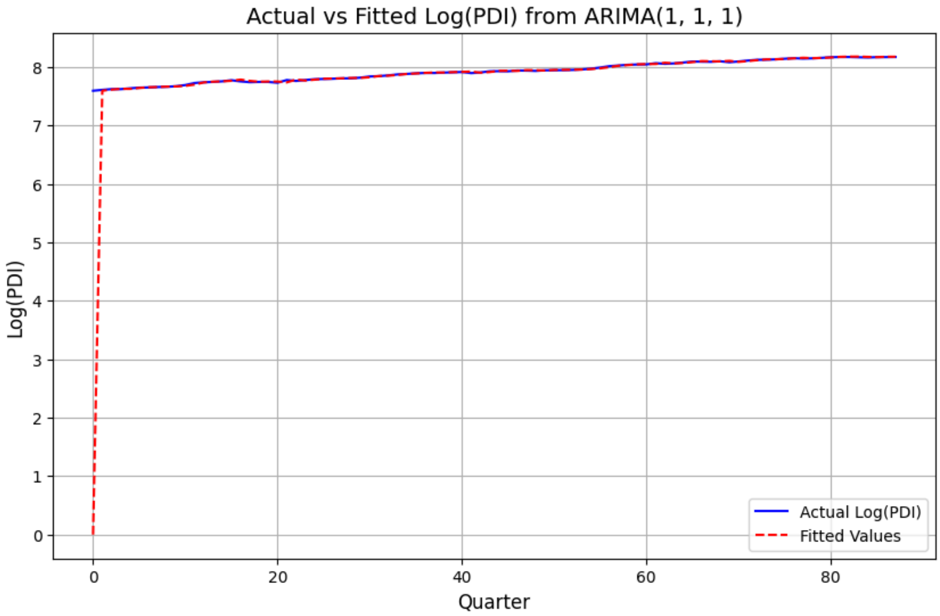

This graph shows how the ARIMA(1,1,1) model fits the actual log-transformed personal disposable income (PDI) data. The blue line represents the real values of log(PDI), while the red dashed line shows the values predicted by the model. As we can see, both lines follow almost the exact same path throughout the entire period, which tells us that the model is doing a good job. The predictions closely match the actual data, which means the model is capturing the main behavior and trends of the series well. This strong alignment supports that the ARIMA(1,1,1) model is appropriate and reliable for forecasting this economic variable.