

Campus Monterrey

EXAMEN INDIVIDUAL - PREGUNTA 18

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Profesor:

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Materia:

Series de Tiempo

Grupo:

302

Viernes 13 de Junio del 2025



Link Github:

https://github.com/Alessandro09-code/Examen Pregunta-18 Series-de-Tiempo.git

Link Collab:

https://colab.research.google.com/drive/1cw4ryei0WasyJx1QO87NWzlZFPur30Ke#scrollTo=R2NXyf8TOz11

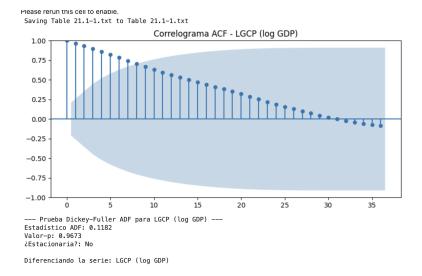
Link prompt from ChatGPT:

https://chatgpt.com/share/684c5e8f-d480-8007-a3b0-089aba6b36cf

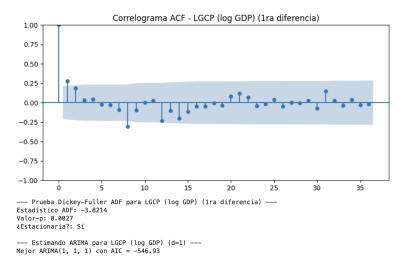
Interpretación:

Interpretation for LGCP:

Beginning with LGCP (log GDP), the initial ACF plot exhibited a slow decay, with autocorrelations remaining significantly positive over a large number of lags. This is a classic signature of a non-stationary process—often described as having a stochastic trend. The ADF test supported this visual interpretation with a test statistic close to zero (0.1182) and a high p-value (0.9673), indicating a failure to reject the null hypothesis of a unit root. Consequently, the series was differenced once. The first difference of LGCP showed a dramatic improvement in stationarity. The ACF of the differenced series quickly dampened, and the ADF test now yielded a highly significant result (p = 0.0027), allowing us to reject the null hypothesis of a unit root. Thus, the series is integrated of order one, denoted as I(1). The best-fitting ARIMA model based on AIC was ARIMA(1,1,1), indicating that after differencing, the series could be modeled using one autoregressive and one moving average component. This implies that both the past value of the series and the past forecast errors contribute to predicting current changes in log GDP.

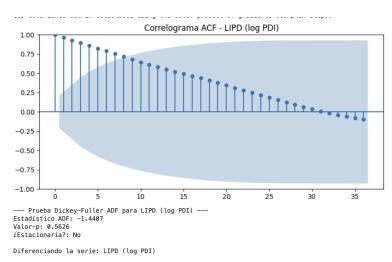




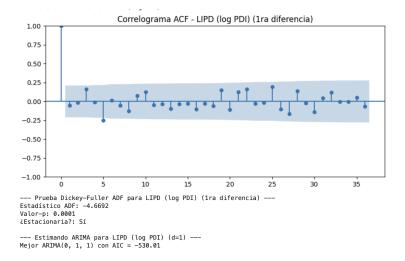


Interpretation for LIPD (Log Personal Disposable Income):

A similar pattern was observed in the case of LIPD (log Personal Disposable Income). The original ACF plot again demonstrated persistent autocorrelations across many lags, and the ADF test yielded a p-value of 0.5626, suggesting non-stationarity. Upon taking the first difference, the ACF plot revealed minimal autocorrelations, a sign of weak memory in the differenced data. The ADF test confirmed stationarity with a p-value well below 0.05 (p = 0.0001). The best model based on AIC was ARIMA(0,1,1), indicating that the differenced LIPD series could be captured with only one MA term. In practical terms, this suggests that shocks or errors in one period have a direct but limited impact on the next, with no persistent autoregressive structure. It reflects a dynamic in which disposable income adjusts relatively quickly to external shocks, without sustained trends in the differenced data.

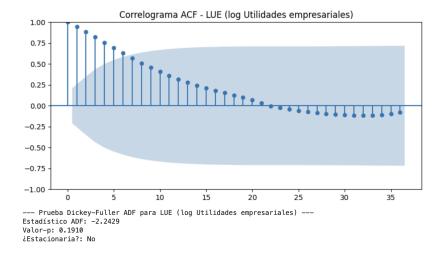




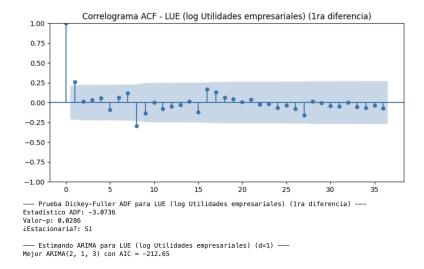


Interpretation for LUE:

The third variable, LUE (log Corporate Profits), showed slightly more complexity. The ACF plot of the original series again indicated non-stationarity, with a gradual decay in correlations. The ADF test statistic of -2.2429 and p-value of 0.1910 failed to reject the null hypothesis of a unit root. Once different, the stationarity was achieved (p = 0.0286), and the ACF showed patterns consistent with more structured dependence, both in the autoregressive and moving average sense. This is reflected in the selected ARIMA(2,1,3) model. The presence of multiple AR and MA components suggests that the dynamics of corporate profits are influenced by a longer memory process, potentially due to lagged reactions to economic cycles, fiscal policy effects, or market inertia. A complex ARIMA model like (2,1,3) captures these delayed and intertwined adjustments, which is consistent with how profits in the business sector often respond with lag to macroeconomic changes.

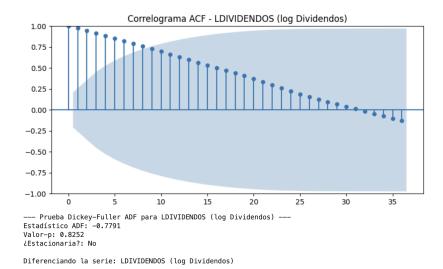




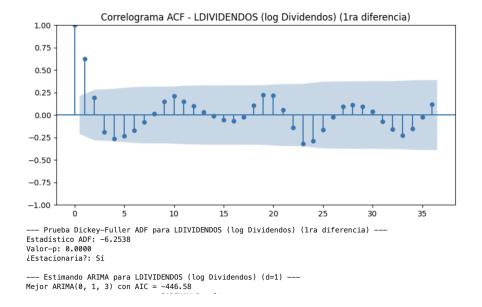


Interpretation for LDIVIDENDOS (log Dividends):

Also demonstrated non-stationary behavior in its level form. The ACF again showed slowly decaying autocorrelations, and the ADF p-value (0.8252) clearly indicated non-stationarity. After first differencing, the stationarity was achieved with a p-value of 0.0000. The selected model, ARIMA(0,1,3), points to a strong moving average process in the differenced series. The absence of autoregressive terms and the presence of three MA terms suggests that the dividends' growth process is primarily governed by a series of forecast errors or shocks, which echo through several periods. This might be interpreted as dividends being managed reactively based on unexpected changes in earnings, tax policies, or cash flow conditions, rather than following a smooth predictable trend.







Conclusion:

In conclusion, all four macroeconomic series were initially non-stationary and became stationary after first differencing. This means they are all integrated of order one, or I(1). According to Box-Jenkins methodology, this justifies the modeling approach using ARIMA(p,1,q). The order of differencing (d=1) was the same for all, but the complexity of the dynamics, captured by the values of p and q, varied across the series. LGCP and LIPD had simpler models (with one or no AR/MA terms), while LUE and LDIVIDENDOS required more parameters, reflecting more intricate temporal dependencies. Importantly, this modeling process is not just about achieving statistical fit. It reflects underlying economic behaviors: GDP and income tend to evolve with inertia but limited complexity, while profits and dividends are subject to multiple delayed responses and external shocks. The use of AIC for model selection ensured parsimony without sacrificing accuracy. Now that stationarity has been achieved and appropriate models have been fitted, these ARIMA models can be used reliably for forecasting, policy simulation, and further macroeconomic analysis, fulfilling the Box-Jenkins requirement that future behavior of a system be inferred from a stable and consistent statistical structure.