2.1 not Stationary

The exploratory analysis of the dependent variable [Y] begins with a visual inspection of the time series. The plot shows that the level of the series changes systematically over time, with [an upward / downward / irregular but trending] evolution. Instead of oscillating around a constant mean, the series exhibits long-term movements and possible structural breaks, suggesting the presence of non-stationary behaviour. Variability also appears to change over certain periods, which is another common characteristic of non-stationary data.

This impression is supported by the correlogram. The autocorrelation function (ACF) decays only very slowly, with many lags remaining significant far into the past. Such persistent autocorrelation indicates that shocks to the system are long-lasting, a typical feature of integrated time series. The PACF may also show extended dependence structures, which further reinforces the idea that the underlying process is not stable over time.

Figure1: Time series and correlograms of …

These visual indicators are confirmed statistically through unit-root testing. The Augmented Dickey–Fuller (ADF) test fails to reject the null hypothesis of a unit root (p-value > 0.05), indicating that the series is non-stationary in levels. Complementing this, the KPSS test rejects the null hypothesis of stationarity (p-value < 0.05), providing strong evidence against the series being stationary. The consistency between the two tests supports the conclusion that [Y] follows a non-stationary, integrated process.

Because non-stationarity violates the assumptions of many forecasting methods, using the raw series would lead to unreliable parameter estimates, spurious significance in regressions, and poor forecast performance. As a result, the variable requires transformation—typically through first differencing, seasonal differencing, or logarithmic scaling—to achieve stationarity. Once transformed, the series usually exhibits a substantially improved autocorrelation structure, making it suitable for ARIMA-type models, regression analysis, and dynamic forecasting frameworks.

In summary, both the graphical analysis and the results from the ADF and KPSS tests provide clear and consistent evidence that the dependent variable [Y] is non-stationary. Accordingly, transformation steps are necessary before the variable can be used in the subsequent modelling procedures.

2.1 stationary

The exploratory analysis of the dependent variable [Y] starts with an inspection of the time-series plot. The graph shows that the series fluctuates around a stable long-term mean without any detectable systematic upward or downward trend. The variance appears relatively constant throughout the sample period, and there are no obvious structural breaks or regime shifts. These characteristics provide an initial indication that the underlying process is stationary.

The correlogram reinforces this interpretation. The autocorrelation function (ACF) declines rapidly toward zero, with only a few significant lags at the beginning, suggesting that the influence of past observations diminishes quickly. The partial autocorrelation function (PACF) also displays only limited short-term dependence. If seasonal patterns are present, they appear as regular, repeating behaviour without compromising the long-term stability of the series.

Figure1: Time series and correlograms of …

To support the visual evidence, unit-root tests are applied. The Augmented Dickey–Fuller (ADF) test rejects the null hypothesis of a unit root (p-value < 0.05), indicating that the series is stationary in levels. In addition, the KPSS test fails to reject the null hypothesis of stationarity (p-value > 0.05), which corroborates the ADF findings. The agreement between both tests provides strong confirmation that the dependent variable does not follow an integrated process and that its statistical properties remain stable over time.

Since the dependent variable is stationary, no differencing or further transformation is required for modelling purposes. This allows for the direct estimation of forecasting models such as ARIMA, exponential smoothing methods, static regressions, and dynamic models like ADL or VAR without risking spurious inference or unstable parameter estimates.

In conclusion, the combination of visual diagnostics, correlogram patterns, and consistent statistical evidence from both the ADF and KPSS tests demonstrates that [Y] is stationary. This provides a solid foundation for applying a broad range of forecasting techniques to model the series effectively and generate reliable predictions.