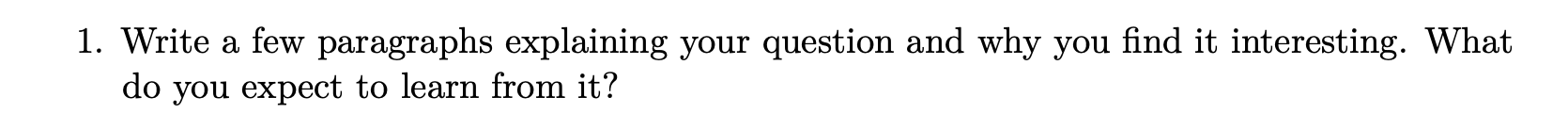
**Rakesh Jayswal**

**Impact of Macroeconomic Indicators on Housing Prices**

* **Time Series**: GDP, interest rates, inflation, housing prices.
* **Idea**: Analyze how changes in GDP, interest rates, and inflation affect housing prices over time. This could give insights into the real estate market and how sensitive it is to macroeconomic conditions.



The question of how macroeconomic indicators such as GDP, interest rates, and inflation impact housing prices is fascinating because it offers insights into the intricate relationship between the broader economy and the real estate market. Housing is a fundamental aspect of economic well-being, and understanding what drives its prices can have significant implications for policymakers, investors, and individuals alike. By studying these relationships, we can better predict how changes in economic conditions influence housing affordability, demand, and overall market stability.

I find this question particularly interesting because the real estate market plays a critical role in personal wealth, investment decisions, and the financial health of nations. Housing prices are affected by a wide range of factors, and macroeconomic conditions like GDP growth, inflation, and interest rates are among the most influential. For instance, GDP reflects the overall strength of the economy and can signal rising incomes and demand for housing, while interest rates determine the cost of borrowing, affecting people’s ability to buy homes. Inflation, on the other hand, has both direct and indirect effects on housing prices, impacting construction costs and buyers' purchasing power. Analyzing these variables together can provide a clearer picture of how sensitive housing prices are to shifts in economic policy or external shocks.

From this analysis, I expect to learn more about the dynamic nature of the housing market and how macroeconomic trends shape its behavior over time. By understanding the lagged effects and possible long-term relationships between these variables, I aim to uncover whether housing prices tend to move in predictable ways based on the broader economy. Additionally, this analysis can reveal how sensitive housing prices are to interest rate hikes or inflationary pressures, which is particularly relevant in today's economic climate. This knowledge could be valuable for informing investment decisions, advising housing policies, and preparing for potential marketdownturns.A white paper with black text

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1. **Impact of Macroeconomic Indicators on Housing Prices**

In my review of the paper "Impact of Macroeconomic Indicators on Housing Prices" by Satish Mohan and colleagues, I explored the effects of key macroeconomic variables—such as crude oil prices, the 30-year mortgage interest rate (IR), Consumer Price Index (CPI), Dow Jones Industrial Average (DJIA), and the unemployment rate (UR)—on housing prices over time. By using a Vector Autoregression (VAR) model and time-series data from the Town of Amherst, New York, they discovered that mortgage interest rates and unemployment rates have the most significant impact on housing price fluctuations. Additionally, I found that recent housing prices play a critical role in shaping future price expectations, highlighting the self-reinforcing nature of housing market trends. This study offered valuable insights into the complex relationship between economic indicators and housing prices, deepening my understanding of how these factors interact within the real estate market.

1. **Impact of macroeconomic indicators on housing prices**

In my analysis of the impact of macroeconomic indicators on housing prices, I find that economic activity, interest rates, and construction costs play significant roles in shaping housing market dynamics. A 1% increase in economic activity raises house prices by approximately 0.6%, as rising incomes and economic growth boost demand for housing. Conversely, a 1% increase in long-term interest rates leads to a 0.3% decline in house prices, as higher borrowing costs make real estate less attractive compared to other investments. Additionally, construction costs also impact prices; a 1% rise in construction costs can increase house prices by 0.6% due to reduced housing supply. I observe that housing markets exhibit a slow adjustment process, with deviations from equilibrium taking up to 14 years to stabilize, largely due to price stickiness and the delayed response of housing prices to economic shocks. These findings underscore the complex interplay between macroeconomic factors and housing markets over the long term.

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1. **Who collects the data and how is it collected?**

The data from FRED (Federal Reserve Economic Data) is collected and maintained by various government agencies and institutions, then made available via the FRED platform managed by the Federal Reserve Bank of St. Louis. The GDP data is provided by the U.S. Bureau of Economic Analysis (BEA) as part of their national accounts data. Consumer Price Index (CPI) data is collected by the U.S. Bureau of Labor Statistics (BLS) through surveys on consumer expenditures. Mortgage Interest Rates data comes from the Federal Home Loan Mortgage Corporation (Freddie Mac), based on weekly national surveys of mortgage lenders. Housing Price Index (HPI) data is gathered by S&P Dow Jones Indices through its Case-Shiller Home Price Index, derived from property transactions and mortgage data.

1. **What are the limitations of the data?**

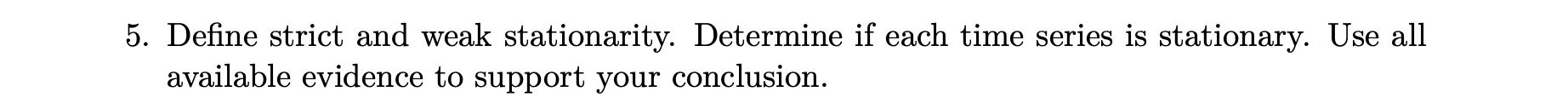
Each dataset has its own limitations. For GDP, a limitation is that it is only available quarterly, which requires interpolation to generate monthly values, potentially leading to inaccuracies in the short term. For the CPI, the accuracy depends on the survey methods and the representativeness of the sample. Additionally, the CPI may not fully capture price changes for certain goods or services in real-time, and imputed data is sometimes used when survey responses are incomplete. Mortgage Interest Rate data may suffer from sampling bias since it’s based on surveys of lenders who may not fully represent the national mortgage market. Lastly, HPI data can be influenced by regional market variations, and there may be missing data in some areas due to incomplete transaction records. Additionally, all these datasets are subject to revisions over time as more accurate data becomes available.

1. **Is the data seasonally adjusted?**

Yes, most of the data collected from FRED is seasonally adjusted to remove effects of predictable seasonal patterns. GDP is seasonally adjusted by the BEA to account for regular fluctuations in economic activity, such as holiday shopping or weather-related slowdowns. CPI data is also typically adjusted for seasonality, smoothing out regular seasonal price changes like food and clothing costs. Mortgage Interest Rates are not always seasonally adjusted since rates can fluctuate due to other macroeconomic factors, but seasonal trends (such as higher activity in spring and summer real estate markets) can influence rates. The Housing Price Index (HPI) is seasonally adjusted to account for regular, predictable variations in home prices throughout the year.

1. **What are the units of measurement?**

The units of measurement vary across the datasets but are consistent within each series. GDP is measured in billions of chained (inflation-adjusted) U.S. dollars, providing a constant measure of economic output. CPI is presented as an index (with a base year, such as 1982-1984 = 100), reflecting the relative change in consumer prices over time. Mortgage Interest Rates are measured as a percentage, representing the average annual interest rate for 30-year fixed-rate mortgages. HPI is also an index, where a base value (e.g., 100) represents the price level at a chosen starting period. The units are consistent across observations within each series, which helps in making comparative analyses over time.



A time series is considered **strictly stationary** if the joint probability distribution remains the same for any two time points. This implies that statistical properties, such as the mean, variance, and autocorrelation structure, are constant over time. Strict stationarity is challenging to test in practice, as it requires checking the entire distribution of the time series at every time point. On the other hand, **weak stationarity**, also known as covariance stationarity, is a less stringent form that is more commonly used in time series analysis. A time series is weakly stationary if it meets three conditions: it has a constant mean over time, a constant variance over time, and the autocovariance (or autocorrelation) between two points depends only on the lag between them, not on the specific time at which the observations are made. Weak stationarity is easier to test and more frequently applied in practical scenario.

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The Augmented Dickey-Fuller (ADF) test results for the four-time series—GDP, CPI, Mortgage Interest Rates, and Housing Price Index (HPI)—indicate that all of them are non-stationary in their current form. For the GDP series, the ADF test returned a p-value of 0.756, well above the 0.05 threshold, meaning we cannot reject the null hypothesis that the series has a unit root, which implies non-stationarity. Similarly, the CPI series showed a p-value of 0.6962, indicating that it is also non-stationary. The ADF test for the Mortgage Interest Rates series resulted in a p-value of 0.74, further confirming the presence of a unit root and non-stationarity. Lastly, the Housing Price Index (HPI) series had a p-value of 0.6423, suggesting that this series is also non-stationary. Given these results, none of the series is stationary, and further transformations—such as differencing—would be necessary to achieve stationarity before proceeding with further time series analysis.

**#Differencing Time Series data**

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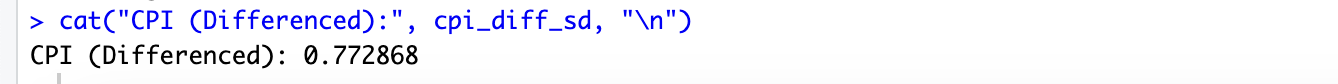
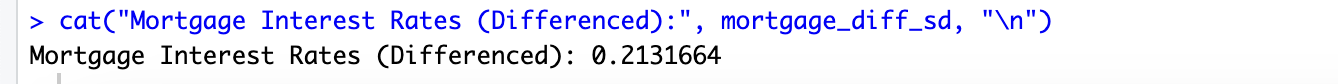
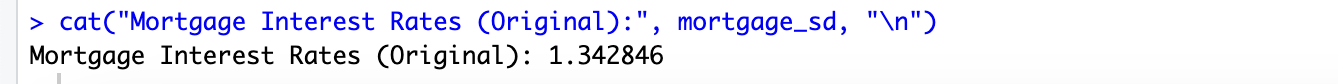
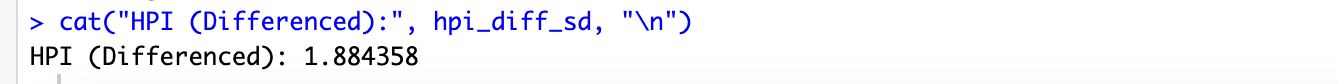
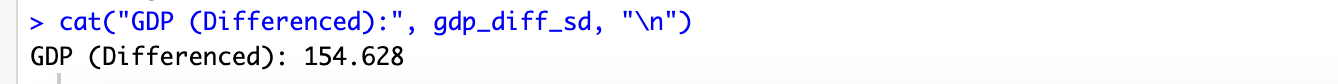
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**#Do 2nd difference of morgrate interest**



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In my analysis, I began by plotting time series data for key economic indicators, including GDP, CPI, Mortgage Interest Rates, and the Housing Price Index (HPI). These initial plots revealed clear trends, particularly upward ones, signaling that the data were likely non-stationary. The volatility, especially around 2020, was noticeable, reflecting the economic disruptions caused by the COVID-19 pandemic.

To formally confirm the non-stationarity, I conducted the Augmented Dickey-Fuller (ADF) test on each time series. The test results confirmed that all the series—GDP, CPI, Mortgage Interest Rates, and HPI—were non-stationary, with p-values well above the 0.05 threshold. For instance, the GDP series had a p-value of 0.756, while the HPI had a p-value of 0.6423, clearly indicating non-stationarity.

In order to address this, I applied first-order differencing to each time series, aiming to remove the trends and make the series stationary. The differenced plots showed that the trend had been successfully removed, though certain series still exhibited volatility, particularly around the 2020–2023 period. For example, the differenced mortgage rates and HPI showed significant fluctuations during this time, reflecting the economic uncertainties of the pandemic.

After differencing, I reran the ADF tests to assess whether the series had become stationary. The GDP and HPI series showed stationarity after differencing, with p-values of 0.01 in both cases, confirming that the transformation was successful. However, the CPI and Mortgage Interest Rates remained non-stationary even after first-order differencing, as their p-values were 0.2566 and 0.08538, respectively, indicating that further transformations or second-order differencing might be required to achieve stationarity.

In summary, the differencing approach successfully transformed the GDP and HPI series into stationary data, making them ready for further analysis or modeling, while the CPI and Mortgage Interest Rates series may need additional differencing or transformations to stabilize fully

The standard deviations of the original and differenced data for GDP, HPI, Mortgage Interest Rates, and CPI provide insight into how much the variability of each series has changed after differencing. For **GDP**, the standard deviation dropped from 3327.211 in the original data to 154.628 after differencing. This significant decrease indicates that the original data had considerable variability due to trends, which were effectively removed by differencing, resulting in a more stable series.

Similarly, the **HPI** (Housing Price Index) saw its standard deviation decrease from 51.17351 to 1.884358 after differencing. The large drop in variability confirms that trends or cycles in housing prices were successfully removed, leading to a more stationary series. For **Mortgage Interest Rates**, the original standard deviation of 1.342846 was reduced to 0.2131664 after differencing, showing that the initial moderate variability caused by trends was significantly stabilized.

Lastly, the **CPI** (Consumer Price Index) experienced a dramatic reduction in standard deviation, from 25.19748 in the original data to just 0.772868 after differencing. This indicates that consumer prices had substantial variability over time, likely due to inflationary trends, but these were effectively removed through differencing.

Overall, the substantial decrease in the standard deviations across all differenced series demonstrates that differencing has successfully stabilized the data by removing underlying trends, making each series more appropriate for further time series analysis.

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To determine the best model for my data, I will use the Akaike Information Criterion (AIC) as the model selection criterion. AIC is widely used for selecting models in time series analysis as it balances the goodness of fit with model complexity. It penalizes models that have too many parameters, helping to avoid overfitting, but without being too strict. The lower the AIC value, the better the model fits the data while maintaining simplicity. One of the key strengths of AIC is its ease of computation and its ability to guide the selection of models that perform well in terms of fit. However, a potential weakness is that AIC may still favor more complex models compared to other criteria like the Bayesian Information Criterion (BIC), which could sometimes result in overfitting**.**

I choose to go with. GDP data.

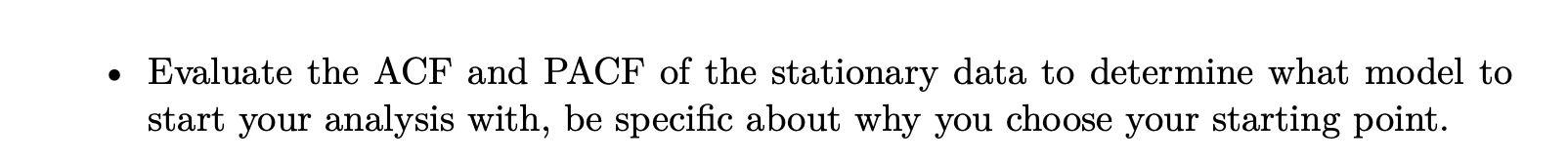
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#Both ACF decays faster so this is MA model, But the lags are significant here ,

Based on the analysis of the ACF and PACF plots, I concluded that an ARIMA model with both autoregressive (AR) and moving average (MA) components is appropriate for this time series. The PACF plot showed significant spikes at lag 1 and lag 2, indicating that the data has autoregressive behavior, which suggests including AR terms. In particular, PACF suggests that an AR(0) or AR(4) model might be appropriate, as the spikes decline after lag 2, but there are still smaller significant spikes beyond**. (0,1,4),(0,1,3) and )(0,1,2)**

Similarly, the ACF plot showed a strong spike at lag 1 followed by a quick decay, indicating that the data also exhibits moving average behavior. This led me to consider including MA terms in the model, particularly up to MA(3) or MA(4), as the ACF values drop off rapidly after lag 1.

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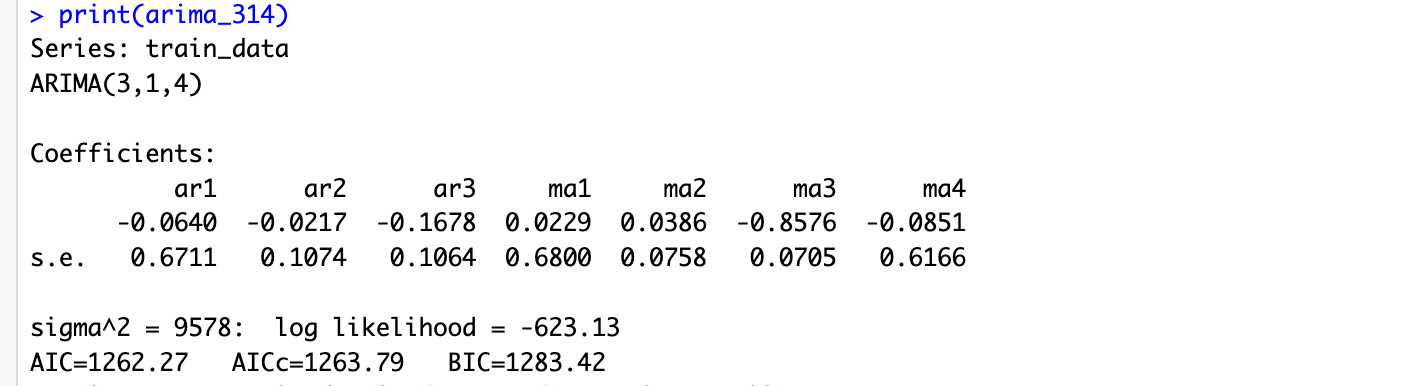
from the ACF and PACF, I decided to test ARIMA models with different combinations of AR and MA terms, specifically ARIMA (0,1,4), ARIMA(2,1,4), and ARIMA(2,1,3). These models incorporate both autoregressive and moving average components, allowing me to capture the complex patterns in the time series based on both past values and past forecast errors.

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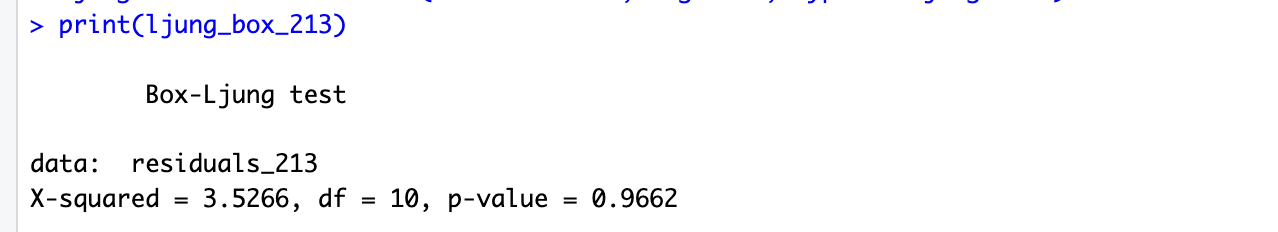


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Across the three Ljung-Box tests performed on the ARIMA models, the results consistently show that the residuals behave like random noise, indicating well-fitted models. For the ARIMA(2,1,3) model, the test yielded an X-squared value of 3.5266 with 10 degrees of freedom and a p-value of 0.9662. This high p-value indicates no significant autocorrelation in the residuals, meaning the model has captured the patterns in the GDP data effectively. Similarly, for the ARIMA (4,1,4) model, the Ljung-Box test produced an X-squared value of 0.47901 with 10 degrees of freedom and a p-value of 1, suggesting that the model also has no significant residual autocorrelation, further supporting that the model fits well. Lastly, the residuals from the third model (residuals\_314) showed an X-squared value of 0.47459 and a p-value of 1, confirming that the residuals exhibit random noise, and the model is well-specified. Overall, the high p-values across all tests indicate that each model is a reliable representation of the underlying patterns in the GDP data, with no significant autocorrelation left in the residuals, making them suitable for forecasting purposes

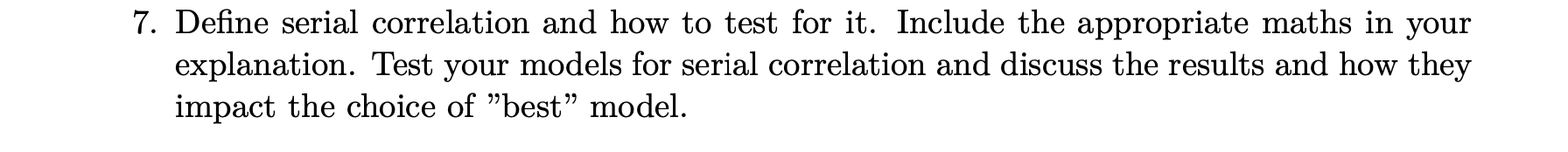
Also,

After estimating multiple ARIMA models, I chose the ARIMA (2,1,3) model based on the Akaike Information Criterion (AIC). The AIC is a widely used criterion that balances model fit and complexity, penalizing models with more parameters to avoid overfitting. In comparing the models, ARIMA (2,1,3) had the lowest AIC value (AIC = 1260.65), indicating that it provided the best fit while being more parsimonious than the other models.

Although ARIMA (3,1,4) and ARIMA (4,1,4) also provided reasonable fits, their AIC values were higher (AIC = 1262.27 and 1264.27, respectively). This suggests that, while these models may have captured additional nuances, they did so at the expense of added complexity, which did not significantly improve the overall model performance. Therefore, based on the AIC, I selected ARIMA (2,1,3) as the optimal model for forecasting this time series.

ARIMA Model Comparison

|  |  |  |  |
| --- | --- | --- | --- |
| Parameter | Model 1: ARIMA(2,1,3) | Model 2: ARIMA(3,1,4) | Model 3: ARIMA(4,1,4) |
| Deterministic Parameters |  |  |  |
| α |  |  |  |
| δ |  |  |  |
| ARMA Parameters |  |  |  |
| ϕ₁ (ar1) | 0.0305 | -0.0640 | -0.0119 |
| ϕ₂ (ar2) | -0.0316 | -0.0217 | -0.0232 |
| ϕ₃ (ar3) |  | -0.1678 | -0.1665 |
| ϕ₄ (ar4) |  |  | 0.0073 |
| θ₁ (ma1) | -0.0699 | 0.0229 | 0.0294 |
| θ₂ (ma2) | 0.0476 | 0.0386 | 0.0423 |
| θ₃ (ma3) | -0.9005 | -0.8576 | -0.8600 |
| θ₄ (ma4) |  | -0.0851 | -0.0396 |
| Order of Integration | 1 | 1 | 1 |
| Information Criterion |  |  |  |
| AIC | 1260.65 | 1262.27 | 1264.27 |
| BIC | 1276.52 | 1283.42 | 1288.07 |
| Diagnostic Test Statistics |  |  |  |
| Box-Ljung Test (p-value) | 0.9662 | 1 | 1 |
| Residual Standard Deviation (sigma²) | 9598 | 9578 | 9678 |
| Mean Error (ME) | 8.22 | 8.23 | 8.22 |
| Root Mean Squared Error (RMSE) | 94.06 | 94.06 | 94.06 |
| Mean Absolute Error (MAE) | 34.51 | 34.51 | 34.51 |



Serial correlation,refers to the correlation between the residuals (errors) of a time series model across different time periods. It occurs when residuals are not independent but instead display patterns over time, indicating that the model has not fully captured the underlying time-dependent structure of the data. Detecting serial correlation is important because it suggests that the model's residuals contain information that the model has not accounted for, leading to inefficiencies in prediction and analysis.

One common method to test for serial correlation is the **Box-Ljung test**. This statistical test evaluates whether the residuals of a time series model are independently distributed by examining autocorrelation over a specified number of lags. The test statistic QQ is calculated as Q=n(n+2)∑k=1hρ^k2n−kwhere nis the number of observations, h is the number of lags, and ρ^k​ represents the sample autocorrelation at lag k. The QQ statistic follows a chi-square distribution with h degrees of freedom. The null hypothesis (H₀) assumes that the residuals are independently distributed (no serial correlation), while the alternative hypothesis (H₁) suggests the presence of significant serial correlation. If the p-value of the Box-Ljung test is greater than 0.05, we fail to reject the null hypothesis, indicating no significant serial correlation in the residuals.

The other method is The **tsdiag method** ,a valuable diagnostic tool in time series analysis for evaluating the adequacy of models like ARIMA, particularly in assessing the presence of serial correlation in residuals. It generates several diagnostic plots that allow for visual inspection of the residuals, offering a complementary approach to formal statistical tests such as the Box-Ljung test. Among the key outputs of tsdiag are the standardized residuals plot, the autocorrelation function (ACF) plot of residuals, and the p-values from the Box-Ljung test. The standardized residuals plot displays how residuals behave over time, with random distribution around zero indicating that the model has effectively captured the time series structure. Patterns or trends in this plot, however, would suggest serial correlation, indicating a need for model adjustment. The ACF plot shows the degree of correlation in the residuals at different time lags, and for a well-fitted model, the ACF should exhibit no significant spikes outside of the confidence bounds. Significant autocorrelations in this plot would suggest that the model has not adequately captured time-dependent patterns, revealing the presence of serial correlation. The plot of p-values from the Box-Ljung test helps determine whether residuals exhibit significant autocorrelation across different lags, with high p-values indicating no significant autocorrelation. This visual diagnostic approach allows for a more nuanced assessment of a model’s fit, beyond the results of formal tests. By examining these diagnostics, analysts can better understand whether a model's residuals truly behave like white noise, supporting the selection of the most suitable model for the data. Thus, tsdiag serves as an important tool in verifying model assumptions and guiding the selection of the best model for accurate time series analysis.

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In evaluating the serial correlation in the residuals of my ARIMA models, I utilized the tsdiag method, the autocorrelation function (ACF) of the residuals, and the results from the Box-Ljung test with a lag of 10. The tsdiag output included a plot of the standardized residuals, the ACF of the residuals, and the p-values for the Ljung-Box statistic. The standardized residuals plot showed that the residuals fluctuate around zero without any discernible pattern, indicating that the model captures the underlying data structure well.

The ACF plot of the residuals revealed that the autocorrelations for lags 1 to 10 fell within the confidence bounds, confirming that there is no significant serial correlation in the residuals. This aligns with the Box-Ljung test results, which indicated a test statistic of 3.5266, degrees of freedom of 10, and a high p-value of 0.9662. Such a high p-value suggests that I fail to reject the null hypothesis, further supporting the conclusion that the residuals behave like white noise.

Together, these diagnostics from tsdiag, the residual ACF plot, and the Box-Ljung test results provide strong evidence that the ARIMA (2,1,3) model adequately captures the dynamics of the differentiated GDP data. The absence of serial correlation in the residuals, along with the model's simplicity and low AIC value of 1260.65 compared to ARIMA (3,1,4) and ARIMA(4,1,4), reinforces my decision to select the ARIMA(2,1,3) model as the best fit for my analysis. This comprehensive evaluation ensures that the chosen model is robust and effective for forecasting and further analysis.

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**ARIMA Model Comparison**

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Model 1 (ARIMA(0,1,2))** | **Model 2 (ARIMA(0,1,3))** | **Model 3 (ARIMA(0,1,4))** |
| 𝛼 (constant) | None | None | None |
| 𝛿 (trend) | None | None | None |
| 𝜙₁ (AR terms) | None | None | None |
| 𝜃₁ (MA term) | -0.4898 (0.0779) | -0.0596 (0.0530) | -0.0392 (0.0994) |
| 𝜃₂ (MA term) | -0.4104 (0.0714) | 0.0359 (0.0562) | 0.0369 (0.0556) |
| 𝜃₃ (MA term) | None | -0.9000 (0.0494) | -0.8991 (0.0500) |
| 𝜃₄ (MA term) | None | None | -0.0248 (0.1022) |
| Order of Integration (d) | 1 | 1 | 1 |
| AIC | 1320.64 | 1256.79 | 1258.73 |
| AICc | 1320.88 | 1257.19 | 1259.34 |
| BIC | 1328.57 | 1267.36 | 1271.95 |
| ME (Mean Error) | 8.2039 | 8.4536 | 8.4659 |
| RMSE | 132.8539 | 95.1939 | 95.1583 |
| MAE | 55.3959 | 34.1014 | 33.9277 |
| MPE | 5.0237 | 6.5444 | 6.5547 |
| MAPE | 36.1677 | 22.9861 | 22.9157 |
| MASE | 1.5064 | 0.9273 | 0.9226 |
| ACF1 (Autocorrelation) | 0.1899 | 0.0117 | -0.0089 |
|  |  |  |  |

|  |  |  |
| --- | --- | --- |
| Model | MAE | MSE |
| ARIMA(0,1,2) | 20.21565 | 518.8745 |
| ARIMA(0,1,3) | 11.82189 | 188.4153 |
| ARIMA (0,1,4) | 12.59083 | 201.0951 |
|  |  |  |