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FORECASTING EXPORTS IN ALBANIA

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ABSTRACT

Time series forecasting is a significant domain, in fields such as economics, finance, and weather forecasting. The paper assesses time series forecasting that project forward-looking values based on on historical data. The common models used to capture the trend, seasonality, and anomalies within the time series data are ARIMA, SARIMA, and exponential smoothing. Forecast accuracy depends on the model choice and fine-tuning. Validation and continuous refinement are necessary for reliability and adaptability to changing conditions. Time series forecasting is a valuable tool for decision-making, resource allocation, and planning. An ARIMA model forecasted Albanian exports, providing reliable forecasts for the near future and prioritizing recent observations over past data. One drawback is that new data were not applied to different models for improving future forecasts. Given Albania's reliance on exports, periodic validation and refinement of model-building are critical. The ARIMA findings recommend 3, 2, and 3, applied in forecasting. Forecast errors were tested, proving model efficiency. Performance may vary by situation, so model assessment over time is essential. These models help researchers forecast Albania's annual exports.

Keywords:
ARIMA Model, Albanian Exports, Forecast Accuracy, Trend and Seasonality, Model Validation, Resource Allocation.

1. Introduction

Albania, a small country located in South-eastern Europe, has made significant strides in its export sector, contributing to its economic growth and development. With its rich cultural heritage and diverse geography, Albania has leveraged its resources and strategic location to establish a presence in international markets. This article provides a concise background and introduction to Albanian exports, highlighting their importance, composition, and key trade partners.

Exports play a vital role in Albania's economy, driving economic growth, generating foreign exchange earnings, and creating employment opportunities. The country's export sector has diversified over time, encompassing a wide range of products that showcase Albania's natural resources, agricultural potential, and industrial capabilities.

Albanian exports comprise various categories, including agricultural products, minerals, textiles, footwear, metals, and energy-related goods. The agricultural sector benefits from the country's fertile land and favourable climate, enabling the production of fruits, vegetables, tobacco, olive oil, and medicinal plants. Albania's mineral resources, particularly chromium, copper, and nickel, contribute significantly to its export revenue. The country's textile and footwear industries have experienced remarkable growth, driven by a skilled workforce, competitive labor costs, and proximity to European markets. Additionally, Albania has a notable presence in the metal industry, exporting iron, steel, and aluminium products. Furthermore, Albania's energy-related exports, such as electricity and petroleum products, play a significant role in its export earnings.

Albania's export partners have also diversified over time, providing new opportunities for market expansion. The European Union (EU) represents a crucial market for Albanian exports, with countries like Italy, Germany, Greece, and Spain serving as key trade partners. Albania's proximity to Europe and its aspiration for EU membership further strengthen its trade ties with European nations. Regional markets, including Kosovo, Serbia, Montenegro, and North Macedonia, also present significant trade opportunities through agreements like the Central European Free Trade Agreement (CEFTA). Additionally, Albania has explored emerging markets in the Middle East, North Africa, Asia, and the Americas to diversify its export destinations and reduce dependence on traditional markets.

The Albanian government has implemented initiatives to promote exports and enhance the competitiveness of domestic industries. Export promotion agencies, such as the Albanian Investment Development Agency (AIDA) and the Albanian Export Centre (AEC), provide support services, market intelligence, and networking opportunities to exporters. The government offers financial incentives, tax breaks, and grants to encourage export-oriented businesses. Infrastructure development, including transportation networks, ports, and customs procedures, is a priority to facilitate trade and improve logistics. Additionally, efforts have been made to improve product quality, adhere to global standards, and ensure a favourable business environment for exporters.

While Albanian exports have shown remarkable progress, challenges remain. Inadequate infrastructure, bureaucratic hurdles, limited access to finance, and the need for market diversification are among the obstacles that require attention. However, with continued support from the government, investments in infrastructure, and effective policies, Albania has the potential to further capitalize on its exports and achieve sustainable economic growth.

In conclusion, Albanian exports play a crucial role in the country's economic development. With a diverse range of products and growing trade partnerships, Albania has positioned itself as an emerging player in international markets. Government initiatives and ongoing efforts to address challenges will be instrumental in further enhancing Albania's export sector and ensuring long-term economic prosperity.

2. Literature Review

The following authors have contributed significantly to the field of time series analysis through their compelling articles. These individuals have delved into the intricacies of time-dependent data, employing various methodologies to uncover patterns, forecast trends, and explore the underlying dynamics of temporal phenomena. Their collective body of work has enriched our understanding of time series analysis, offering valuable insights into its applications across diverse domains. By examining the distinct perspectives and innovative techniques showcased in their articles, we can gain a comprehensive grasp of the advancements made in this field.

Ghafoor & Hanif (2005)used secondary data from the Statistical Bureau, Export Promotion Bureau of Pakistan, and different issues of the economic survey provided by the Ministry of Finance Pakistan. The time series data was from 1971 to 2003. The first step in analysing data for forecasting was checking the stationary of the data. First glance from the correlogram showed that the series was no stationary. The series was then difference, and it turned out that the series was stationary on the first order. Hence, the best fit model was ARIMA 1, 1, 0 with a constant term.

The paper by Farooqi (2014) attempts to develop an ARIMA model following the approach developed by Box and Jenkins, between the annual total Imports and Exports of Pakistan ranging from 1947 to 2013. This analysis applies the statistical package R. The adequacy of this model is evaluated through standard statistical methods. Finally, with the help of the fitted model, it predicted future values of Imports and Exports of Pakistan. From the results, it is concluded that ARIMA at order (2,2,2) is fit for annual Import of Pakistan, while for Export, the best fitted is ARIMA (1, 2, 2).

Moreover, from study, it can also be deduced that in the overall analysis time, Import and Export show an uptrend.

Ghosh (2017)study deals with the application of a univariate time series model, namely the Autoregressive Integrated Moving Average or ARIMA, in predicting short-term cotton exports within the country. Based on this, 63 monthly observations have been considered for the research study. Further, the ARIMA model built has been tested on different diagnostics and investigative tests to establish its efficiency. The ARIMA 1, 1, 0 model with two parameters presented minimum AIC and BIC criteria values according to the principle of parsimony among a set of various ARIMA models considered. The fitted study has forecasted cotton exports for the ensuing five periods, showing a positive slope in the export volumes. The comparison is, therefore, done to analyse the accuracy of the ARIMA model with other models in time series forecasting, such as Simple Exponential Smoothing SES and Holt Two Parameters Exponential Smoothing HES.

The Braimllari's study (2016)aimed to build a model for monthly exports in Albania, which would extend from January 2005 to January 2016. Through the descriptive analysis, the results indicated that the export value increased annually, with three outstanding commodities: textile and leather manufactures, minerals, fuels, and electricity, and construction materials and metals. The exports presented a positive trend without seasonal variations over time. It was found that fitting a SARIMA (0, 1, 1)××(3,0,0)12 model on the natural logarithm of the monthly exports series produced an AIC value of -205.56. The model was then used to predict the monthly export values for the months ranging from January to December 2016. The predictions show that on average, the export values are forecasted to drop by 7.34% per month or 1620 Million ALL per month for the year 2016, in comparison to corresponding months in 2015.

Upadhyay (2013) applied the Box-Jenkins methodology to identify the best ARIMA model to forecast export and import of the wood-based panel in India. The couple studied time series data from 16 years, starting from 1996-97 to 2011-12. The various test criteria such as the lowest Bayesian Information Criterion, R2 value, lowest mean absolute percentage error, etc. were used to test the goodness of fit for the model. The best models that resulted were the ARIMA model of the order of 0,1,0, with R2 0.83 suitable for export, while the one for import forecasting of wood-based panels was an ARIMA model of order 0,1,1 with an R2 of 0.87. This segment forecasted that in the year 2020, export and import of the wood-based panel would increase by 170% and 127%, respectively, from the values in the year 2012.

3. Dataset and Time Series Models

The information regarding the monthly total exports of Albania was gathered from the Albania instant. The dataset covers the period from 2012 to 2022 and is presented in Albanian lake. A time series is a sequence of data points recorded in fixed intervals over a specific time period. A time series defines the time factor of data, wherein the order and time of observation should be proper. Time series data is met quite usually in several domains like finance, economics, meteorology, stock market analyses, to name a few. It would, therefore, mean that a time series would depict variable values against regular time intervals, which could be in the forms of hourly, daily, weekly, or monthly forms of time-based intervals. These may be variables like stock price, temperature, sales, population, or any measurable quantity changing with time.

These activities include an understanding of the past observations to describe, predict, or forecast the future values using the techniques of time series analysis. The statistical approaches include moving average, exponential smoothing, and the ARIMA model, along with other advanced methods including ARIMAX, STL decomposition of time series, and machine learning algorithms like RNNs and LSTMs.

In a general sense, time series analysis is an important dimension for drawing meaningful conclusions and making decisions based on the lessons of the past to make reasonable predictions and plans that would lie in the temporal dependencies of the future.

4. Data Analysis for Exports in Albania

Descriptive statistics play a crucial role in analysing and understanding data exports. They provide valuable insights into the characteristics and patterns of exported goods or services. In this section, we will present descriptive statistics for a specific dataset of data exports

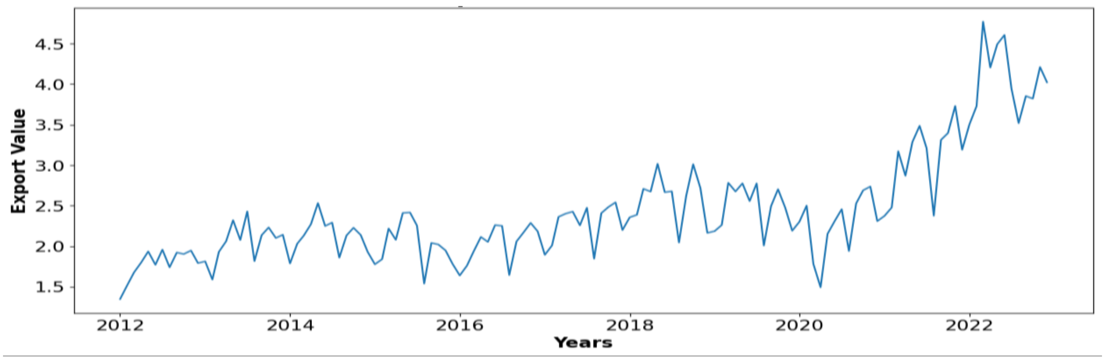
Table 1: *Descriptive Statistics*

count	1.32E+02	**25%**	1.99E+10
mean	2.43E+10	**50%**	2.26E+10
std	6.79E+09	**75%**	2.67E+10
min	1.35E+10	**max**	4.77E+10

(*Source: Author's Calculations*)

The graph generated using the plot (data) function in Python illustrates that the eksports of Albania have shown a gradual increase and decrease over time.

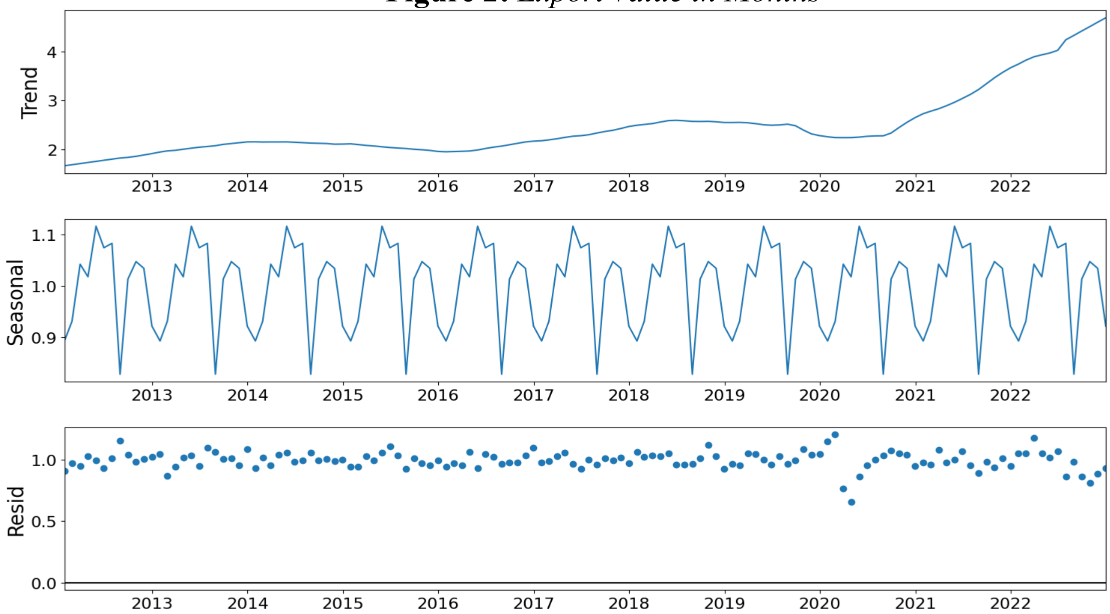
Figure 1: *Export Value in Months*



(Source: Authors' Own Illustration)

In the Figure 2 we see series decomposition which is a technique used in time series analysis to break down a time series into its underlying components. It aims to separate the different patterns and variations within the data, allowing for a better understanding of the series and facilitating further analysis. The three main components of series decomposition are Trend, Seasonality and Residual. By decomposing a time series into these components, we can gain insights into the underlying structure and dynamics of the data. This knowledge can be useful for forecasting future values, identifying outliers or anomalies, and understanding the overall behaviour of the series. Various decomposition methods exist, but in this case we used a multiplicative model.

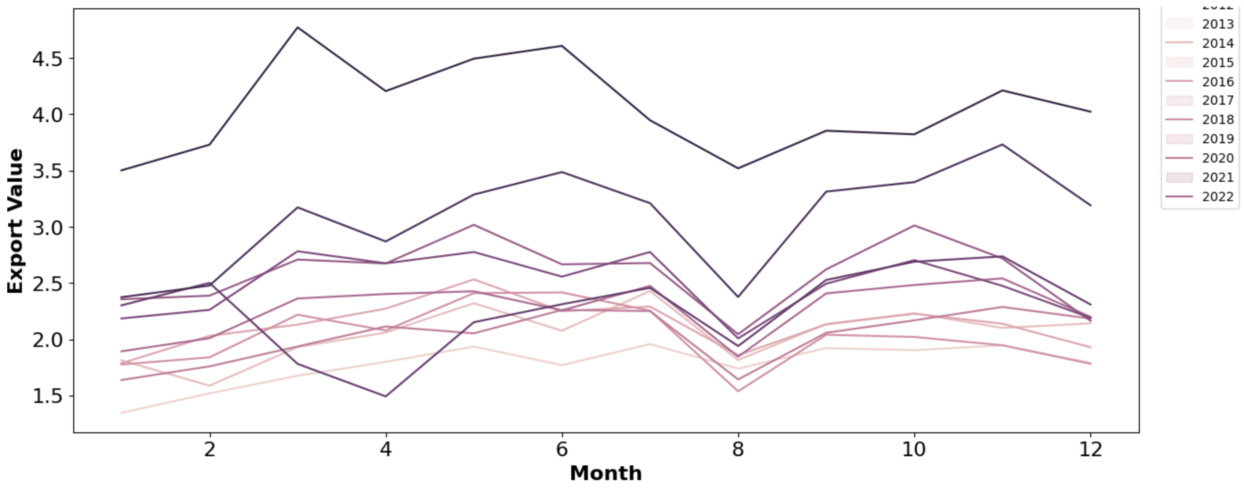
Figure 2: *Export Value in Months*



(Source: Authors' Own Illustration)

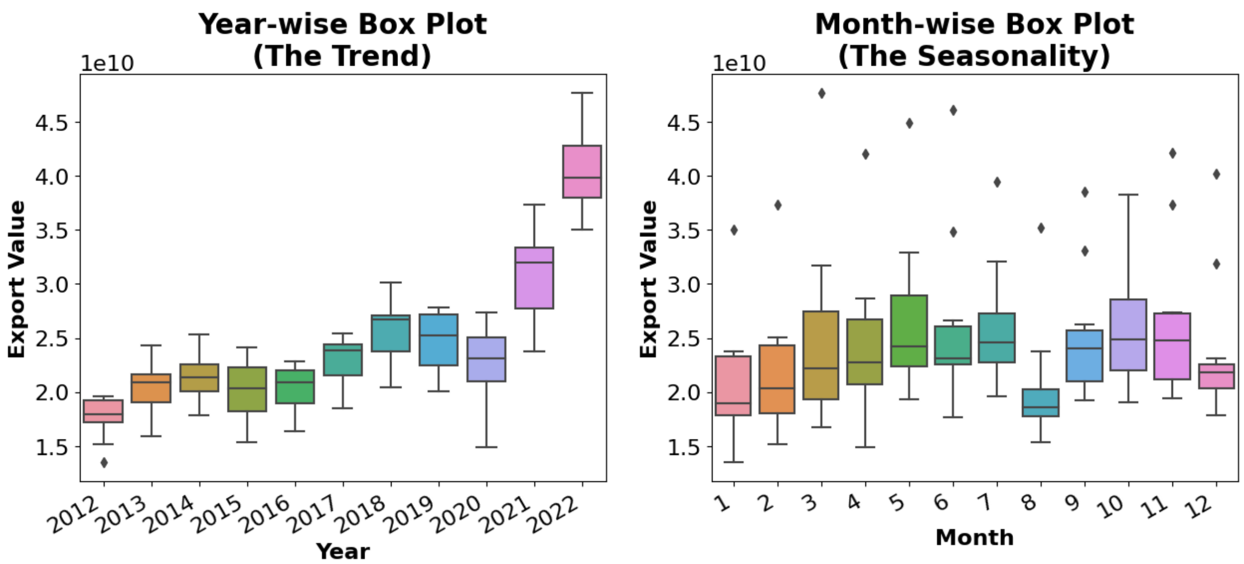
In the Figure 3 consist of the seasonal plot of export values, the year-wise box plot and the month-wise box plot. In the seasonal plot of export values we see that 2021 was a highly successful year for Albania, with the sum of total exports surging from 2.72E+11 to 4.86E+11 ALL. This constitutes the most significant increase within the past decade.

Figure 3: *Seasonal Plot of Export Values*



(Source: Authors' Own Illustration)

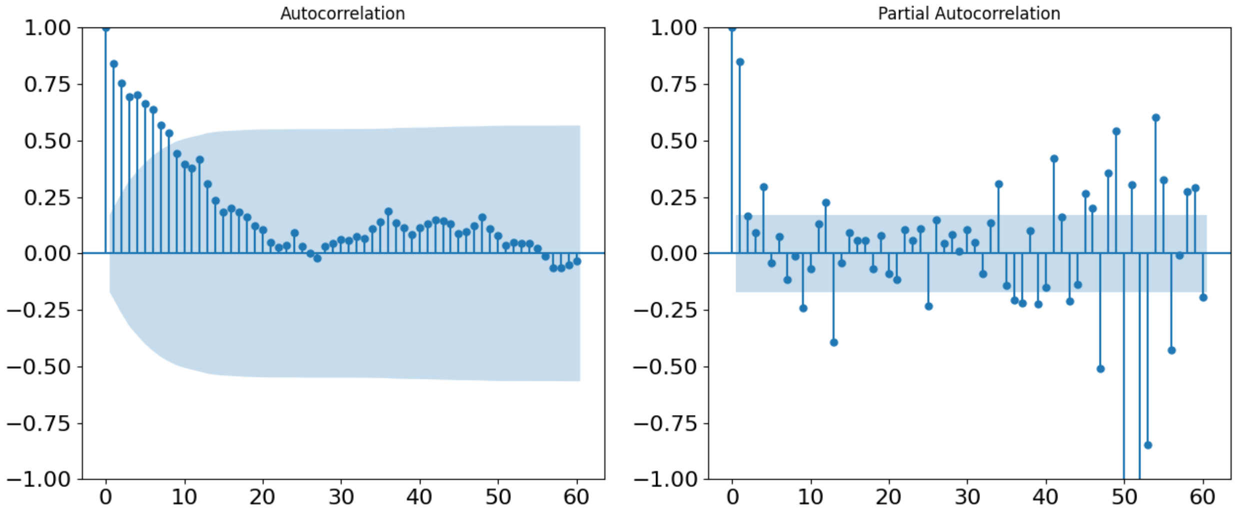
In the year-wise box plot a general uptrend over the last eleven years can be observed, with the exception of 2020. In the month-wise box plot we see a limited number of outliers and the minimal differences between each category results in the slight influence of seasonality.



(Source: Authors' Own Illustration)

In Python, the ACF and PACF functions can be used to compute and plot the autocorrelation and partial autocorrelation. The ACF plot reveals that the sample autocorrelations are positive, strong, and exhibit a slow decay. This suggests the presence of potential shifts in both the mean and variability of the series over time. It implies that the average import values might be gradually increasing, while the variability may be expanding. To address the mean trend, differencing the data once or twice can be considered, and controlling the variability can be achieved by applying the Seasonal ARIMA model on the exports of Albania.

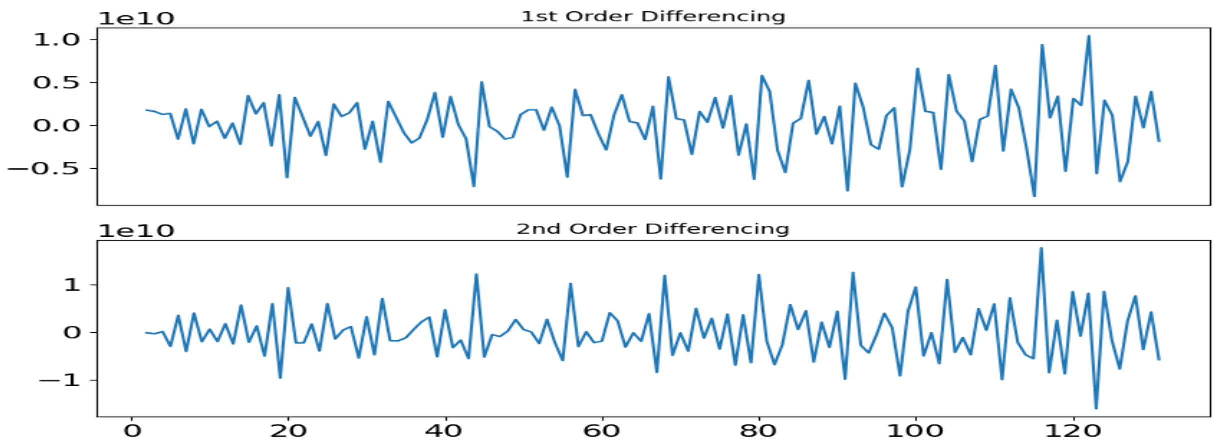
Figure 4: *Auto-Correlation and Partial Auto-Correlation of Original Data*



(Source: Authors' Own Illustration)

A stationary series implies that the observations exhibit a constant variance and mean over time. Initially, it is determined whether the series of observations in the sample data is stationary or not.

Figure 5: *1st and 2nd Order Differencing*



(Source: Authors' Own Illustration)

Figure 5 indicates that the series is non-stationary. To address the non-stationary in the mean, the data series is differenced appropriately. Figure 3 demonstrates that the first difference of the series becomes stationary. The stationary of the series is further assessed using the Augmented Dickey Fuller (ADF) unit root test. The results of the estimated ADF test are presented in Table 2.

Table 2: *Results of Dickey-Fuller Test*

	Original Series	1st Order Differencing	2nd Order Differencing
Test Statistic	0.271757	-2.71184	-7.82E+00
p-value	0.976011	0.072013	6.76E-12
Lags Used	12	11	1.10E+01
Number of Observations Used	119	119	1.18E+02
Critical Value (1%)	-3.48654	-3.48654	-3.49E+00
Critical Value (5%)	-2.88615	-2.88615	-2.89E+00
Critical Value (10%)	-2.5799	-2.5799	-2.58E+00

(Source: Authors' Own Illustration)

The Table 2 indicates that the series, when transformed into the second difference, becomes stationary. Therefore, for our Seasonal ARIMA model, we adopt d=2, indicating the differencing order required to achieve stationary in the series. After trying many Sarima models we did not find optimal parameters for which the probability of Ljung-Box, Jarque-Bera and Heteroskedasticity is less than 0.05. Under these conditions, we tried to find optimal parameters for the Arima model. Through an iterative process, multiple ARIMA models were fitted, and the model with the lowest normalized AIC and BIC values was selected.

Based on the provided statistics, Arima (3,2,3) is the best choice among the three models. Here's why:

1. AIC and BIC: Arima (3,2,3) has the lowest AIC (6062) and BIC (6082) values, indicating a better fit to the data compared to the other models.
2. Ljung-Box (Q-statistic): Arima (3,2,1) has the smallest Q-statistic (0.02), indicating a better fit in terms of lack of autocorrelations in the residuals. However, the Q-statistic for Arima (3,2,3) is also quite low (0.26), suggesting a good fit.
3. Jarque-Bera test: Arima(3,2,1) has the smallest Jarque-Bera statistic (0.85), indicating a better fit in terms of normality of residuals. However, Arima (3, 2, 3) has a relatively low Jarque-Bera statistic (1.64), suggesting a reasonably good fit as well.
4. Heteroskedasticity test: Arima (3, 2, 2) has the smallest p-value (0.08) for the Heteroskedasticity test, indicating a better fit in terms of constant variance of residuals. However, Arima(3,2,3) has a similar p-value (0.09), suggesting a comparable fit.

5. Skewness and Kurtosis: Arima(3,2,2) has the lowest skewness (-0.23), but Arima(3,2,3) has a slightly higher kurtosis (3.48). However, these differences are relatively small among the models.

Considering the overall performance across these criteria, Arima (3,2,and 3) consistently demonstrates a good fit to the data, with the lowest AIC and BIC values. While Arima (3,2,1) and Arima(3, 2,2) have some advantages in specific tests, Arima(3,2,3) remains the strongest option overall.

Table 4: *Results of Arima (3, 2, and 3) and coefficients*

Dep. Variable	Exports
Model	ARIMA(3, 2, 3)
No. Observations	132
Log Likelihood	-3024.063
AIC	6062.126
BIC	6082.199
HQIC	6070.283

(Source: Authors' Own Illustration)

Table 5: *Arima (3, 2, and 3) coefficients*

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.6083	0.225	-2.709	0.007	-1.048	-0.168
ar.L2	0.0850	0.289	0.294	0.769	-0.482	0.652
ar.L3	-0.3038	0.128	-2.371	0.018	-0.555	-0.053
ma.L1	-0.5284	0.262	-2.014	0.044	-1.043	-0.014
ma.L2	-0.9664	0.091	-10.652	0.000	-1.144	-0.789
ma.L3	0.4960	0.220	2.257	0.024	0.065	0.927

(Source: Authors' Own Illustration)

Table 6: *Statistical test results*

Ljung-Box (L1) (Q)	0.26
Prob(Q)	0.61
Heteroskedasticity (H)	1.69
Prob(H) (two-sided)	0.09
Jarque-Bera (JB)	1.64
Prob(JB)	0.44
Skew	-0.13
Kurtosis	3.48

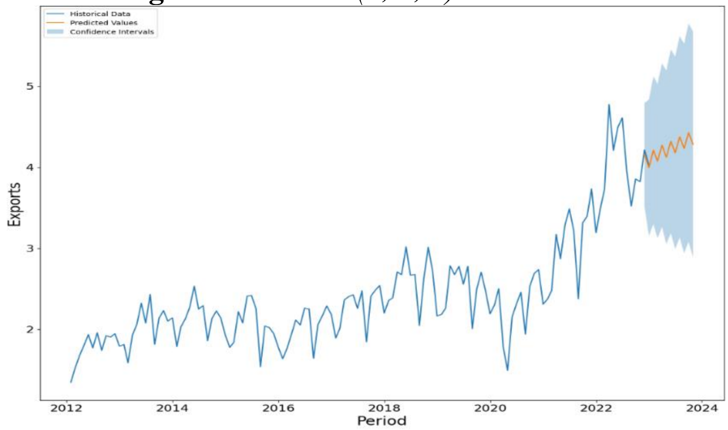
(Source: Author's calculations)

In the Table 4 (Table 5, Table 6) we see the coefficients of *Arima (3, 2, 3)* model. Here's an interpretation of each coefficient:

- Ar.L1: This coefficient represents the first lag of the autoregressive component. It has a value of -0.6083, indicating that there is a negative relationship between the current observation and the observation one time step ago. The coefficient is statistically significant at the 0.05 level ($P < 0.05$), as the absolute value of the z-statistic (-2.709) is greater than the critical value. The 95% confidence interval for this coefficient is approximately [-1.048, -0.168].
- Ar.L2: This coefficient represents the second lag of the autoregressive component. It has a value of 0.0850, which suggests a weak positive relationship between the current observation and the observation two time steps ago. However, this coefficient is not statistically significant at the 0.05 level ($P > 0.05$), as the absolute value of the z-statistic (0.294) is smaller than the critical value. The 95% confidence interval for this coefficient is approximately [-0.482, 0.652].
- Ar.L3: This coefficient represents the third lag of the autoregressive component. It has a value of -0.3038, indicating a negative relationship between the current observation and the observation three time steps ago. The coefficient is statistically significant at the 0.05 level ($P < 0.05$), as the absolute value of the z-statistic (-2.371) exceeds the critical value. The 95% confidence interval for this coefficient is approximately [-0.555, -0.053].
- Ma.L1: This coefficient represents the first lag of the moving average component. It has a value of -0.5284, suggesting a negative relationship between the current observation and the residual (error term) one time step ago. The coefficient is statistically significant at the 0.05 level ($P < 0.05$), as the absolute value of the z-statistic (-2.014) exceeds the critical value. The 95% confidence interval for this coefficient is approximately [-1.043, -0.014].
- Ma.L2: This coefficient represents the second lag of the moving average component. It has a value of -0.9664, indicating a strong negative relationship between the current observation and the residual two time steps ago. The coefficient is highly statistically significant ($P < 0.001$), as the absolute value of the z-statistic (-10.652) is much larger than the critical value. The 95% confidence interval for this coefficient is approximately [-1.144, -0.789].
- Ma.L3: This coefficient represents the third lag of the moving average component. It has a value of 0.4960, suggesting a positive relationship between the current observation and the residual three time steps ago. The coefficient is statistically significant at the 0.05 level ($P < 0.05$), as the absolute value of the z-statistic (2.257) exceeds the critical value. The 95% confidence interval for this coefficient is approximately [0.065, 0.927].

These coefficients help to describe the dynamics and dependencies in the time series model. They indicate the impact of past observations and residuals on the current observation. The significance of each coefficient is determined by the corresponding z-statistic and compared to the critical value at a chosen significance level (usually 0.05). The confidence intervals provide a range of plausible values for each coefficient at a given confidence level (usually 95%). In the Figure 6 we see a prediction for future values with *Arima (3, 2, and 3) model*.

Figure 6: *ARIMA (3, 2, 3) Future Predictions*



(Source: Author's calculations)

5. Conclusions

In this study, an ARIMA model was used to forecast Albanian exports. From this, the ARIMA models yielded reliable forecasts for the near future and also placed a greater emphasis on recent observations rather than observations from a distant past. The limitation of this study is the absence of running multiple models on new observations to improve future forecasts. In view of the export importance of Albania, it is advisable that model-building exercises are periodically validated and refined. From the results of the study, it can be induced that ARIMA 3, 2, 3 is the best fitted model for forecast. Forecast errors were also statistically tested for validation, showing how robust this model is for prediction. It is relevant to consider that a forecasting technique that may work well in one situation may not be suitable in another. The validation of a certain model should, therefore, be regularly evaluated as time progresses. For the case of forecasting annual Exports of Albanian, these models can be applied by researchers.

REFERENCES

Braimllari, A. (2016). Modeling Of Exports in Albania. 3rd International Conference on Recent Trends in Engineering Science and Management, (pp. 142-148). Bundi, Rajasthan. Retrieved from https://www.researchgate.net/publication/316134418_MODELING_OF_EXPORTS_IN_ALBANIA

Farooqi, A. (2014). ARIMA Model Building and Forecasting on Imports and Exports of Pakistan. Pakistan Journal of Statistics and Operation Research, 157-168. https://doi.org/10.18187/pjsor.v10i2.732

Ghafoor, A., & Hanif, S. (2005). Analysis of the Trade Pattern of Pakistan: Past Trends and. Journal of Agriculture & Social Sciences, 346-349.

Ghosh, S. (2017). Forecasting Cotton Exports in India using the ARIMA model. Amity Journal of Economics, 36-52.

Upadhyay, V. (2013). Modeling and forecasting export and import of Indian wood based panel using. Elixir International Journal, Statistics, 63, 18145-18148. Retrieved from https://www.researchgate.net/publication/271833558_Modelling_and_forecasting_export_and_import_of_Indian_wood_based_panel_using_ARIMA_models