Conference Name: International Conference on Business, Economics, Law, Language & Psychology, 19-20 June 2024, Amsterdam
Conference Dates: 19-Jun- 2024 to 20-Jun- 2024
Conference Venue: NH Hotel Amsterdam-Zuid, Amsterdam, Netherlands
Appears in: PEOPLE: International Journal of Social Sciences (ISSN 2454-5899)
Publication year: 2024

Brikena Sulejmani, 2024

Volume 2024, pp. 376-389.

DOI- https://doi.org/10.20319/icssh.2024.376389.

This paper can be cited as: Sulejmani, B. (2024). Forecasting Exports in Albania. International Conference on Business, Economics, Law, Language & Psychology, 19-20 June 2024, Amsterdam. Proceedings of Social Science and Humanities Research Association (SSHRA), 2024, 376-389

FORECASTING EXPORTS IN ALBANIA

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ABSTRACT

Time series forecasting plays a crucial role in various fields, including economics, finance, and weather prediction. This study explores the application of time series forecasting techniques to predict future values based on historical data patterns. Different models, such as ARIMA, SARIMA, and exponential smoothing, are commonly employed to capture the underlying trends, seasonality, and irregularities in time series data. The accuracy of the forecasts depends on selecting the appropriate model and fine-tuning its parameters. Regular validation and refinement of the forecasting models are essential to ensure their reliability and adaptability to changing conditions. Overall, time series forecasting serves as a valuable tool for decision-making, resource allocation, and planning in numerous domains. The Autoregressive Integrated Moving Average (ARIMA) model was used in this research to predict Albanian exports. The ARIMA models provided reliable forecasts for the near future and placed more importance on recent observations rather than distant past data. However, a limitation of this study is the lack of using multiple models on new data to improve future forecasts. Considering the significance of exports in Albania, it is crucial to periodically validate and refine the model-building exercises. Based on the findings, the study recommends using the ARIMA (3,2,3) model for forecasting. Furthermore, the forecast errors were statistically tested and validated, *confirming the model's strong predictive ability. It is important to note that a forecasting technique that performs well in one situation may not be suitable for another. Therefore, the validation of a specific model should be regularly assessed as time progresses. For the purpose of forecasting the annual exports of Albania, researchers can employ these models.*

Keywords:
Export Forecasting, ARIMA Model, Time Series Analysis, Forecast Accuracy, Albania.

1. Introduction

Albania, a small country located in Southeastern 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 favorable 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 aluminum 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 favorable 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.

The researchers Ghafoor & Hanif (2005) utilized secondary data obtained from several institutions, including the Statistical Bureau, Export Promotion Bureau of Pakistan, and various issues of the economic survey from the Ministry of Finance Pakistan. A time series dataset spanning from 1971 to 2003 was employed for analysis. The first step in analyzing the data for forecasting involved assessing its stationarity. The initial examination of the correlogram revealed that the data exhibited non-stationarity. To address this, a simple differencing technique was applied, resulting in stationary data after the first order. Consequently, an ARIMA (1, 1, 0) model with a constant term was selected as the best fit model.

The paper by Farooqi (2014) aims to construct an ARIMA (Auto Regressive Integrated Moving Average) model using the Box and Jenkins approach, specifically focusing on the annual total Imports and Exports of Pakistan from 1947 to 2013. The statistical software R was utilized for this analysis. The adequacy of the model was assessed using standard statistical techniques. Subsequently, the fitted model was employed to forecast future values of Pakistan's Imports and Exports. The results indicate that an ARIMA (2, 2, 2) model is suitable for forecasting annual Imports, while an ARIMA (1, 2, 2) model is suitable for forecasting Exports. Additionally, the study reveals an upward trend in both Imports and Exports throughout the analysis period.

The Ghosh (2017) study focuses on the utilization of a time series model called Autoregressive Integrated Moving Average (ARIMA) to forecast short-term cotton exports in India. The research is based on 63 monthly observations. The developed ARIMA model is subjected to various diagnostic and investigative tests to assess its effectiveness. Among different ARIMA models considered, ARIMA (1,1,0) with two parameters is selected as it exhibits the lowest values for the AIC and BIC criteria, aligning with the principle of simplicity. The study predicts cotton exports for the next five periods, revealing a positive trend in export volumes. To evaluate the accuracy of the ARIMA model compared to other time series forecasting models like simple exponential smoothing (SES) and Holt two parameters exponential smoothing (HES), a comparison is conducted.

This study of Braimllari (2016) aims to create a model for the monthly exports in Albania from January 2005 to January 2016. The findings of the descriptive analysis revealed that the export value increased annually, with three groups of commodities standing out: textile and leather manufactures, minerals, fuels, and electricity, and construction materials and metals. The exports over time displayed a positive trend and no seasonal patterns. By applying the SARIMA(0,1,1)x(3,0,0)12 model to the natural logarithm of the monthly exports series, an

AICc value of -205.56 was obtained. This model was then utilized to forecast the monthly export values from January to December 2016. The predictions indicate that, on average, the export values are expected to decrease by 7.34% per month or 1620 Million ALL per month for the year 2016, in comparison to the corresponding months in 2015.

Upadhyay (2013)used the Box-Jenkins methodology to determine the appropriate ARIMA model for forecasting the export and import of wood-based panels in India. They analyzed time series data spanning 16 years, from 1996-97 to 2011-12. Various test criteria, such as the lowest Bayesian Information Criterion (BIC), R2 value, and lowest mean absolute percentage error (MAPE), were employed to assess the accuracy of the model. The results of the study indicated that an ARIMA (0,1,0) model with an R2 value of 0.83 was suitable for forecasting export, while an ARIMA (0,1,1) model with an R2 value of 0.87 was appropriate for import forecasting of wood-based panels. According to the predictions, the estimated export and import of wood-based panels in the year 2020 would show an increase of 170% and 127%, respectively, compared to the values in 2012.

3. Dataset and Time Series Models

The information regarding the monthly total exports of Albania was gathered from the Albania instat. The dataset covers the period from 2012 to 2022 and is presented in albanian leke.Time series refers to a sequence of data points collected and recorded at regular intervals over time. It represents the temporal aspect of data, where the order and timing of observations are crucial. Time series data is commonly encountered in various domains, such as finance, economics, meteorology, stock market analysis, and many others. In a time series, each data point is associated with a specific timestamp or time period, which could be hourly, daily, weekly, monthly, or even more granular intervals. These data points can represent a wide range of variables, such as stock prices, temperature readings, sales figures, population counts, or any measurable quantity that changes over time.

Time series analysis techniques are employed to gain insights, make predictions, and forecast future values based on historical observations. These techniques include statistical methods, such as moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA) models, as well as more advanced approaches like autoregressive integrated moving average with exogenous variables (ARIMAX), seasonal decomposition of time series (STL), and machine learning algorithms such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks.

Overall, time series analysis plays a crucial role in understanding and making informed decisions based on historical patterns, enabling us to predict and plan for the future by leveraging the temporal dependencies in the data.

4. Data analysis for exports in Albania

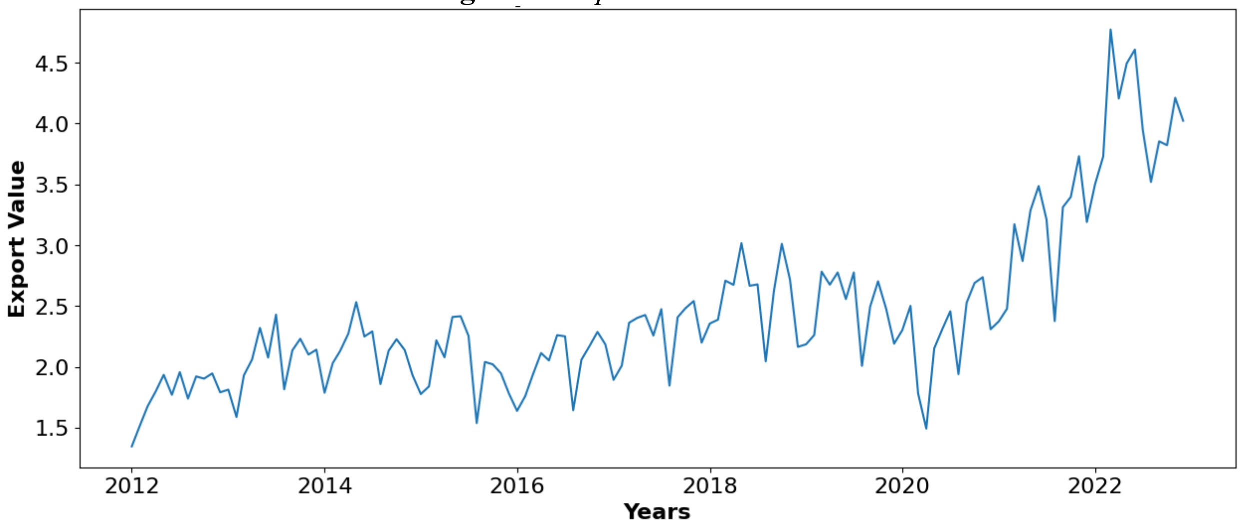
Descriptive statistics play a crucial role in analyzing and understanding data exports. They provide valuable insights into the characteristics and patterns of exported goods or services. In this section, we will present descriptive statistics for a specific dataset of data exports

Table 1: *Descriptive Statistics*

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

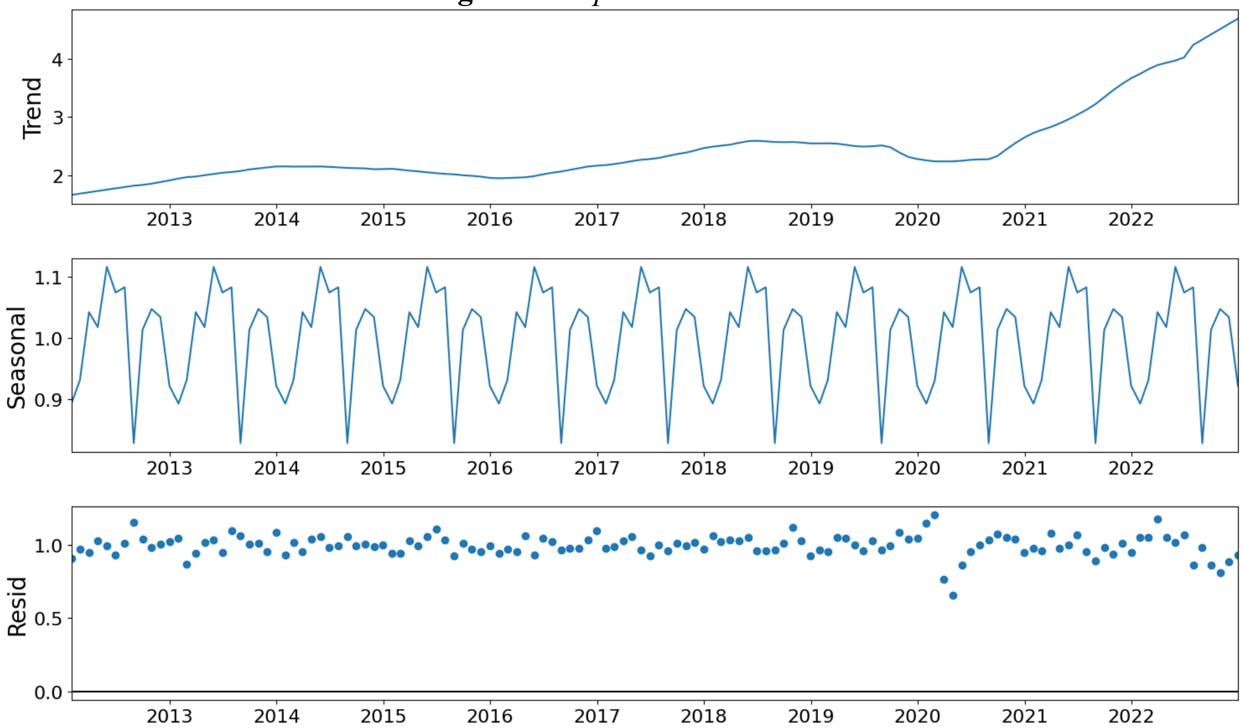
The graph generated using the plot(data) function in Python illustrates that the eksports of Albania have shown a gradual increase and decrease over time.

Figure 1: *Export Value in Months*



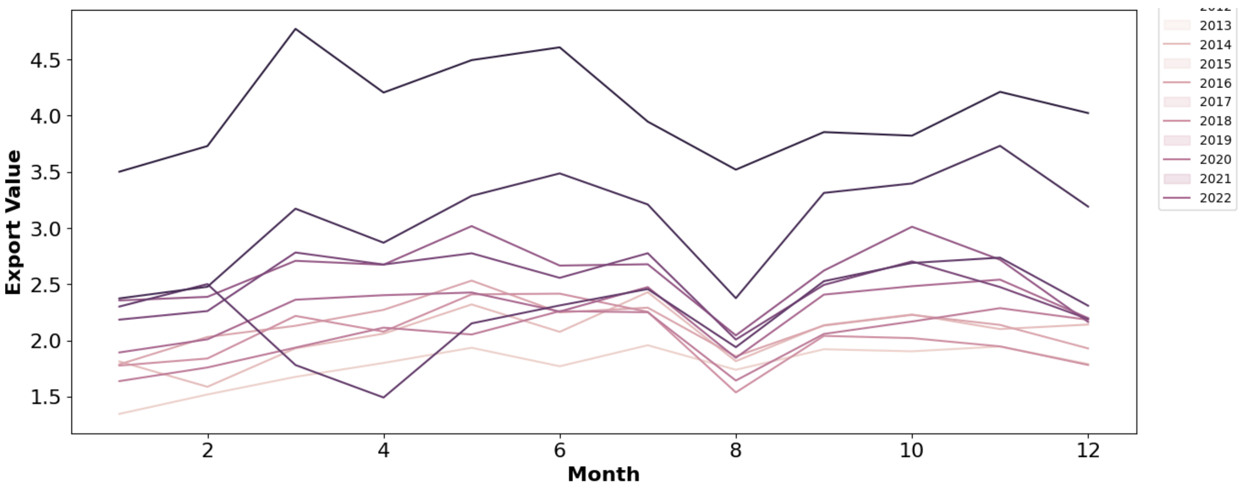
In the Figure 2 we see series decomposition which is a technique used in time series analysis to break down a time series into its underlying components. It aims to separate the different patterns and variations within the data, allowing for a better understanding of the series and facilitating further 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 behavior of the series. Various decomposition methods exist, but in this case we used a multiplicative model.

Figure 2: *Export Value in Months*

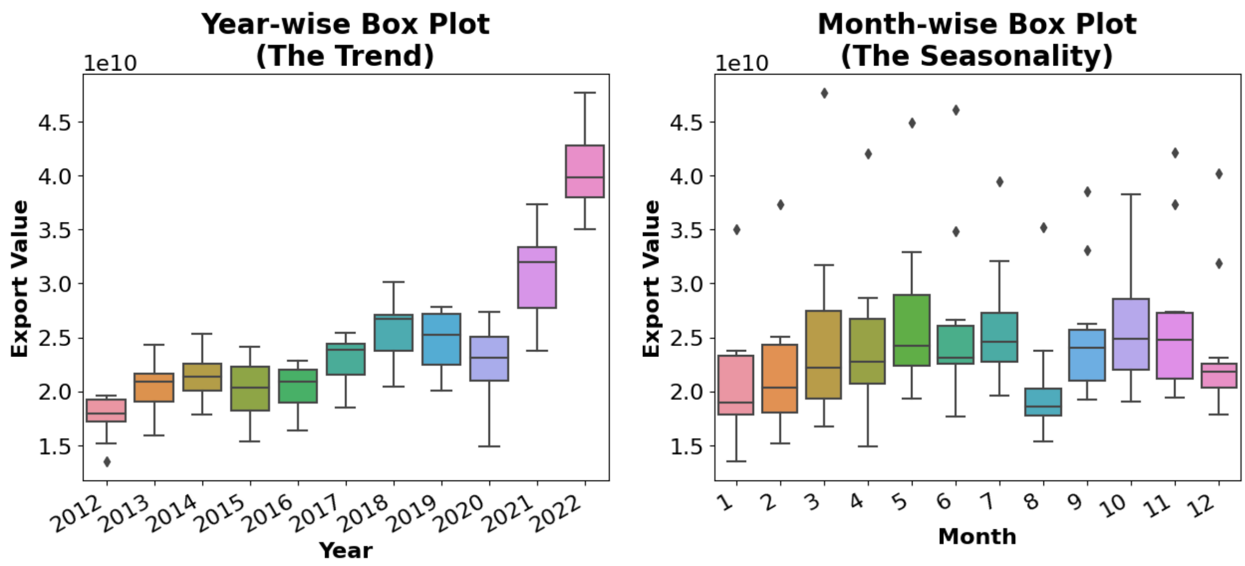


In the Figure 3 consist of the seasonal plot of export values, the year-wise box plot and the month-wise box plot. In the seasonal plot of export values we see that 2021 was a highly successful year for Albania, with the sum of total exports surging from 2.72E+11 to 4.86E+11 ALL. This constitutes the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

Figure 3: *Seasonal plot of Export Values*

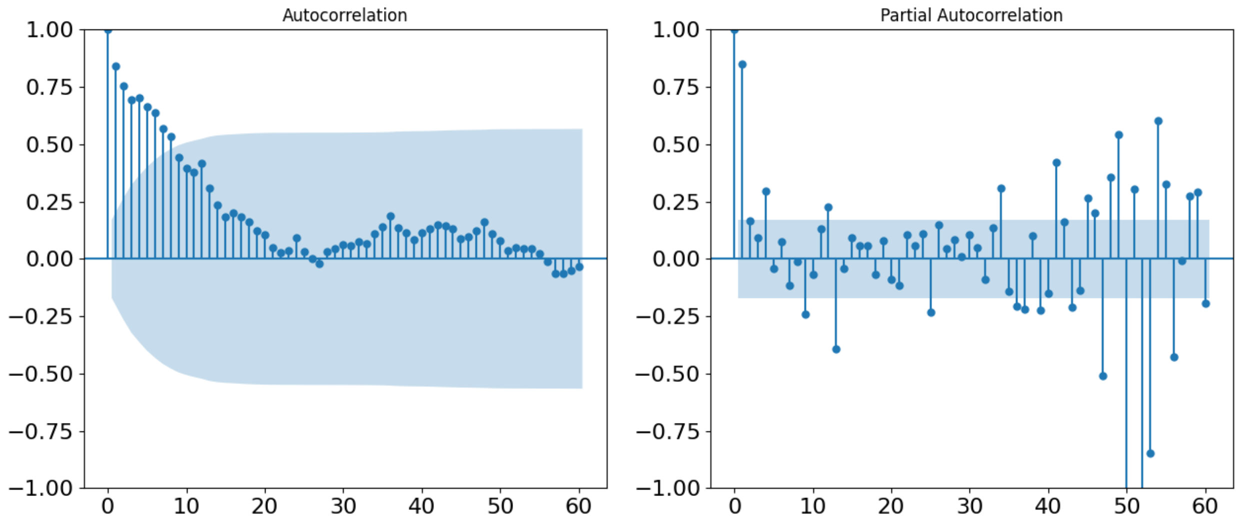


In the year-wise box plot a general uptrend over the last eleven years can be observed, with the exception of 2020. In the month-wise box plot we see a limited number of outliers and the minimal differences between each category results in the slight influence of seasonality.



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: *Autocorrelation and Partial Autocorrelation of original data*



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*

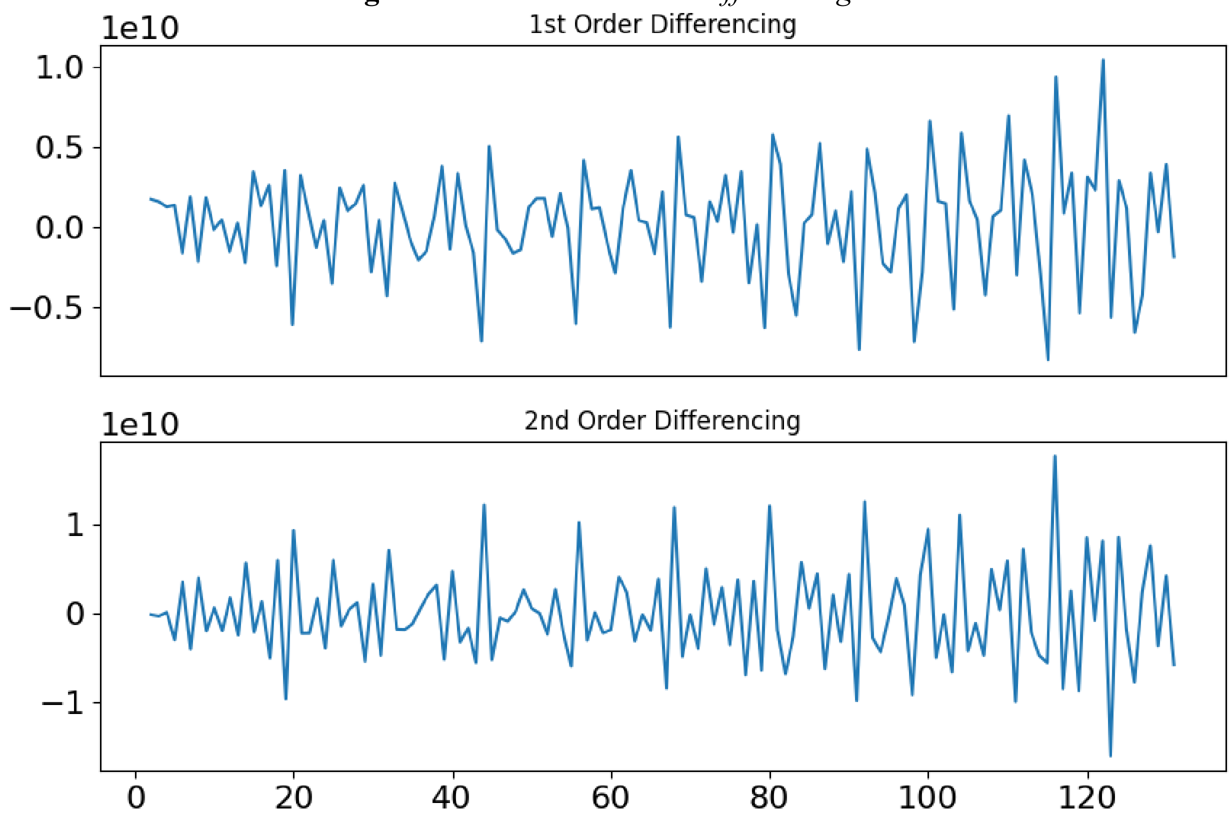


Figure 5 indicates that the series is non-stationary. To address the non-stationarity in the mean, the data series is differenced appropriately. Figure 3 demonstrates that the first difference of the series becomes stationary. The stationarity of the series is further assessed using the Augmented Dickey 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

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 stationarity 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.

Table 3: *Results of Arima model (p,2,q)*

	ARIMA (p,d,q)	AIC	BIC
1	ARIMA(0,2,0)	149254	149257
2	ARIMA(0,2,1)	6096	6102
3	ARIMA(0,2,2)	6092	6101
4	ARIMA(0,2,3)	6088	6099
5	ARIMA(1,2,0)	6150	6156
6	ARIMA(1,2,1)	6092	6101
7	ARIMA(1,2,2)	6074	6085
8	ARIMA(1,2,3)	6073	6088
9	ARIMA(2,2,0)	6143	6152
10	ARIMA(2,2,1)	6088	6100
11	ARIMA(2,2,2)	6075	6090
12	ARIMA(2,2,3)	6069	6086
13	ARIMA(3,2,0)	6105	6117
14	ARIMA(3,2,1)	6078	6092
15	ARIMA(3,2,2)	6066	6083
16	ARIMA(3,2,3)	6062	6082

Table 4: *Results of Arima model (p,2,q)*

	ARIMA (p,d,q)	Ljung-Box	Jarque-Bera	Heteroskedasticity
1	ARIMA(1,2,2)	0.41	0.83	0.01
2	ARIMA(1,2,3)	0.90	0.86	0.02
3	ARIMA(2,2,2)	0.58	0.84	0.01
4	ARIMA(2,2,3)	0.28	0.60	0.04
5	ARIMA(3,2,1)	0.89	0.65	0.07
6	ARIMA(3,2,2)	0.34	0.39	0.08
7	ARIMA(3,2,3)	0.61	0.44	0.09

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(3,2,3) 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: *Arima (3,2,3) results*

Dep. Variable:	Eksporte	No. Observations:	132
Model:	ARIMA(3, 2, 3)	Log Likelihood	-3024.063
Date:	Mon, 22 May 2023	AIC	6062.126
Time:	07:27:40	BIC	6082.199
Covariance Type:	opg	HQIC	6070.283

	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

Ljung-Box (L1) (Q):	0.26	Jarque-Bera (JB):	1.64
Prob(Q):	0.61	Prob(JB):	0.44
Heteroskedasticity (H):	1.69	Skew:	-0.13

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Prob(H) (two-sided):                  0.09   Kurtosis:                         3.48
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In the Table 4 we see the coefficients of *Arima (3,2,3)* model. Here's an interpretation of each coefficient:

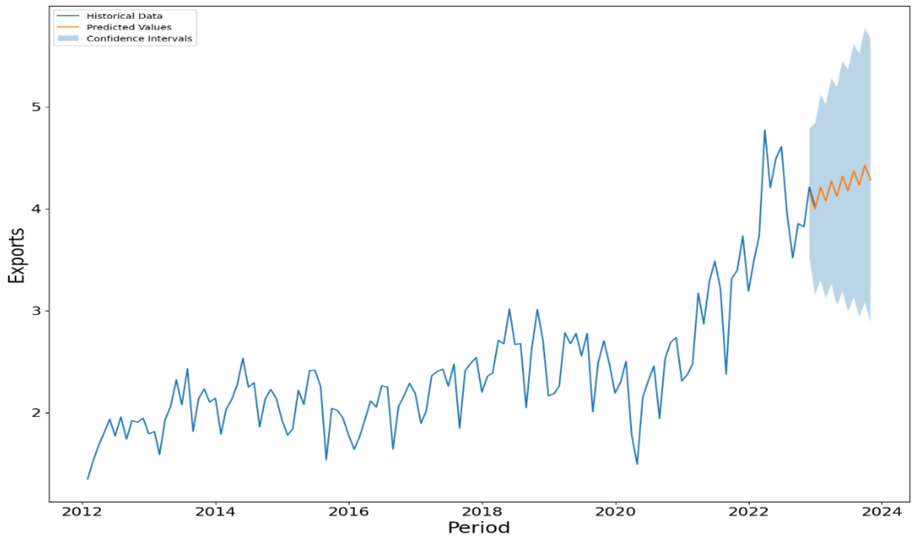
- ar.L1: This coefficient represents the first lag of the autoregressive component. It has a value of -0.6083, indicating that there is a negative relationship between the current observation and the observation one time step ago. The coefficient is statistically significant at the 0.05 level ($P < 0.05$), 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 (3,2,3) model*.

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



5. Conclusions

In this study, the Autoregressive Integrated Moving Average (ARIMA) model was employed to predict Albanian exports. The ARIMA models produced reliable forecasts for the near future and placed greater emphasis on recent observations rather than those from a distant past. However, a limitation of this study is the absence of running multiple models on new observations to improve future forecasts. Given the significance of exports in Albania, it is important to periodically validate and refine the model-building exercises. Based on the results, the study suggests that the ARIMA (3,2,3) model is the most suitable for forecasting. Additionally, the forecast errors were statistically tested and validated, demonstrating the robust predictive capability of the model. It is important to consider that a forecasting technique that works well in one situation may not be suitable for another. Therefore, the validation of a specific model should be regularly evaluated as time progresses. In the case of forecasting annual Exports of Albanian, researchers can employ these model.