The Influence of Russia Ukraine Conflict on China's New Energy Vehicles Sales

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Abstract. The Russian-Ukrainian conflict, which began in February 2022, has had a tremendous influence on the world economy, especially the oil industry. The war has directly influenced demand and market dynamics for oil replacements and other energy sources. However, the confrontation between Russia and Ukraine over China's new energy vehicles remains unresolved, whether favorable or bad. Therefore, the goal of this article is to examine the probable influence of the Russia-Ukraine war on the sales of new energy cars in China using the ARIMA model, as stated. This study provides statistics on the sales of new energy cars in China between March 2021 and December 2022. Based on the commencement date of the Russia-Ukraine war in February 2022, it is separated into two datasets: the base dataset from March 2021 to January 2022, and the actual sales data from February 2022 to December 2022.Finally, this part applies an ARIMA model based on the underlying dataset to forecast data during the Russia-Ukraine war and compares the projected outcomes to the actual dataset. This technique allows for a thorough examination of the real impact of the Russia-Ukraine war on new energy vehicle sales in China. After analysis of the environment for new energy vehicles in China, this research found that although the overall trend shows that the conflict does have a positive impact on new energy vehicle sales in China; it is also influenced by China's policies. This provides a more comprehensive perspective for policymakers to adjust policies based on actual differences.

Keywords: ARIMA model, ADF unit root test, Forecast.

1 Introduction

As the world continues to develop, the direction of world energy development has gradually shifted from traditional fossil fuels, such as coal, to more environmentally friendly renewable energy, such as hydrogen and electricity. Renewable energy accounts for an increasingly larger share of overall energy production [1]. The automotive industry is definitely an important area of energy conversion. In 1887, William Morrison constructed the world's first electric car, and the Toyota Prius was the first mass-produced hybrid vehicle. Since then, prominent manufacturers as Tesla and BYD have begun to focus on the research and production of new energy cars [2]. The

Q. Wu et al. (eds.), *Proceedings of the 2024 3rd International Conference on Public Service, Economic Management and Sustainable Development (PESD 2024)*, Advances in Economics, Business and Management Research 309,
https://doi.org/10.2991/978-94-6463-598-0_25

new energy vehicle business has risen considerably in recent years. In 2012, the worldwide electric vehicle market was estimated to be 1.7 million units, with a projected growth to 5.3 million units by 2020 [3].

The conflict between Russia and Ukraine began in February 2022 and has had a wide-ranging influence on the worldwide new energy vehicle (NEV) business. In February 2022, Russia began a massive military invasion in Ukraine. This battle is primarily Russia's attempt to prevent Ukraine from joining NATO as part of the 'anti-Russian strategy'.[4]. However, this conflict is not just a conflict between Russia and Ukraine, but also brought great changes to the economy of the whole world. Russia is the third-biggest producer of oil and liquid fuels in the world. It is also one of the biggest exporters of crude oil, therefore its direct military involvement in Ukraine has a direct impact on the rise and fall of crude oil prices worldwide [5]. Especially in the context of rapid growth of world oil and gradual decline in crude oil supply and production, global oil prices have risen sharply. Recession in the economy as a whole is more likely when unanticipated events like the conflict between Russia and Ukraine impact oil prices [6]. As one of the few alternative resources to alleviate the lack of oil as the mainstay of energy in industrial society, new energy has become a good opportunity to invest in times of economic turmoil [7]. The cost of fueling a car increases significantly for owners of automobiles due to rising oil prices, which forces people to look for alternate energy sources. In this regard, new energy sources will surely become increasingly in demand on the worldwide market as more affordable alternative energy sources. To ease the pressure on the price of fuel-powered automobiles, consumers could be more likely to select electric or other alternative-energy vehicles [8]. In order to support the expansion of the industry and lower the cost of new energy vehicle purchases for consumers, the Chinese government had in fact put in place a number of subsidy programs targeted at boosting the manufacturing and purchase of new energy cars. Additionally, in order to lessen reliance on fossil fuels and to support sustainable growth and environmental conservation, the Chinese government supports the gradual replacement of conventional energy sources with renewable energy sources. In fact, these provisions have gone a long way towards supporting the development and rapid expansion of China's new energy vehicle market. R&D subsidies and dual credit schemes have encouraged active innovation and increased output in the industry. [9]. The double credit strategy promotes the innovation of key technologies of new energy vehicles by limiting fuel consumption. It is unclear, therefore, if China's sales of new energy vehicles would be impacted by the conflict between Russia and Ukraine.

This study deeply examines the impact of the Russia-Ukraine conflict on China's new energy vehicle sales. This paper first uses the sales data of new energy vehicles in my country before the Russo-Ukrainian conflict to predict the data in the middle of the Russo-Ukrainian conflict, so as to obtain the sales data of new energy vehicles in my country that are not affected by the Russo-Ukrainian conflict. Then this research compares the predicted data with the actual data affected by the Russo-Ukrainian conflict. Finally, this paper analyzes the specific impact of the Russo-Ukrainian conflict on the sales of new energy vehicles in my country through the difference between the predicted values and the actual values.

2 Research Design

This research compared the sales of new energy cars with and without the Russo-Ukrainian conflict in order to examine the effects of the conflict on new energy vehicle sales in mainland China. Firstly, sales figures for China's new energy vehicles from March 2021 to December 2022 will be decoupled from February 2022 (the date of the crisis between Russia and Ukraine). This allowed for the collection of two sets of data for the study: the first set, which served as the baseline dataset, spanned the period from March 2021 to January 2022, while the second set, which served as the real dataset, included the period from February 2022 until some point in 2022.The first step is to take the logarithm and logarithmic difference series of the sales of the first set of data. The logarithmic transformation step can help stabilize the variance. In general, sales data may be heteroskedastic, that is, the variance changes over time, and using logarithmic transformation can make the variance more constant for comparison. Logarithmic differences can eliminate trends and seasonality in the data and make the series stationary. When the ARIMA model is used for forecasting, stable data variance guarantees that the time series is more accurate and dependable. Using the autocorrelation function (ACF), partial autocorrelation function (PACF), and extended autocorrelation function (EACF) is the second stage in figuring out the ARIMA model's order. The correlation between a time series' observations across k time units is calculated using the ACF. The order of the moving average component (MA(q)) in the ARIMA model may be ascertained with great assistance using ACF. After removing the influence of shorter delayed correlations, the partial autocorrelation function (PACF) is primarily used to assess the correlation between observations separated by k time units in a time series. It helps identify the order of the AR (p) part of the model. EACF is used to jointly identify the AR and MA orders by extending the concepts of ACF and PACF. EACF helps identify p and q by examining patterns in the correlation matrix, making it easier to determine the correct order of the AR and MA parts at the same time. Ultimately, the values of p, d, and q that were previously selected determine the ARIMA model. The moving average component (q), difference order (d), and autoregressive component (p) are represented by these variables, in that order.

2.1 Data Source

To analyze how the war between Russia and Ukraine impacts new energy vehicle sales in mainland China, sales are compared before and after the conflict. From March 2021 to December 2022, the new energy vehicle sales data used came from the China Automobile Dealers Association (CADA) and the China Passenger Car Market Information Joint Conference (CPCA). These institutions are known for their authoritative and accurate data collection, which ensures the reliability of information. Their comprehensive and precise data sets provide valuable insights into the automotive market and are very suitable for in-depth analysis and research. First, this paper splits the Chinese new energy vehicle sales data from March 2021 to December 2022 by February 2022 (the start time of the Russian-Ukrainian conflict).As a result, two sets of data are identified in this section: one from March 2021 to January 2022, and another from February 2022 to December 2022.The first data set is the baseline, whereas the second is the actual data set. The former is utilized as the baseline data set, whereas the latter is the actual data set for this investigation. This base dataset will be used to develop an ARIMA model for projecting new energy vehicle sales and to further examine the influence of the February 2022 Russia-Ukraine crisis on the Chinese market.

2.2 ADF Unit Root Test

Unit root testing (see Table 1) is a key step in time series analysis to assess stationarity, which is essential for reliable modeling. For this, the Augmented Dickey-Fuller (ADF) test is frequently employed. The null hypothesis, which is predicated on the presence of a unit root, is used to determine if the time series has a unit root and so is non-stationary. The test statistic from the ADF helps determine the significance of the result. As can be seen in Table 1, using the MacKinnon approximation the p-value is 0 and this part assess the strength of the evidence against the null hypothesis.

In ARIMA modeling, if the ADF test reveals the presence of a unit root (i.e., the series is not smooth), a first-order differencing (i.e., (d=1)) is commonly conducted on the series to achieve smoothness. This implies that each observation in the original time series is subtracted from the preceding observation, removing the series' trend or seasonality impact and smoothing it out. This means taking first-order differences of the series to stabilize its mean and variance over time. Once stationarity is confirmed after differencing, the parameters of the ARIMA model (Autoregressive Integrated Moving Average) can be selected, where "d" represents the number of differences required.

Because of this, the ADF test statistic is not only essential for assessing the time series' smoothness but also for directing the ARIMA model's design, guaranteeing reliable time series analysis and precise forecasting.

Table 1. ADF test results.

ADF statistics	0.1143
P-value	0.05
1% critical value	-3.067
5% critical value	-3.512
10% critical value	-3.187

2.3 ARIMA Model Setting

The ARIMA model is parameterized by examining the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Where p is the number of lagged data in the model, implying that the model predicts the current time step using p earlier time steps from the regression equation. The exact mathematical equation is as follows:

$$x_t = \varphi_0 + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots \varphi_P x_{t-p} + \varepsilon_t \quad (1)$$

d (the number of times the original observations are differenced to remove trend and seasonality). The exact mathematical equation is as follows:

$$x_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots \cdot - \theta cc_P \varepsilon_{t-p} \quad (2)$$

q (the number of lagged forecast errors in the forecast equation).

3 Empirical Results and Analysis

3.1 Order Determination and Residual Test

In this stage of the research, the logarithmic series of sales must first be analyzed and ranked using the autocorrelation function (ACF, Figure 1) and partial autocorrelation function (PACF, Figure 2).

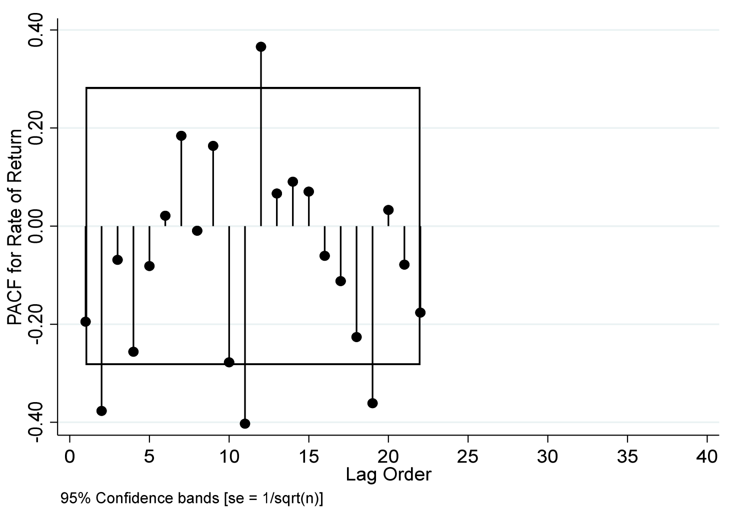

Fig. 1. PACF.
Photo credit: Original

If the ACF plot exhibits a tailing pattern and the PACF plot shows a considerable truncation of the tail, it typically means that the AR model can handle the time series data. The MA model is frequently advised when the PACF plot displays a trailing pattern and the ACF plot indicates a sudden truncation. The lag order of the ACF truncation influences the value of the parameter q. The MA model may be used to help determine the value of the parameter [10]. Based on this, this part can construct an ARIMA(p,d,q) model for these four data sets in a fixed order. After building the model, a residual test is performed, and result is shown: the portmanteau statistics value (q) is 20.8722 and the p-value is 0.9718 under the circumstance of degree of freedom equals to 35. They obviously pass the residual test, indicating that they exhibit good unpredictability and that the error term corresponds to a white noise sequence [10].

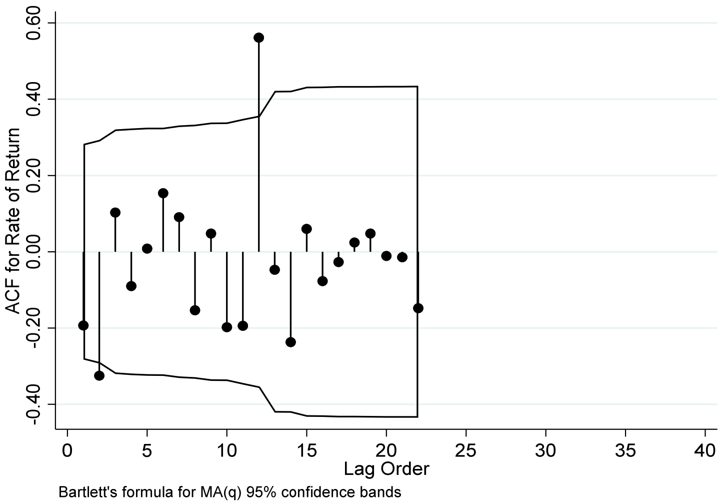

Fig. 2. ACF.
Photo credit: Original

3.2 Forecast Results and Interpretations

This paper made forecasts using the ARIMA model (11,1,2) with data from March 2021 to February 2022. The model considers seasonality (11 periods), first difference (reducing trend) and autoregressive terms (2 lag periods), which help us capture trends and cyclical changes in sales data.

The following Table 2 shows the values predicted based on the basic data set and the ARIMA model.

Table 2. Comparison.

	Sales	PV	Difference	%
2021-03-01	226000			
2021-04-01	206000			
2021-05-01	217000			
2021-06-01	256000			
2021-07-01	271000			
2021-08-01	321000			
2021-09-01	357000			
2021-10-01	383000			
2021-11-01	450000			
2021-12-01	531000			

2022-01-01	431000			
2022-02-01	334000	337527.7	-3527.74	-1.05%
2022-03-01	484000	517611.3	-33611.3	-6.49%
2022-04-01	299000	493878.7	-194879	-39.46%
2022-05-01	447000	444486.9	2513.09	0.57%
2022-06-01	596000	497380	98620.01	19.83%
2022-07-01	593000	476587.8	116412.2	24.43%
2022-08-01	666000	482024.6	183975.4	38.17%
2022-09-01	708000	509168.4	198831.6	39.05%
2022-10-01	714000	546672.5	167327.5	30.61%
2022-11-01	786000	588537.2	197462.8	33.55%
2022-12-01	814000	669492.4	144507.6	21.58%

It can be seen from the sales data from March 2021 to December 2022 that sales volume shows fluctuations and growth in most months. Sales are predicted to expand considerably after June 2022, owing to rising market demand and the development of new energy technologies.

The following predictions and interpretations may be drawn by contrasting the ARIMA model's forecast results with the actual sales data:

Sales trend in 2023: According to the ARIMA model prediction, new energy sales are expected to continue to grow in 2023. From historical data, sales usually have a significant growth cycle in the second quarter of each year, which may be due to seasonal demand and market dynamics.

Monthly growth rate: According to the data of the past few months, the sales growth rate has improved significantly after June 2022. It is expected that this growth trend may continue until 2023, especially if there is more progress in new energy technology innovation and market promotion.

Technological advancements and government backing for new energy: These two factors have been crucial in driving sales growth.With the increase of environmental awareness and the decrease of the cost of new energy technology, consumers' acceptance of new energy products may further increase, thereby driving sales growth.

Uncertain factors:

The conflict between Russia and Ukraine has had a major impact on new energy vehicle sales in China.The fact that the actual data set exceeds the anticipated data set further demonstrates the beneficial effect of the Russia-Ukraine crisis for China's new energy vehicle sales.

Market fluctuations and competition: Although the forecast shows a clear growth trend, market fluctuations and competition remain uncertain factors that affect sales data. Changes in the global energy market and geopolitical events may have an impact on the new energy industry, and market dynamics need to be closely monitored.

4 Discussion

Comparing the model's forecast results with the actual sales data helps to gain a deeper understanding of the model's accuracy and its forecast bias. From the actual sales data from February to December 2022, people can observe some differences and trends between the model forecast and the actual data:

In the sales data for April 2022, the actual sales volume was significantly lower than the forecast, which may be affected by market fluctuations or unconsidered factors such as increased competition or supply chain problems.

On the contrary, in June and July 2022, actual sales were higher than the forecast, indicating an increase in market demand or an underestimation of the market response speed by the model.

Factor analysis:

External conditions: The Russian-Ukrainian conflict inevitably raised the price of crude oil throughout the world, which also forced consumers to look for cheaper and more cost-effective alternatives, such as new energy vehicles. This directly led to a sharp increase in the sales of new energy vehicles in China.

Policy and market environment: Policymakers can learn from these data the direct impact of policy support and changes in the market environment on new energy sales. For example, the policy push and fluctuations in market demand will have an important impact on sales data.

Technological progress and cost changes: With the advancement of technology and changes in costs, the market competitiveness and consumer acceptance of new energy products are also evolving, and these factors need to be fully considered in future policy making.

Research significance and policy implications

The significance of this study is that it offers a comprehensive insight of the dynamics of the new energy market and provides the following implications for policymakers:

Quantitative analysis support: The application of the ARIMA model provides policymakers with a quantitative analysis tool to predict future new energy sales trends and changes in market demand. This helps to formulate more targeted and sustainable policy measures.

Market response speed: By comparing actual data with model predictions, policymakers can evaluate the market's response speed to policy changes and technological progress in order to adjust the strategy and timing of policy implementation.

Risk management and policy adjustment: Identifying the difference between model predictions and actual data can help to warn of market risks in advance and adjust policy measures promptly to encourage the healthy development of the new energy market.

5 Conclusion

Based on the analysis and comparison of ARIMA model prediction results and actual sales data, this study draws the following main conclusions:

Research shows that the ARIMA model (11, 1, 2) performs well in predicting China's new energy sales data in 2023. The model successfully captures seasonal changes and trends in sales data, and forecast accuracy improves significantly, especially after taking into account market dynamics over the past few months. However, there are certain deviations between actual sales data and model predictions, especially during periods of high market volatility. This shows that future sales trends are affected by many factors, including policy changes, external conditions, market competition and technological progress. As a result, policymakers should employ adaptable policies to respond to changes in market dynamics and maximize the growth environment of the new energy market through continual monitoring and modification. Of course, there are also some flaws in this study. As mentioned above, this study only compared China's new energy vehicle sales data when there was a conflict between Russia and Ukraine and when there was no conflict between Russia and Ukraine. In this case without controlling variable, there are too many confounding variables, and the true relationship cannot be completely determined. This analysis fails to account for the influence of China's new energy subsidy program enacted during the Russia-Ukraine war on new energy vehicle sales.

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