Yield and Volatility of Tesla Stock under the Normalized Covid-19 Pandemic

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Abstract. Due to the changing national and local policies worldwide caused by the raging situation of COVID-19, the car chip supply chain across the world has been impacted severely. This paper assesses the yield and volatility of, an American automobile and clean energy company, Tesla's stock price with the dreadful COVID-19 pandemic. To study the changes in yield and volatility of the selected stock price with two influencing factors, which are exchange rate (USD to CNY) and automobile chip shortage, a VAR model and an ARMA-GARCH model are used in this research. Empirical results indicate that, during the COVID-19 pandemic, increasing the exchange rate has a negative impact on Tesla's stock return as well as enlarging its volatility, when the previous stock price has been considered as a significant implication on its hereafter price.

Keywords: Exchange rate, COVID-19 pandemic, Automobile chip industry, Stock volatility, Stock price fluctuation.

1. Introduction

In late December 2019, people in Wuhan, China began to contract a never-before-seen infectious disease that was later confirmed and named coronavirus (COVID-19). The disease outbreak spread rapidly and escalated dramatically around the world, with unexpectedly high numbers of infections and deaths. Facing such a crisis, substantial economic loss happens in every nation [1]. As of July 11, 2022, there were 556.8 million confirmed cases worldwide and 6.36 million deaths. Faced with such a significant public health threat, many countries are beginning to limit unnecessary behavior by citizens to prevent further damage. With the introduction of self-isolation and lockdown policies, people have become accustomed to working and living online. With fewer economic activities, many industries were struck, like the transportation industry, manufacturing industry, and finance industry.

There are works of literature that have shown there is a non-negligible relationship between stock yield and pandemic outbreaks, and governments' strategies on public health, including restricting public gatherings and canceling public events, have a positive effect on stock return in the same period [2, 3]. During the pandemic, the federal government and state governments of the United States appealed to citizens to stay at home and self-quarantined if they are feeling uncomfortable with a certain amount of subsidy provided to get through this hard moment. With fewer economic activities and a shortage, the United States has an increasing unemployment rate and higher inflation rate. To accommodate the circumstances, U.S. Federal Reserve System has raised the federal interest rate multiple times. The most recent announcement was to raise the federal funds rate by 75 basis points to a range of 2.25% to 2.5%, in July 2022. With increasing federal interest rates, the market reacts immediately. Primarily having the phenomenon that more investors favor U.S. dollars and U.S. financial market.

The epidemic disrupts people's normal life, macroeconomic development, and business operation. Across the industries, many companies have experienced up and down even multiple times along with the increasing number of infected cases, the invention of COVID-19 treatments, and income subsidies during the epidemic. The transportation industry and semiconductor for auto industry which relate to population mobility are hit like many others [4]. For there are fewer human activity and hurt on the global supply chain brought by lockdown docks and delayed cargo ships since the COVID-19 outbreak, the hefty hit on these industries is fundamental to areas and nations. After ships were forced to stay near docks with not enough labor restoring and delivering the cargos, automobile chips, as one of many required raw and processed materials for human society, became rarer for manufacturing new vehicles and repairing the old ones. The supply chain system disruptions impact entire industries [5]. As an inevitable result, the price of brand-new and used vehicles rises in both the United States and China, and the sales volume decrease in the whole auto industry [6]. Although in countries that loosen the restricting policies, initial signs show the auto market may recover very fast, it may need more time than expected [6]. The hardness companies facing may be the catalyst to accelerate the process of making changes, like building their supply chain and inventing new models, to accommodate the new threats and customers' new demand. In the post-pandemic era, an innovative online EV selling model might be the primary channel for purchasing EVs if the isolating policy continues [7].

All these findings show the harm and seriousness of the impact of the epidemic on the auto industry while revealing the uncertainty of how the auto industry performed in the late COVID-19 era, which has inspired further research into the performance of the global automotive industry during COVID-19. Develop from this idea, this paper intends to discover advanced corresponding relationships between the automotive industry and COVID-19. To achieve the goal, Tesla, which has a stock ticker as TSLA, is chosen as the case.

This paper researches the TSLA stock price fluctuation, primarily focusing on TSLA's value and volatility. First, this paper will research TSLA's value of price, which gives the stock return and shed some light on the whole industry's return. This paper builds a VAR model, creating a three variables model, to find out the relationship between exchange rate and stock price; and exchange rate and automobile chip index in logarithmic data series. VAR model will give us the values in future periods based on the past values. With impulse response graphs drawn to visualize the future periods of variables' values, the change and demonstration of the value are direct and obvious. Second, this paper constructs an ARMA-GARCH model to discover whether the exchange rate and automobile chip index influence Tesla's stock volatility, which indicates the risk and how influential they are quantitatively in processed data series. In the last section of the paper, researcher analyzes the gathered information from both the VAR model and the ARMA-GARCH model. The importance of the result found from the GARCH term is also discussed in the section. Finally, this paper draws conclusions based on what's found in the model.

2. Research Design

2.1 Data Source

Data that relates to the COVID-19 pandemic worldwide is derived from the Global COVID-19 Tracker of Kaiser Family Found. This COVID-19 tracker visualizes data of confirmed cases and deaths from John Hopkins University Coronavirus Resource Center and the World Health Organization (WHO), with data table provided, by population, income level, and region. It uses Population data from United Nations World Population Prospect for most of the countries listed by region, country, income-level data from World Bank Country and Lending Groups, and regional classifications from WHO. By separating the features, the public and policymakers can easily see the difference between the different groups in these categories.

This paper uses exchange rate, stock price data, and automobile chip index data according to the data from East Money Information Co. Since stock price and automobile chip index change during trading days when the exchange rate fluctuates continuously, the research only contains the trading days and sort them by date. In this research, Stata is used to process data and solve the encountered matters.

2.2 Unit Root Test

To confirm the stationarity of a time series, a Unit Root Test is introduced in the research. A stationarity check is necessary since most of the quantificational analyses of time series that are not stationary are hard to predict the results in future periods. The research has the presumption that the time series is stationary. If the time series is stationary, the research can proceed to the next step. Otherwise, another method should be introduced to ameliorate the result.

When doing a Unit Root Test to check the stationarity, this paper assumes that the time series x_t is:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \, \Delta x_{t-i} \; + \; \varepsilon_t \tag{1}$$

In the statistical hypothesis testing, the null hypothesis is that the coefficient $\beta = 1$, which indicates that the series under test is not stationary, and an additional method to improve the result is needed. The alternative hypothesis of the test is the coefficient $\beta < 1$, which indicates the series under test is stationary.

Table 1 provides the t-statistics and p-value as test results of raw data and the logarithm series of the original data:

Table 1. ADF test

Variables	t-statistic	p-value
Price		
Tesla	-1.953	0.6268
Automobile chip	-1.573	0.8029
US-RMB	-0.813	0.9646
Yield		
Tesla	-12.704	0.0000***
Automobile chip	-13.932	0.0000***
US-RMB	-13.210	0.0000***

Note: *, **, and *** indicate the significance level of 10%, 5%, 1%, correspondingly.

Raw data of Tesla, Automobile chip, and US-RMB (exchange rate) is observed as not statistically significant while all processed data is statistically significant under even 99% confidence intervals. Table 1 has provided sufficient evidence for the fact that the research can proceed to build the models with stationary series.

2.3 VAR Model Specification

The Vector Autoregressive (VAR) model is based on the Autoregressive (AR) model. The VAR model allows researchers to discover the relationship between interested variables and predict them based on the system. It mainly focuses on the prediction and dynamic dependencies of variables of a multivariate time series model.

Expanding from the structure of AR model, VAR introduces each variable separately, having a linear combination of its past value and others' past values, in the system.

A bivariate VAR(p) system that has two response variables $\{y_{1t}, y_{2t}\}$ and explanatory variables as their lagging value after 1 lag terms can be written as:

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \gamma_{11} y_{2,t-1} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \varepsilon_{2t} \end{cases} \tag{2}$$

When the bivariate VAR(p) System above has variables' lagging value after p lag terms can be written as:

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \cdots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{2,t-1} + \cdots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-1} + \cdots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{cases} \tag{3}$$

In (2) and (3), as described above, $\{y_{1t}, y_{2t}\}$ are two response variables. β_t and γ_t are corresponding terms in period t in the system. ε_t is the error term in period t.

2.4 ARMA-GARCH Model Specification

2.4.1 ARMA Model Specification

An ARMA model, designed to make use of the feature of both AR model and MA model, is a combination of an Autoregressive (AR) process and a Moving Average (MA) process. It utilizes past values and errors to predict future values.

An AR process is on the condition that assuming data of the time series in the past is considered an important variable when estimating the value of the future term. In an AR(p) model, the parameter p is the largest lag order of the lag terms. An AR(p) model has the formula:

$$y_t = \emptyset_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

where the $\emptyset_0$ is the fixed value, y_t is the value of the sequence in period t, and ε_t is the stochastic term in period t.

The function of a MA process is predicting the value in the next period based on the current and past data of stochastic terms. These data represent the error of predictions in the known periods. A MA(q) model has the formula:

$$y_t = c_0 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{5}$$

where c_0 is the fixed value, y_t is the value of the sequence in period t, and ε_t is the stochastic term in period t.

Composing the AR model and the MA model, the ARMA(p,q) model has a formula:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{6}$$

where c is the constant, y_t is the value of the series in period t, and ε_t is the stochastic term in period t.

2.4.2 ARCH Model Specification

Before 1982, a lot of economic time series exhibited agglomeration of volatility, which is a valid reason for researchers and scholars to introduce a new variance equation. In 1982, the autoregressive conditional heteroskedasticity (ARCH) model, invented by Engle, solves the problems caused by assuming the variance of times series is a fixed value in the traditional econometrics model. All the currently available information, and past values, are used in the ARCH model. In the meantime, the model uses some autoregressive form to represent the changing variance [8, 9]. For a time series, due to the limitation of having the available information at a different moment, the corresponding conditional variance changes accordingly. The ARCH model can distinguish the changing conditional variance as time goes by. The ARCH(p) model has a formula:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{7}$$

where ω is an unchanged constant, σ_t^2 is the square of the forecast variance in period t, and ε_{t-i}^2 is the square of the actual variance in period t.

2.4.3 GARCH Model Specification

To fully describe the fluctuation process of stock prices, it is often necessary to introduce many parameters. In 1986, the invention of Generalized ARCH (GARCH) by Bollerslev is an advanced model that was inspired by the basis of the ARCH model but with a more flexible lag structure. It is designed to meet the demand for higher order in the model [9, 10]. A GARCH (p, q) model can be written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{p} \beta_i \varepsilon_{t-i}^2 \quad (8)$$

In the model, ω is a constant. ε_t is a series of independent and identically distributed (i.i.d) stochastic variables, following a standard normal distribution. σ_t^2 is variance.

2.4.4 ARMA-GARCH Model Specification

Volatility and risk are considered ones of the most important factors in financial markets and many other industries. To focus on estimating the risk and stock return, ARMA-GARCH model uses the strength of ARMA model to analyze past values and GARCH model to predict past error terms. In this section, the paper uses three stationary series to select the VAR order: logarithmic Tesla stock price, logarithmic exchange rate, and logarithmic automobile chip index in China. By using VARSOC in Stata, Table 2 VAR model identification, which is shown below, provides evidence that 5 orders will be used.

3. Empirical Result

3.1 VAR identification and its stability

In this section, the paper uses three stationary series to select the VAR order: logarithmic Tesla stock price, logarithmic exchange rate, and logarithmic automobile chip index in China. By using VARSOC in Stata, Table 2 VAR model identification, which is shown below, provides evidence that 5 orders will be used. After building VAR (5) model, using varstable in Stata, figure 1 is drawn. If the condition of the eigenvalue is stable is confirmed, after evaluating the variables of a vector autoregression, the dots that represent the eigenvalues will fall inside the unit circle. By reading figure 1, the paper confirms that this VAR system is stable.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2859.78				3.9e-12	-17.744	-17.7299	-17.7088*
1	2879.62	39.685	9	0.000	3.7e-12*	-17.8113*	-17.7552*	-17.6707
2	2885.91	12.573	9	0.183	3.8e-12	-17.7945	-17.6962	-17.5483
3	2888.5	5.1882	9	0.818	3.9e-12	-17.7547	-17.6143	-17.403
4	2892.58	8.1467	9	0.519	4.0e-12	-17.7241	17.5416	-17.2669
5	2904.86	24.572*	9	0.003	3.9e-12	-17.7445	-17.5198	-17.1818
6	2908.81	7.9008	9	0.544	4.1e-12	-17.7131	-17.4464	-17.045
7	2914.61	11.605	9	0.236	4.2e-12	-17.6933	-17.3844	-16.9196
8	2917.36	5.4983	9	0.789	4.3e-12	-17.6544	-17.3034	-16.7753
9	2922.22	9.7203	9	0.374	4.4e-12	-17.6287	-17.2356	-16.6441
10	2929.43	14.419	9	0.108	4.5e-12	-17.6176	-17.1824	-16.5274
11	2934.23	9.5932	9	0.384	4.6e-12	-17.5915	-17.1141	-16.3958
12	2935.32	2.178	9	0.988	4.8e-12	-17.5424	-17.0229	-16.2412

After building VAR (5) model, using varstable in Stata, figure 1 is drawn. If the condition of the eigenvalue is stable is confirmed, after having the parametric estimation of a vector autoregression, the dots that represent the eigenvalues will fall inside the unit circle. By reading figure 1, the paper confirms that this VAR system is stable.

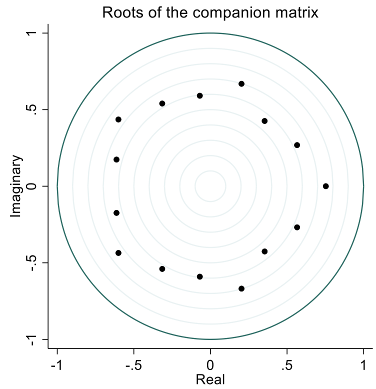

Figure 1 VAR stability

3.2 Impulse Response Graph of the VAR Model

Figure 2 shows the impulse response results of variable Tesla stock price and variable Automobile chip index. It can be observed that the change in exchange rate has affected the Tesla stock return negatively in short term. Specifically, if the exchange rate in the current period rises by 1%, that is, in the case of the appreciation of the US dollar and the depreciation of the RMB, the net impact of exchange rate changes on Tesla's stock returns in the next 10 periods will be negative, and the impact will reach its maximum value in the fifth period, which is about 0.15%. In terms of the time effect, the effect gradually decays to 0 after 10 periods, which are trading days.

From the graph results of the automobile chip on the right side of figure 2, the current appreciation of USD has a negative effect on the automobile chip index. Since China is dependent on automobile chips, there may be an overreaction in the market in the current period. In the future, the emission is positive. Overall, it has zero effect.

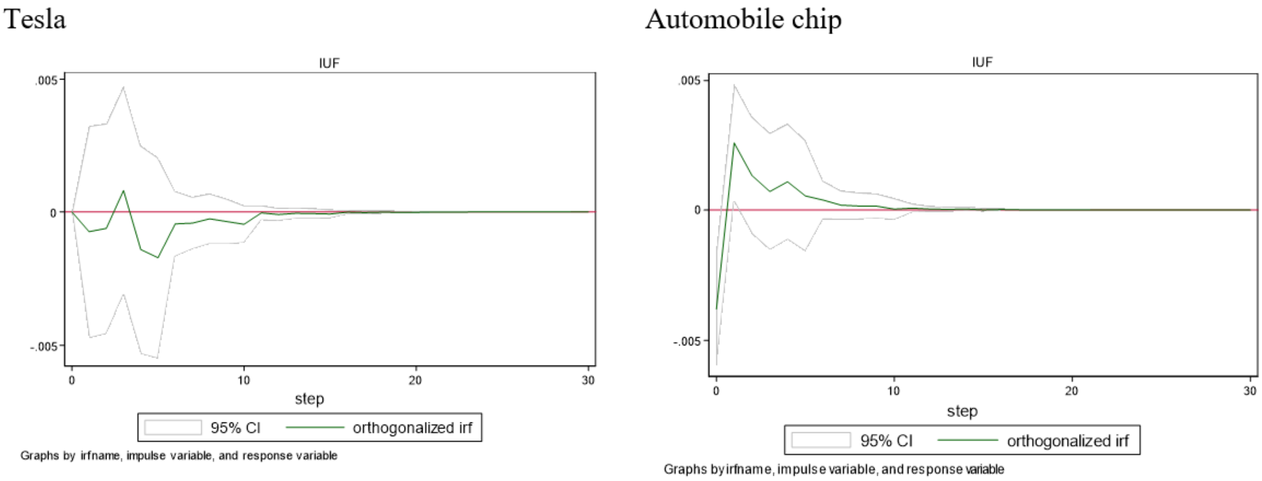

Figure 2 Impulse and response

3.3 ARMA identification

To build an ARMA-GARCH model, using the series in Stata, the paper selects the order of the AR process through the Partial Autocorrelation Function (PACF) and the order of the MA process through Autocorrelation Function (ACF). PACF and ACF are shown in Figure 3. The black rectangle and vertical lines are the ones used to check if there is a statistically significant term in AR process. The selected orders will be the ones where the dot lies outside of the rectangle. From the PACF point of view, the paper found that the lags of 15 terms, 31 terms, and 33 terms of the processed data sequence possibly have a remarkable effect on the present period data.

From the ACF Plot, which determines the MA process of the series, it is perceived that lag 15 term is the only feasible choice.

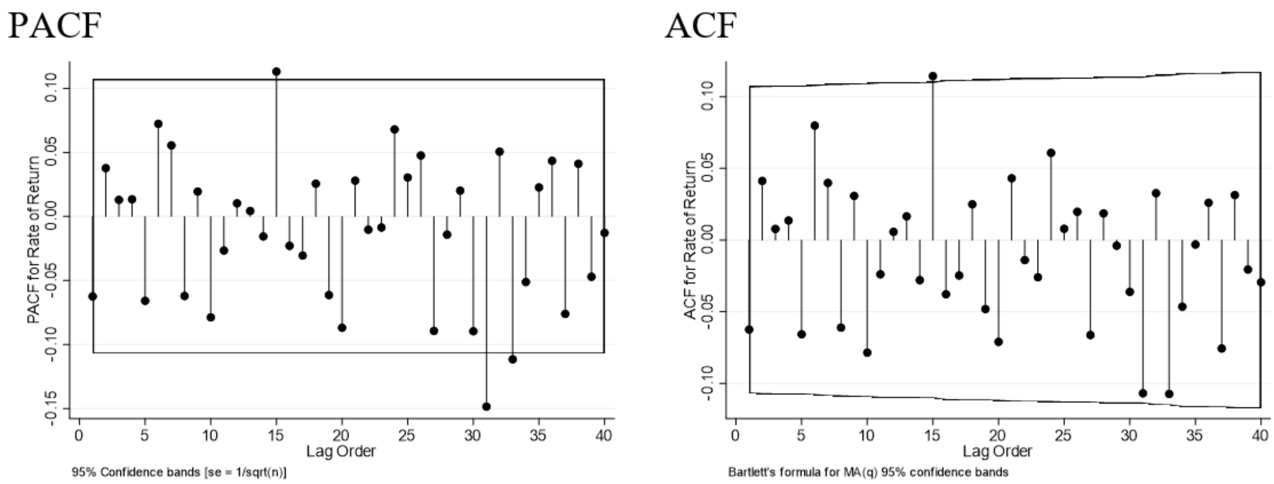

Figure 3. PACF and ACF

3.4 ARMA-GARCH Model Result

Building the ARMA-GARCH model with the arch in Stata and setting ARMA (15,15)-GARCH (1,1), Table 3 is printed. This ARMA-GARCH model is with exogenous lag terms of the Exchange Rate or the Automobile Chip Index. As mentioned before, this research is more interested in the variance equation of the model which represents whether the volatility of the Exchange Rate and the Automobile Chip Index would be the causation of the change of stock in Table 3.

Table 3. ARMA-GARCH estimation results, The variance equation

Variables	(1)		(2)	
	Coef.	Std. err	Coef.	Std. err
Exchange rate	367.3245***	71.7330		
Automobile chip			-40.8511***	10.18472
ARCH (-1)	0.0789***	0.0301	0.0695***	0.0236
GARCH (-1)	0.8841***	0.0375	0.9037***	0.0346
Constant	-10.2239***	0.4085	-10.5596***	0.5505

According to the result of the variance equation with multiplicative heteroskedasticity, the rise in the exchange rate has a significant influence on the daily volatility of Tesla stock. When the logarithmic rate of return of the exchange rate increases by 1 unit, the daily volatility of Tesla stock increases by 367.3245, with a coefficient that is statistically significant at the 1% level.

Over and above that, an increase in the automobile chip's logarithmic yield reduces the daily volatility of Tesla's stock returns. When the logarithmic rate of return of the Automobile chip index increases by 1 unit, the daily, the daily volatility of Tesla stock decrease by 40.8511. The coefficient is statistically significant at the 1% level.

4. Discussion

This article primarily focuses on how Tesla stock price volatilizes along with the changing exchange rate and automobile chip index under the COVID-19 global pandemic. The research discovers that Tesla's stock price strongly relies on its past value when it is also severely impacted by the current events like the changing exchange rate and volatilizing automobile chip index in the short run. However, influences of exchange rate and automobile chip index on Tesla stock price are invisible in the long run.

The outcome from the VAR model indicates the fact that when the value of USD increases against CNY, there is a volatile range over time. Interpreted from the graph, it is 10 periods. As an American company, when the US dollar is appreciated and the CNY is depreciated, considering that Tesla's sales in China account for a very high proportion if it is assumed that there is price rigidity, that is, the price cannot be adjusted in the short term, then the increase in the exchange rate will have a negative impact on Tesla.

The ARMA-GARCH model variance equation finds that the exchange rate has a positive effect on Tesla's stock volatility and the automobile chip index has a negative effect on Tesla’s stock volatility. It is most likely that when U.S. dollars are favored, global investors would favor stocks in the U.S. market more than the Chinese stock market. When the market reacts to the currency exchange rate quickly, U.S. companies’ stock prices increase immediately. Secondly, companies that rely on imports, like Tesla which has a Shanghai factory as a primary vehicle exporting hub, will have lower costs and higher gross margin rates overall in its annual financial report. Changing exchange rates and the lockdown policies in China also affected the expectation of investors of Tesla’s annual profit in USD. Worrying about if the expected return will be hit, the daily trade volume of Tesla stock increases which leads to higher volatility. Moreover, the automobile chip index has a negative effect on Tesla’s stock volatility. It might happen because a stable index price reflects investors’ confidence in the industry. As one of many companies in the automobile industry, Tesla takes benefits from it. Instead of trading the shares, during certain trading periods, investors were more likely to hold the shares which lead to lower trading volume and lower volatility [11].

Further research on Tesla’s stock price can be carried out from two aspects: First, the model could be optimized by adding in other exogenous variables like inflation rate and unemployment rate. With more exogenous variables, future researchers can conduct research on the long past of time. Second, to further work on the relationship between stock return and risk. GARCH-M model, which primarily studies if there is a risk premium and how much it would be, can be introduced [12].

As a leading company in the clean energy industry and automotive industry, Tesla has many edging technologies, and predicting its future stock price has important meaning to the development of the industries. Especially during this hard moment, the change in Tesla stock price is a weathervane for investors.

5. Conclusion

COVID-19 Pandemic hit the global economy hard with no exceptions. Data is collected from the data between January 2021 and July 2022, a period during the COVID-19 pandemic. This is the period when nations have published policies and reacted to the serve contagious public health situation. While efforts were made in the period, the epidemic continues to jeopardize the global economy. Of all the industries and companies, the automobile industry is selected, and Tesla is studied as the targeted company in this research to reflect how a multinational company’s stock price volatilizes along with the changing exchange rate and industry-related index during this extreme period, considering its past value plays a vital role. Based on what the study found, this paper discovers currency exchange rate has a positive relationship with the volatility of Tesla’s stock through the ARMA-GARCH model and a negative relationship between the exchange rate and Tesla’s stock return through the VAR model.

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