Portfolio Optimization for New Energy Vehicles and Traditional Vehicles Enterprises

Yu Chen[1, *, †], Jiaheng Zhang[2, *, †]

[1]College of Information Engineering Shanghai Maritime University Shanghai, China

[2]College of Applied Maths Duke Kunshan University Kunshan, China

*Corresponding author: 201810311143@stu.shmtu.edu.cn, jz372@duke.edu.cn

[†] These authors contributed equally.

Keywords: GARCH, CCC-GARCH, ARIMA

Abstract: This paper performs asset portfolio allocation on new energy vehicles and conventional energy vehicles assets. The comparison of asset ratios allows us to know which enterprises are more worthy to invest which has rarely been studied. This paper use GARCH MODEL, CCC-GARCH model, ARIMA model and optimization model to study the performance six stocks of traditional vehicles enterprises and new energy vehicles enterprises. The results show that traditional energy vehicles enterprises are more stable and worthy of investment than new energy vehicle enterprises; future stocks of new energy vehicles enterprises have higher share price but relatively unstable; if some want minimum risk portfolio then traditional vehicles enterprises need investing more; If some want to get high return, then new energy vehicles enterprises need investing more. The results in this paper benefit the related investors in financial markets.

1. Introduction

People are entering an exciting and challenging time for automotive industry. For the first time electric vehicles are starting to displace the 1 billion or so internal combustion engine vehicles (EVs) in the world. In 2019, approximately 6 million EVs were sold out, out of 90 million light vehicles and this number is expected to grow to over 30 million a year by 2030 [1]. Therefore, the stock of new energy vehicles especially like Tesla, the market value of which has reach more than 1 trillion dollars. Before getting to the point, this paper clarifies two concepts: new energy vehicles enterprises and traditional vehicles enterprises. In fact, many old automobile enterprises which founded before 21st century like Benz, Ford are trying to transform themselves into making new energy automobiles. However, the differences between old and new one can be concluded into two aspects: 1. New energy vehicles enterprises only produce new energy vehicles (NEVs) while for the old enterprises, conventional vehicles still occupy their main market at present. 2. The organizational structure of enterprises is completely different in that new energy vehicles enterprises are more based on flat management, and they focus more on consumer experience.

Recently the stocks of NEVs enterprises are turning into hotspot because some of them show high return in a short period. People and some fund companies are sometimes obsessed with whether to buy new energy vehicles enterprises' stocks or continue to buy traditional vehicles enterprises' stocks. This paper is devoted to giving individual investor and fund companies advice on managing their portfolios on investing in vehicles enterprises especially new energy vehicles enterprises according to different types of investment willingness so as to enhance return and help them get through the economic crisis the pandemic brings about. Moreover, authors find out different possible fluctuation of new energy vehicles enterprises and traditional vehicles enterprises so as to avoid some possible risks. Authors also manage to predict the stock of the chosen stocks.

Owing to short marketing time, observations on stocks of new energy vehicles enterprises are few. Bass model was once used to predict EV's stock, which indicated that stock EV would create a boom in China within 10 years [2]. A scholar also once prognosticated the stock of new energy vehicles enterprises in China by logistic model and also try find the future path for these enterprises [3]. Another kind of research is about the factors that affect the stock or market value of electric vehicles enterprises. For this new field, innovations and technology were two essential parts in fierce competition of new energy vehicle [4]. Moreover, appropriate policy was considered as the fundamental driving force of the development of EVs [5].

However, there are few research done studying the stocks of new energy vehicles enterprises and traditional vehicles enterprises and make a comparison. And this paper needs an optimized portfolio study to find out the best one. The empirical investigations can be summarized as follows. First, this paper performs volatility analysis for each asset using the GARCH model. Also, this paper applies the CCC-GARCH model to get the one-step-ahead prediction volatilities. In this step authors get the volatility of each asset and their future volatility trends. Authors eventually find that new energy vehicles' asset volatility is greater than traditional energy vehicles. Second, this paper uses the ARIMA model to analyze the time series of asset prices. In this step authors obtain the historical price changes of the assets and the future price trends. Authors conclude that, compared to traditional energy vehicles, the share price of new energy vehicles is higher but the volatility is relatively greater. Besides, this paper optimizes the portfolios using the Markowitz model and found the efficient frontier using Monte Calo simulations. In this crucial step, this paper finds the maximum Sharpe ratio point and the minimum volatility point. Authors conclude that to get higher returns, invest a greater percentage in new energy vehicles. On the other hand, to reduce volatility, invest a greater percentage in traditional vehicles.

The remainder of the paper is structured as follows. Section 2 details the data as well as the methods and models this paper uses. Section 3 describes the results that authors obtain from the methods. Section 4 elaborates the conclusions.

2. Data and Methods

2.1 Data

The stock prices of TESLA, NIO, BYD, VOLKSWAGEN, BMW and TOYOTA are found on Yahoo Finance (https://finance.yahoo.com). The reason why we choose these six enterprises is that they are all leading ones in automobile industry and is typical of new energy or traditional enterprises. We use the closed price and open price of each stock for around three years and gain the data from Yahoo Finance.

2.2 Methods

The main methods for measuring volatility are traditional regression analysis, time series analysis, value-at-risk modeling, portfolio analysis, capital asset pricing modeling, GARCH family modeling, and so on [6]. In recent years, scholars have argued that GARCH family models can better fit stock market volatility [7]. GARCH family models are based on historical information to determine the future by building up appropriate models and historical information to predict the future. Scholars have used GARCH family models such as ARCH model, GARCH model, EGARCH model, TGARCH models, and GARCH (1, 1) models to measure stock market volatility, and have now reached the unanimous conclusion that GARCH (1, 1) models are the best way to measure stock market volatility. The unanimous conclusion is that the GARCH (1, 1) model is better. Therefore, in this paper, we use the GARCH (1, 1) model for the volatility analysis of assets.

The GARCH (1, 1) model is often used as a modeling tool in real-world problems, and the model is represented as:

$$r_t = \mu_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sigma_t z_t \tag{2}$$

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

In the mean equation, μ_t denotes the expected return and ε_t is the residual term, i.e.

unanticipated return. In the variance equation, ω is the constant term. r_{t-1}^2 is the ARCH term, and the lag of the squared perturbation term of the mean equation is used to measure the volatility information obtained from the previous period. σ_{t-1}^2 is the forecast variance of the previous period which represents the GARCH term.

The CCC-GARCH model is a constant conditional correlation model proposed by Bollerslev [8]. This model is commonly used to estimate and predict the covariance array of financial assets.

According to Bollerslev's study, let the return of k assets rate vector be r_t. Assume that it follows a multivariate normal distribution:

$$r_t \mid \Phi_{t-1} \sim N(0, H_t) \tag{4}$$

$$H_t \equiv D_t R D_t \tag{5}$$

H_t is the constant conditional covariance matrix of k assets. R is the $k \times k$ constant coefficient correlation matrix.

$$D_t^2 = diag\{\omega_i\} + diag\{k_i\} \circ r_{t-1}r'_{t-1} + diag\{\lambda_i\} \circ D_{t-1}^2 \tag{6}$$

$$R = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & 1 & \cdots & \rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1} & \rho_{n2} & \cdots & 1 \end{bmatrix} \tag{7}$$

The main method for predicting the trend is using the ARIMA model, which combines the AR and the MA terms. ARIMA, which is short for 'Auto Regressive Integrated Moving Average' is a kind of models that explains a given time series based on its own past values. It is a model that use its own lags and the lagged forecast errors, so that equation can be used to forecast future values and it is defined as:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p}\epsilon_t + \phi_1\epsilon_{t-1} + \phi_2\epsilon_{t-2} + \cdots + \phi_q\epsilon_{t-q} \tag{8}$$

In ARIMA, "d" refers to differentiation required to make the time series stationary; "p" is the order of AR, which means the number of lags of Y to be used as predictors. And "q" is the order of MA, means the number of lagged forecast errors that should get into ARIMA model [9]. Using ARIMA model, we get the prediction of the six stocks. Using analysis of NIO as an example, we first work out the first order difference and find that the data is stable enough to proceed. We then draw QQ plot to tell whether the differentiated data conform to normal distribution. Acf and Pacf graph is used to obtain "p" and "q".

As for optimization, we first calculate the daily average return of the six stocks. Then we use Markowitz's portfolio theory to conduct the portfolio optimization. There are three hypotheses: single investment period such as one-year, high liquidity no transaction costs, the choice of investors is based on the optimal mean variance. The efficient frontier is used in this optimization model. A portfolio, is referred to as "efficient" if it has the best possible expected level of return for its specific level of risk. Every possible combination of risky assets can be plotted in risk–expected return graph, and the collection of all such possible portfolios defines a region in the graph. And from the efficient frontier graph, we can get the best combination of different stocks. The efficient frontier curve tells us that under the condition of full investment, all investors based on risk aversion should choose the portfolio on the efficient frontier curve, which is the best mean variance. It is a linear combination of minimum risk combination and optimal sharpe combination.

3. Results

3.1 GARCH

Based on the assets that we selected in the paper, we calculate them separately using the GARCH model. We are able to obtain whether the volatility of the historical returns fits a normal distribution. Meanwhile, we are able to get images about the volatility of the historical returns to visualize the results. The results are shown in the figures below.

Fig.1 is the Tesla stock price growth line and Fig.2 is the annualized conditional volatility of Tesla. Fig.1 maintains that Tesla stock prices have risen since May 2020. As shown in Fig.2, the volatility raised around the beginning of 2020, when the COVID-19 broke out.

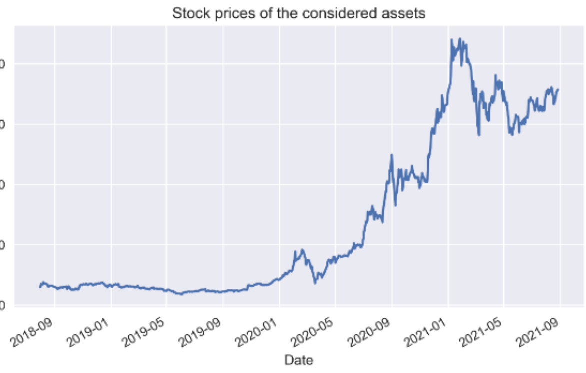

Fig. 1 TSLA Stock Prices

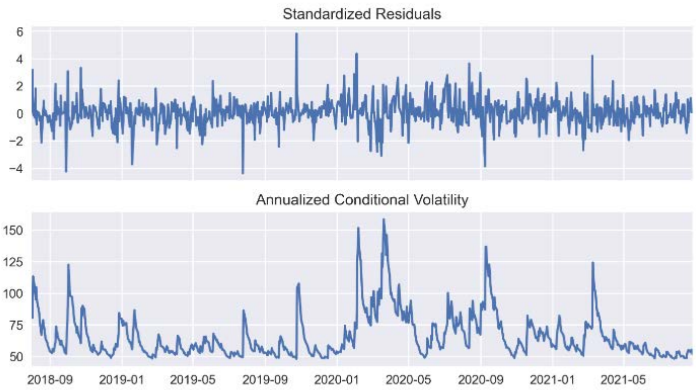

Fig. 2 TSLA Annualized Conditional Volatility

Fig.3 is the NIO stock price growth line and Fig.4 is the annualized conditional volatility of NIO. Fig.3 maintains that the prices were stable until September 2020 and then went up. As shown in Fig.4, the volatility changed little. However, comparing the values, the volatility is greater than the volatility of Tesla stock.

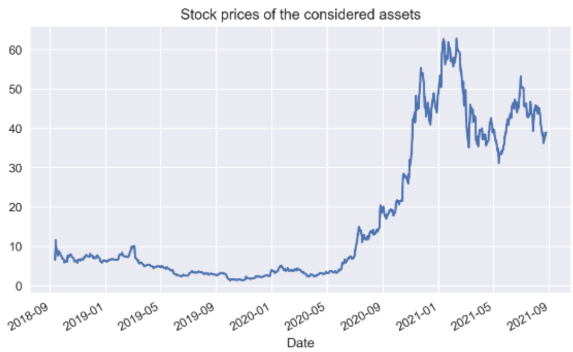

Fig. 3 NIO Stock Prices

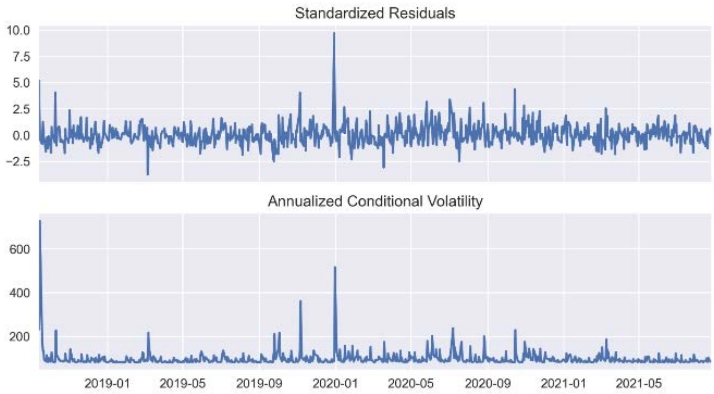

Fig. 4 NIO Annualized Conditional Volatility

Fig.5 is the BYDDF stock price growth line and Fig.6 is the annualized conditional volatility of BYDDF. Fig.5 maintains that the prices were stable until September 2020 and then went up, here is a drop bewteen Feburary 2021 and May 2021. As shown in Fig.6, the volatility was stable until the COVID-19 broke out. And then the data was greater than before.

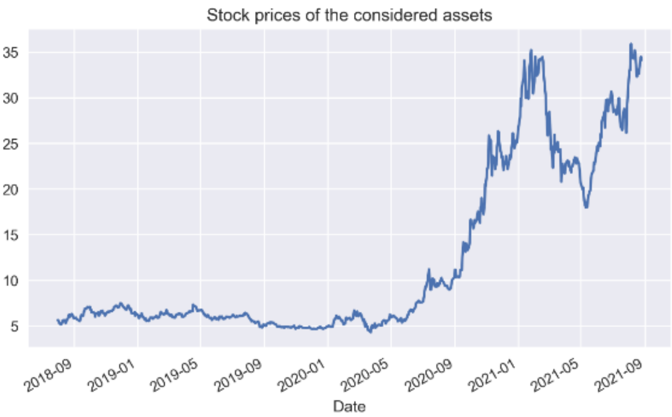

Fig. 5 BYDDF Stock Prices

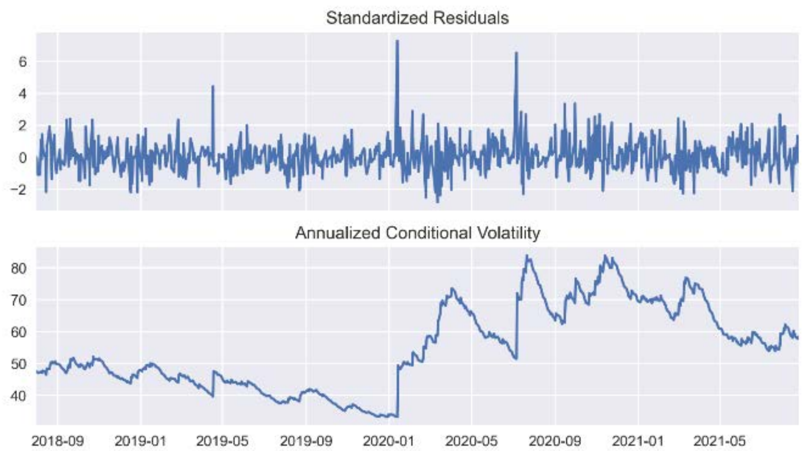

Fig. 6 BYDDF Annualized Conditional Volatility

Fig.7 is the VWAGY stock price growth line and Fig.8 is the annualized conditional volatility of VWAGY. Fig.7 maintains that there was a price spike in March 2021. As shown in Fig.8, the conditional volatility went up at the same time.

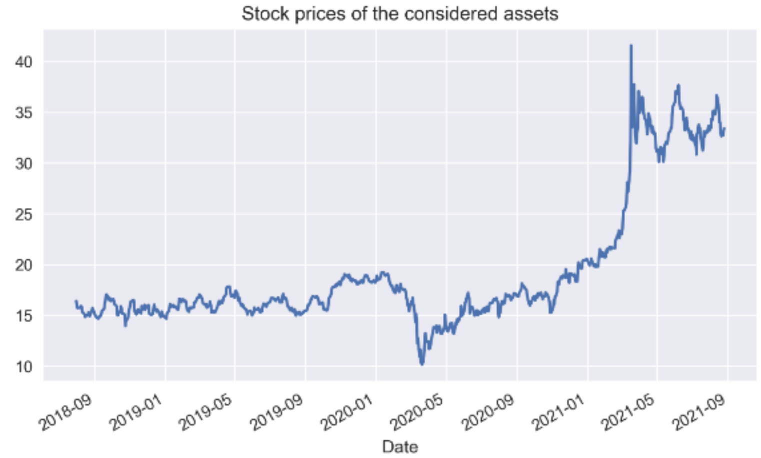

Fig. 7 VWAGY Stock Prices

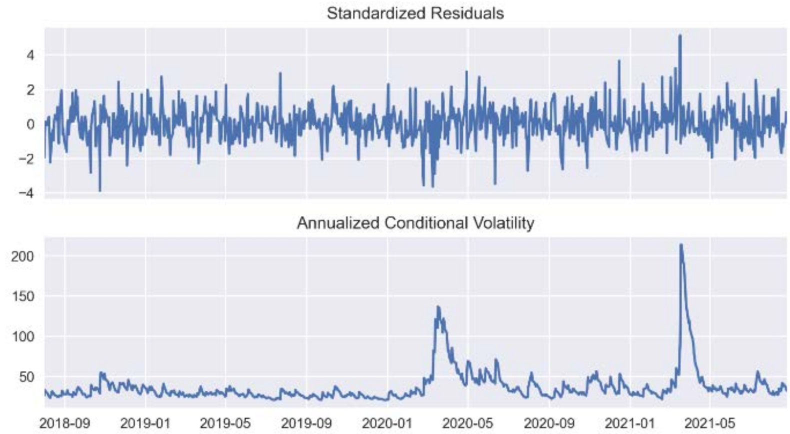

Fig. 8 VWAGY Annualized Conditional Volatility

Fig.9 is the TM stock price growth line and Fig.10 is the annualized conditional volatility of TM. Fig.9 maintains that the prices fell in March 2020 and then keep rising. As shown in Fig.10, at that time the volatility went up, and then it went flat.

Fig. 9 TM Stock Prices

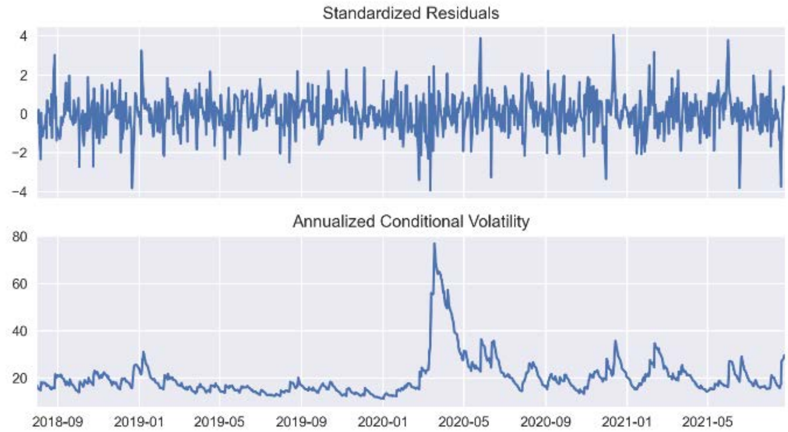

Fig. 10 TM Annualized Conditional Volatility

Fig.11 is the BMWYY stock price growth line and Fig.12 is the annualized conditional volatility of BMWYY. Fig.11 maintains that the prices dropped in March 2020, and then went up. As shown in Fig.12, the volatility increased steeply in March 2020.

Fig. 11 BMWYY Stock Prices

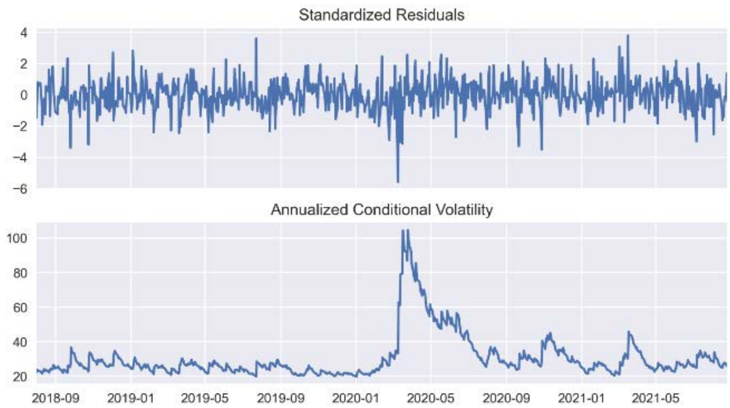

Fig. 12 BMWYY Annualized Conditional Volatility

3.2 CCC-GARCH

In this paper, we use the CCC-GARCH model with six assets that chosen as parameters. We used Python which is an efficient calculation tool to calculate the matrix. The elements on the main diagonal of the result matrix are the one-step-ahead predicted volatilities of their corresponding assets. The results are shown in the Table 1 and Table 2 below.

Table 1 one-step-ahead Predicted Volatilities-1

Asset	TSLA	NIO	BYDDF
Volatility	10.17	26.50	12.65

Table 2 one-step-ahead Predicted Volatilities-2

Asset	VWAGY	TM	BMWYY
Volatility	3.17	2.97	2.55

From Table 1 and Tabel 2, it can be concluded that the predicted volatilities of new energy vehicle stock prices are all higher than those of conventional energy vehicles. In other words, traditional energy vehicle assets are more stable compared to new energy vehicles.

3.3 ARIMA

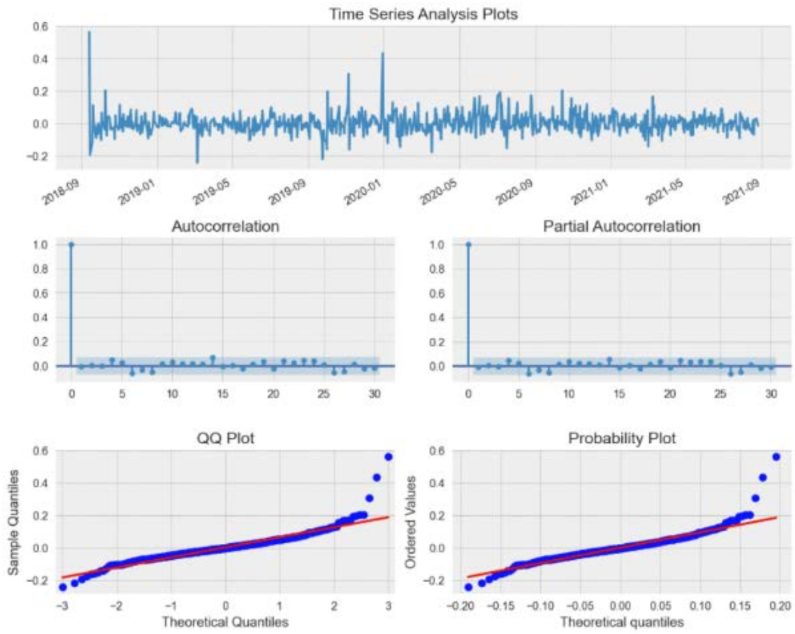

Fig. 13 Time Series Analysis Plots

For the prediction of the six stocks, the qq plot shows the all the data approach normal distribution after first order difference. Fig. 13 is the acf, pacf, QQ and Probility plot, which shows the first order difference of the data of NIO.

In Fig. 14, we can see that NIO keeps relatively stable. The ARIMA model used here is ARIMA (0,1,1). The stability of the predicted data is due to p equals 0 here. Thus, the predicted one showing a stable trend in 19 days.

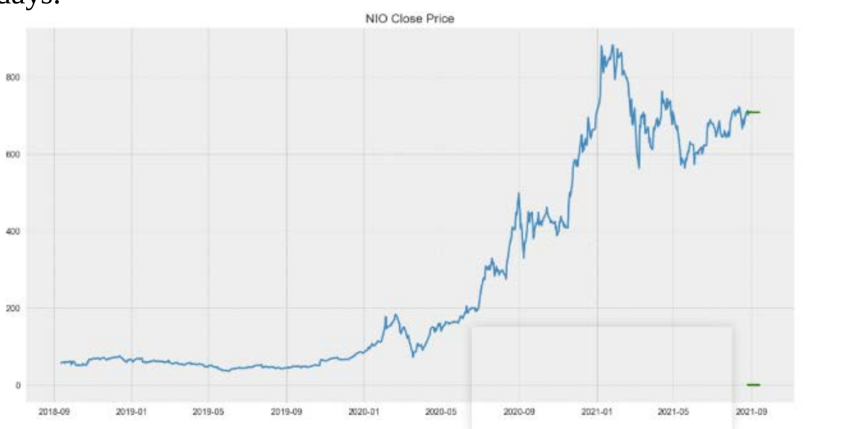

Fig. 14 NIO Close Price

Regarding the stock of Tesla, we use similar strategy to analyze the data like NIO. And we get the ARIMA (2,1,2) model for this stock. As we can see in Fig. 15, 19-days prediction of Tesla's stock shows that it will fluctuate around 708 dollars per share. The price of the share of Tesla is extremely high but the difference can be more than 4 dollars in two weeks.

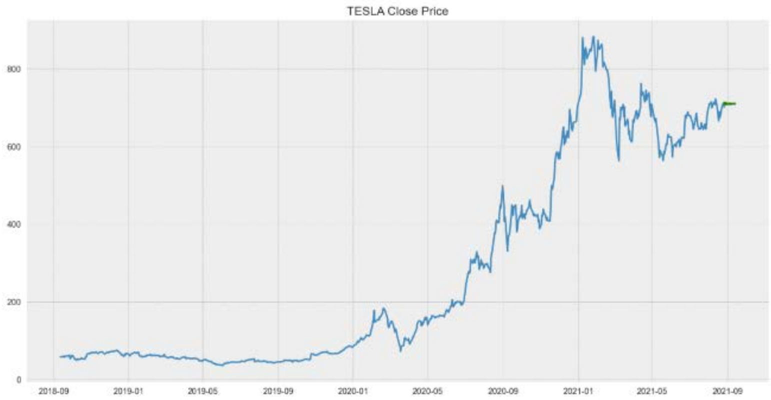

Fig. 15 TESLA Close Price

The stock of BYD is not stable, predicted by the ARIMA model. We obtain that ARIMA (3,1,2) is the most suitable for prediction of BYD. And the Fig. 16 that the price is fluctuate sharply, which as the feature of new enterprises.

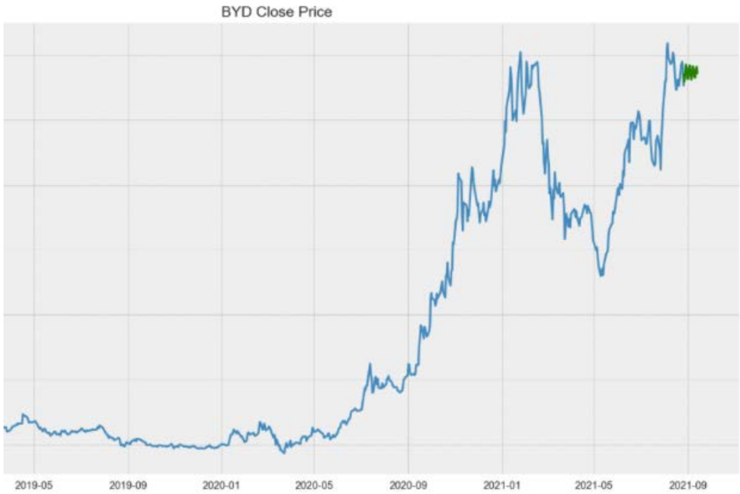

Fig. 16 BYD Close Price

Then we look at the stocks of traditional enterprises. Fig. 17 shows VOLKSWAGEN's stock is truly stable in the 19 days without large fluctuations.

Fig. 17 VOLKSWAGEN Close Price

Fig. 18 shows the close price of BMW. Similarly, BMW’s stock is stable as VOLKSWAGEN, showing the same trend.

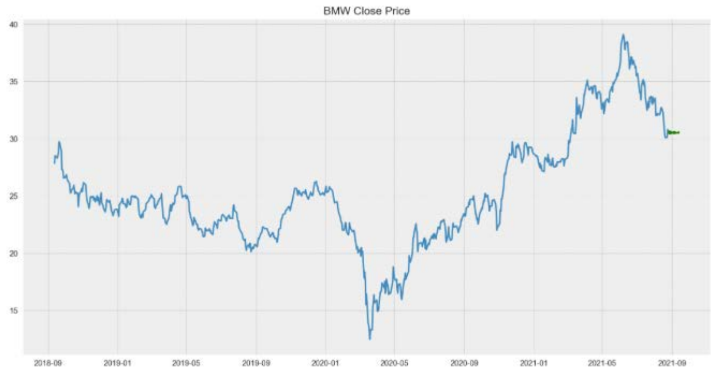

Fig. 18 BMW Close Price

Fig. 19 is the close price of TOYOTA, the stock of which is relatively more volatile, but it remains at a high price.

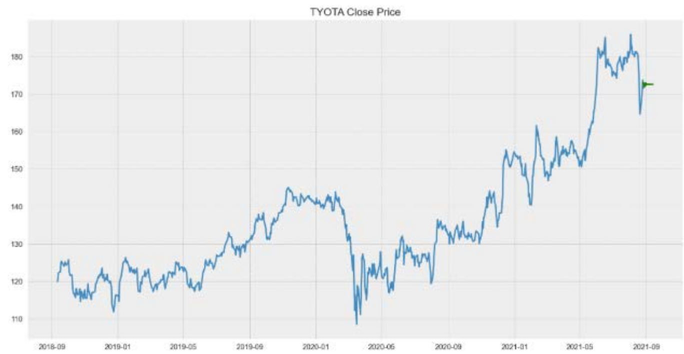

Fig. 19 TOYOTA Close Price

In conclusion, the predicted 19-days’ stock can show the features of new energy vehicles enterprises and traditional vehicles enterprises. For new energy vehicles enterprises, each share is high, but the volatility will also be relatively high. The share price of traditional car companies will not be very high, but the volatility will be lower in the future.

3.4 Optimization

Fig.20 shows the relationship between expected return and volatility. As what we see before, NIO has high return but has rather high volatility. And TOYOTA by contrast is stable.

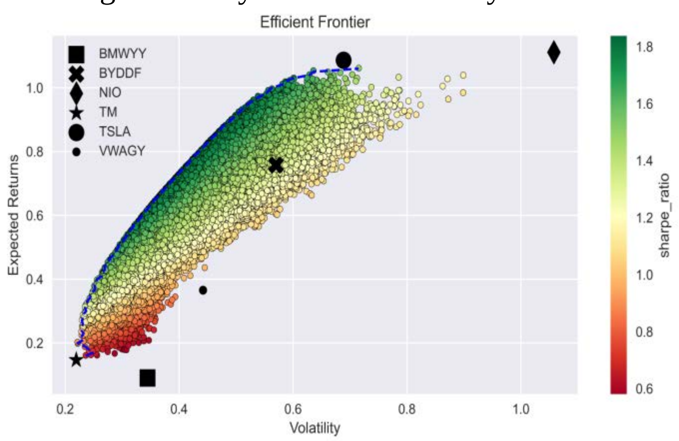

Fig. 20 Expected Returns

As shown in Fig.21, the star point refers to the Max sharpe Ratio, which means that this point is where the highest benefit of unit risk. Under this case, TSLA and BYD occupy the main proportion of the portfolio. It indicates that their return is high enough to cover the potential risk. The minimum volatility portfolio shows relatively low return and TOYOTA occupy the main part of the portfolio because its stock is stable.

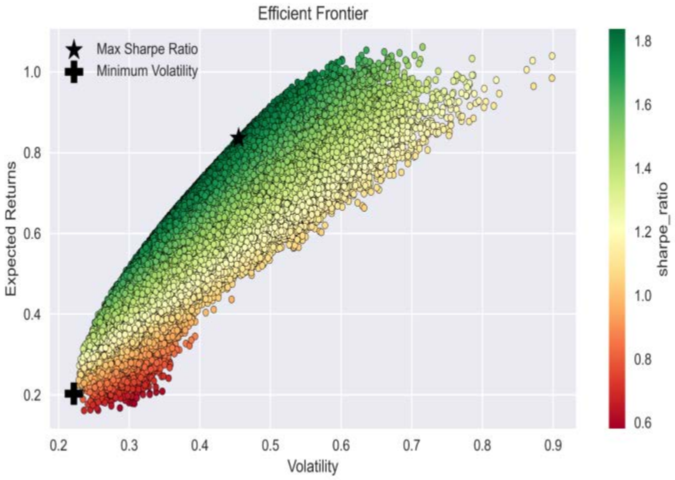

Fig. 21 Two Different Portfolios

Table 3 below shows the performances of two different portfolios including returns and volatility, as well as sharp ratio.

Table 3 Performances of Two Different Portfolios

Performance	**Maximum Sharpe Ratio portfolio**	**Minimum Volatility portfolio**
Returns	83.35%	20.14%
Volatility	45.48%	22.16%
sharpe_ratio	183.25%	90.88%

Table 4 below shows weights of six assets of two different portfolios which are maximum sharpe ratio portfolio and minimum volatility portfolio.

Table 4 Weights of Two Different Portfolios

Weights	**Maximum Sharpe Ratio portfolio**	**Minimum Volatility portfolio**
BMWYY	0.02%	5.66%
BYDDF	33.96%	2.49%
NIO	8.39%	2.90%
TM	5.12%	82.91%
TSLA	39.60%	0.35%
VWAGY	12.90%	5.69%

The results of this study are consistent with our prediction and the growth law of emerging things: enterprises will experience a series of fluctuation periods in the initial stage. Meanwhile, as a trend of future automobile development, electric vehicle companies must be favored by the market. If we want to get high return in minimum risk, then we need to follow the sharpe rule which indicate that we can invest more on new energy vehicles.

4. Conclusion

In conclusion, traditional vehicles enterprises are more stable and get a stable return from the figure of Efficient Frontier. Authors draw a conclusion that Toyota, Volkswagen, BMWYY are all in low volatility and low expected return. One thing that interesting is that these three companies are all traditionally vehicle companies while the other three companies are Tesla, NIO, BYDDF have the highest expected return and highest volatility and they are all new energy vehicles companies. The two classes of assets move in opposite directions. This difference separates new energy vehicles from traditional vehicles well. It can also be used to adjust portfolio according to the needs of different customers. From the Arima model this paper predicts the future trends of six stocks. And it accords to the market performance. This paper manages to analyze the difference of stocks of EV and traditional vehicles companies which give people a new insight into the automobile industry and give a stage for further studies. This paper also gives individual investors and some funds a suggestion who is going to invest in vehicle companies' stock to better manage their portfolio.

This study though only studied three representative new energy vehicle enterprises and three representative traditional vehicle enterprises but did not cover the whole market. Although it is representative, it is not universal. And under the influence of the epidemic, the whole automobile market presents great fluctuations. If the epidemic is considered, a more complex result may be obtained. Authors will study the factors that influence the EV's stock in the future to avoid some possible risk. These factors can be the overall market, sales, market share, policies, patents and so on. Analyzing the policies is important. Especial when it comes to different countries like China and USA, they have different policies towards NEVs so this paper needs to consider their different market environments. Authors are looking forward to seeing the future performance of vehicles enterprises especially new energy ones. In conclusion, the stock of automobile industry is worth studying further and find a better way for both investor and vehicles enterprises.

References

[1] Dong-xiao, Yang; Lin-shu, Qiu; Jian-jun, Yan; Zi-yue, Chen; Mingxing Jiang. (2019). The government regulation and market behavior of the new energy automotive industry, Journal of Cleaner Production, Volume 210, Pages 1281-1288.

[2] M. Zeng, F.X. Zeng, X.L. Zhu, S. Xue. (2013). *Forecast of electric vehicles in China based on bass model*. Electr. Power, 46 (1) (2013), pp. 36-39.

[3] Z.L. Du, B.Q. Lin, C.X. Guan. (2019). Development path of electric vehicles in China under environmental and energy security constraints. Resour. Conserv. Recycl., 143 (2019), pp. 17-26.

[4] Y.W. Li, B.H. Zeng, T. Wu, H. Hao. (2019). Effects of urban environmental policies on improving firm efficiency: Evidence from Chinese new energy vehicle firms.
J. Clean. Prod., 215 (2019), pp. 600-610.

[5] Q.R. Wang, L. Liu, S. Wang, J.Z. Wang, M. Liu. (2017). *Predicting Beijing's tertiary industry with an improved grey model*. Appl. Soft Comput., 57 (2017), pp. 482-494.

[6] Li-ping LIU, Dan MA & Xiao-bin TANG. (2016). *Estimation and Application of the Improved CCC-GARCH Model of High Dimensional Data.* Statics & Information Forum (09),22-28. doi: CNKI: SUN: TJLT.0.2016-09-004.

[7] Jinquan LIU & Yiping LIU. (2021). *Literature Review of GARCH Model on Stock Market Volatility*. China Journal of Commerce (20),110-113. doi: 10.19699/j.cnki.issn2096-0298.2021.20.110.

[8] Dayong ZHONG, Heng ZHANG. *Study of RMB Exchange Rate Volatility based on GARCH Model*[J]. China Price, 2021(10): 24-26.

[9] R.F. Engle. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. Econometrica, 50 (1982), pp. 987-1002.