Analysis on the Stock Market Prospect of New Energy Vehicle Industry

--Taking NIO, XPEV and LI as Examples

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Abstract—This article aims to evaluate the prospect of a new energy vehicle manufacturing stock market. We evaluated the expected risk and expected return of the three new energy vehicle companies through the Conditional Value at Risk (CVaR) and the Capital Asset Pricing Model (CAPM). First, the Capital Asset Pricing Model conveys that the new energy vehicle companies are in a period earning negatively to the market. The other aspect is based on the results of CVaR. By stating the mean-CVaR model to have side-by-side comparisons among returns of three stocks, we find that NIO's stock is the worthiest one to invest among the three stocks. Finally, based on forecasting of one-month period each-day returns of three stocks, we find that both NIO and LI's stocks are expected to have a positive each-day return and worthy of investing. The results of the article giving investors suggestions on investing in new energy vehicle companies. This article's conclusion provides people who hope to invest in the new energy vehicle companies' stocks advice and state theory foundations for advanced research of constructing portfolios in new energy vehicle companies' stock market.

Keywords-component: New energy vehicle stock; risk; return; CAPM; Mean-CVaR; ARIMA

1 INTRODUCTION

On May 18, 2021, U.S. President Joe Biden visited Ford Motor's Rouge Electric Vehicle Center in Michigan. He drove the all-electric F-150 pickup truck personally and announced the electric vehicle support part in the two trillion dollars infrastructure investment plan. Biden said he hoped that the United States would take the lead in new energy vehicle (NEV) manufacturing, market size, and battery innovation. He also said that the U.S. government might provide purchase subsidies for "clean cars." After that, the U.S. new energy vehicle stocks ushered in a substantial rise, the local Chinese brands' new energy vehicle giants NIO Inc. (NIO.US), XPeng Inc.

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(XPEV.US), and Li Auto Inc. (LI.US) led the U.S. NEV stock market. As China has unprecedented support for the development of the new energy vehicle industry, according to the planning requirements of the Chinese government, it will strive to achieve a penetration rate of 20% of new energy vehicles by 2025. Today, the penetration rate of new energy vehicles in China is only 4-5 percentage points, with vehicle inventory at about 3.8 million. There is still a demand gap of more than 10 million vehicles [1]. NIO, XPEV, and LI have gained recognition from consumers and the capital markets. They are the most popular NEV brands in the Chinese market and the hottest NEV investments in China Concept Stocks.

Both domestic and overseas scholars have a long-period development in research of risk measurement in the stock market. Overseas scholars held that risk measures based on VaR adopted in Basel Accord made the investment portfolio model specific that minimizes values of portfolios' VaR under the expected returns, which challenged the traditional mean-variance portfolio theory [2]. However, domestic scholars believed that VaR did not solve its consistency risk measurement effectively [3]. Axioms of a good risk measure named coherent risk measures were proposed in 1999 [4], and VaR did not satisfy Coherent Axiom, so that VaR was not a coherent risk measurement (equivalent to consistency risk measurement) [5]. Also, VaR uses a single quantile point to evaluate the loss of the distribution's whole tail, which will cause insufficiency of measuring loss in distribution's tail. Hence, VaR as a risk measure does not solve consistency risk measurement effectively to lose accuracy in measuring risk. Conditional Tail Expectation (CTE) as a risk measure describes the expected loss given that the loss falls in the worst (1-α) part of the loss distribution (α is confidence coefficient) was presented in 1999 [6]. Equivalently, CTE is known as Conditional Value-at-Risk (CVaR) [7], Tail Conditional Expectation [8], and Tail Value-at-Risk [9]. Compared with VaR, CVaR solved consistency risk measurement effectively since CVaR satisfies Coherent Axiom so that it is a coherent risk measure.

After confirming the exactitude of the risk measure, we need to consider the accuracy of the distribution that we use to describe our data. The conditions that return of risky assets would be assumed to follow normal distribution while computing CVaR was presented in the research [10] since research in financial economics showed actual returns of risky assets is close to the normal distribution for a concise period. Nevertheless, there will be a large deviation from actual returns of risky assets when we still use the normal distribution to forecast returns in the following period (such as one month, half-year, or one year). Hence, when returns of risky assets are distinct from normal distribution, simulation distribution has a significant impact on forecasting accuracy. The linear decomposition model can describe the trend and seasonality of returns of risky assets so that it works well in predicting returns of risky assets in the period. The exponential smoothing can be used for a time series to estimate the process of slowing varying parts in the linear decomposition model. The Holt-Winters method generalizes exponential smoothing to the case where there is a trend and seasonality. ARIMA model can analyze returns of risky assets that are non-stationary processes and close to stationary based on the linear composition model.

According to these previous articles related to risk measures, we find that CVaR is an advanced risk measure in the modern investment theory. It can effectively solve the consistency risk measurement to have a high accuracy in measuring risk. Hence, in the latest research of portfolio investment, scholars will focus on finding fitted models (like copula function) to simulate risky assets and solve the risk dependence among these risky assets [11].

This article will focus on new energy vehicle companies NIO, LI, and XPEV's stocks, use CAPM model to quantify benefits, use risk measures based on Conditional Value at Risk (CVaR) model to quantify risk, predict future stock price with ARIMA model to simulate, then find the most appropriate investment among three stocks.

2 DATA AND METHOD

2.1 Data

This article chose NIO.US, XPEV.US, and LI.US since these three stocks are the top four increasing NEV companies in NEV China Concept Stocks market. All the stock market data came from Yahoo Finance from 28th August 2020 till 2nd July 2021. The data contain a daily historical open price, high price, low price, close adjusted close price, and volume. These are first-hand data. To make a quantitative analysis, we use the adjusted close price of the previous day minus the adjusted close price of the next day divided by the adjusted close price of the previous day as the daily return rate.

2.2 Company and Stock Status

NIO Inc., XPeng Inc., and Li Auto Inc. were all founded within 2014 and 2015, headquartered in Hefei, Guangzhou, Beijing of China and listed in the United States on 12th September 2018, 27th August 2020, and 30th July 2020 respectively. These three new car companies born in China have introduced new energy vehicles into the market with brand-new business concepts. They have invested a large number of scientific research funds in optimizing battery life, engine performance, assisted driving, and on-board artificial intelligence. Because the target price is relatively low and the driving experience is good, the new energy vehicles of these three brands have not been greatly affected by the epidemic in recent years, but their sales have increased significantly, becoming strong competitors of the new energy vehicle giant Tesla. In addition, it is also technologically ahead of traditional auto companies that are transforming.

In the first half of 2021, NIO, XPEV and LI are the top three China Concept Stocks listed on the U.S. NEV stock market. NIO took first place, led the U.S. NEV stock markets with a 13.98% increase and a market cap of 75.93 billion USD. The market cap of XPEV and LI in the first half of the year was 29.68 billion USD and 29.42 billion USD, respectively, ranking 6th and 7th on the list. Although LI ranked slightly behind, its growth rate was the highest, and its market cap increased by 24.38% in the first half of the year 2021, with an increase of about 6 billion USD.

In terms of sales volume, the sales data of the three companies rose rapidly. NIO delivered 8,083 vehicles in June, a year-on-year increase of 116.1%, which set a record high. NIO's cumulative sales in the first half of 2021 were 42,000 vehicles, which has reached 95.9% of the full-year sales in 2020. LI delivered a total of 7713 vehicles in June, a year-on-year increase of 320.6%, setting a new record for monthly deliveries. From January to June in 2021, the cumulative delivery volume of XPEV vehicles has exceeded its delivery volume for the whole year of 2020, reaching 30,738 vehicles, which is 5.6 times in the same period last year.

In general, new energy vehicle-related companies are more and more favored by capital, and the prospects for NEV China Concept Stocks are positive.

2.3 Methods

- Capital Asset Pricing Model (CAPM):

Investors are always pursuing the maximized benefits from investment; however, the return of stocks is never accurately predictable [12]. Hence, the Capital Asset Pricing Model (CAPM) concept is then introduced and developed by William F. Sharp.

The risk of stocks is considered as the uncertainty of future earnings from investments. The risk could be separated into two types -- systematic risk and unsystematic risk. We usually invest in several stocks to avoid or reduce the potential unsystematic risk [13].

Systematic risk is described as a risk inherent to the market. In other words, it exists forever. The systematic risk brings investors additional return [14], which is the risk premium. However, the relationship between systematic risk and return of stock was unclear until CAPM was introduced. The model shows a linear relationship between those. The basic model is shown below.

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big). \quad (1)$$

$E(R_i)$ is the predicted return of certain stock. R_f is the return of risk-free assets available in the market. $E(R_m)$ is the return of an efficient portfolio of all stocks in the market, the share of each portfolio is the percentage of its market gap in terms of the total value of the market. The most significant factor in the model is β_i , which is the measurement of how much risk will be added to the portfolio while the market risk changed. Mathematically, we have

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}. \quad (2)$$

$Cov(R_i, R_m)$ is the covariance between the return of single stock and the return of the market portfolio. Moreover $Var(R_m)$ is the variance of the market portfolio.

CAPM gives investors a simple model deciding the potential return on stocks. The fundamental ideal of CAPM is higher risk brings higher return. Hence, we may start our evaluation based on this concept.

Since CAPM is widely used in stock price prediction, once we have the value of β_i and $E(R_m)$, the approximate return of a single stock is then derivable.

An essential part of model building is the data of the market. The market portfolio, or efficient portfolio, is a theoretical portfolio that contains all the stocks available in the market. However, it is hard to find a perfect market portfolio in real life. Hence we choose the market index instead. Market index, for example, Nasdaq Composite Index (IXIC) measures several stocks in the market and helps investors see the change of stock price. Nasdaq Composite Index shows the development of high-tech companies, which is highly related to our research objects. Therefore, the data of $E(R_m)$ is the percentage change of IXIC in the past year. Another factor in the model is the sensitivity β_i. The parameter shows the linear relationship between stocks and the market. Hence RStudio is used in analyzing the accurate value of β_i.

In order to understand the predicted return of stocks, we rearrange (1) to another equation:

$$E(R_i) = \alpha + \beta \cdot E(R_m) + \varepsilon. \tag{3}$$

The term ε here is the error term to make sure the linear function is accurate. We always have extreme values in our data collection; therefore, we need the error term to correct the outliers. Again, $E(R_i)$ is the predicted return of stocks we selected. $E(R_m)$ is the fluctuation of IXIC in the same period as these stocks.

After the rearrangement, we could clearly see the relationship between stocks and the market. Since α is a fixed parameter and ε is a value changed accordingly. β measures how a stock is affected when the market changes. We could apply our data to find the parameters and the error term. Therefore, the relationship is then fixed.

- Risk Measures:

○ Value-at-Risk (VaR):

We suppose that the distribution function of a random variable L is $F_L(l) = Pr(L \leq l)$. Then we define, for $0 \leq \alpha \leq 1$, VaR of a random variable L is defined as

$$VaR_\alpha = VaR_\alpha(L) = \inf\{l \in R: F_L(l) \geq \alpha\}. \tag{4}$$

In practice, α is close to 1 and usually equal to 90%, 95%, or 99%. In other words, $VaR_\alpha(L)$ represents the loss that, with probability (at least) α will not be exceeded, or equivalently, the risk L has a loss larger than $VaR_\alpha(L)$ in at most $100(1-\alpha)\%$ cases on average. Specifically, for a continuous random variable with strictly increasing CDF $F_L(x)$:

$$Pr[L \leq VaR_\alpha] = \alpha \tag{5}$$

is equivalent to

$$VaR_\alpha = F_L^{-1}(\alpha). \tag{6}$$

○ Expression of VaR in Normal Distribution:

We suppose a random variable $L \sim N(\mu, \sigma^2)$ and Φ to be the CDF of the standard normal distribution. Since normal distribution is continuous, we have:

$$Pr(L \leq l) = Pr\ ((L-\mu)/\sigma \leq (l-\mu)/\sigma) \tag{7}$$

then equation (4) can be simplified in the following:

$$Pr(L \leq l) = \Phi((l-\mu)/\sigma). \tag{8}$$

Then let $\Phi\big((l-\mu)/\sigma\big) = \alpha$ and we have the equation

$$(l-\mu)/\sigma = \Phi^{-1}(\alpha) \tag{9}$$

which is equivalent to

$$VaR_{\alpha}(L) = \mu + \sigma\Phi^{-1}(\alpha). \tag{10}$$

o Conditional Value-at-Risk (CVaR):

We suppose that L is a random variable. Then we define, for $0 \leq \alpha \leq 1$, CVaR of L is

$$CVaR_{\alpha}(L) = \frac{1}{1-\alpha}\int_{\alpha}^{1} VaR_s(L)ds \tag{11}$$

Moreover, if L is continuous, then a more intuitive definition of CTE is

$$CVaR_{\alpha}(L) = E[L \mid L > VaR_{\alpha}(L)]. \tag{12}$$

o Expression of CVaR in Normal Distribution:

We suppose a random variable $L \sim N(\mu, \sigma^2)$ and ϕ and Φ to be the c.d.f and p.d.f of the standard normal distribution, respectively. Since normal distribution is continuous, we have

$$CVaR_{\alpha}(L) = \frac{1}{1-\alpha}\int_{\alpha}^{1} VaR_s(L)ds \tag{13}$$

and

$$VaR_{\alpha}(L) = \mu + \sigma\Phi^{-1}(\alpha). \tag{14}$$

Hence, we have

$$CVaR_{\alpha}(\mathrm{L}) = \mu + \frac{\sigma}{1-\alpha}\phi[\Phi^{-1}(\alpha)]. \tag{15}$$

- Forecasting Models:
- Linear Composition Model:

A linear decomposition model for the time series X_t is decomposition

$$X_t = m_t + s_t + Y_t \tag{16}$$

where $E(Y_t) = 0$, m_t is a slowly varying function, s_t is periodic with period d and, for identification reasons, we further assume

$$\sum_{t=1}^{d} s_t = 0. \quad (17)$$

- Holt-Winters Filtering:

Being similar with the linear decomposition model, Holt-Winters filtering has three terms which depend on time t: a level a_t, the trend b_t and seasonal component s_t. The terms a_t and b_t are considered slowly varying, and the mean of the time series at time $t + h$ is given by

$$m_{t+h} = a_t + b_t h + s_{t+h}. \quad (18)$$

Hence, the Holt-Winters prediction function for h time periods ahead of current time t is

$$x_{prediction} = a_t + b_t h + s_{t+h}. \quad (19)$$

- ARMA Model:

Let $Z_t \sim N(0, \sigma^2)$ are identically independent random variables, and define the polynomial operators

$$\phi(B) := 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \quad (20)$$

and

$$\theta(B) \coloneqq 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q, \quad (21)$$

where B is the backward shift operator, which is defined as

$$BX_t = X_{t-1} \quad (22)$$

where X_t is a time series. Then, the $ARMA(p, q)$ process is the process that is the stationary solution to the difference equations:

$$\phi(B)X_t = \theta(B)Z_t \quad (23)$$

when such a solution exists, and we assume that the polynomials $\phi(z)$ and $\theta(z)$ share no common factor.

- ARIMA Model:

If d is a non-negative integer, then $\{X_t\}$ is an $ARIMA(p, d, q)$ process if

$$Y_t \coloneqq \nabla^d X_t \quad (24)$$

is a causal $ARMA(p, q)$ process, where ∇^d is called the $d^{th} -$ order differencing operator and is defined to be

$$\nabla^d X_t = (1 - B)^d X_t \tag{25}$$

where B is backward shift operator defined above.

3 RESULTS AND DISCUSSION

In this part, we will use the CAPM model to describe the relationship between stocks and markets by computing its estimators and using the mean-CVaR model to effectively solve the consistency risk measurement and measure the risk of portfolios more accurate and sounder than mean-VaR model. Also, in the part of the prediction of these three risky assets, this article will compare both results of Holt-Winters prediction and ARIMA prediction to have a comprehensive and precise conclusion.

3.1 Results of CAPM Model:

As indicated in the method part, the rearrangement of CAPM focuses on the parameter α andβ, they directly determine the mathematical relationship between stocks and the market. The first figure above is the return of stocks in terms of the previous day, while the second table is the solution of α andβ by solving the model.

TABLE I. ESTIMATORS OF CAPM EQUATION

Estimators	Risky Assets		
	LI	***NIO***	***XPEV***
α	0.000180049	0.001834868	0.002345891
β	-0.112592	-0.213923	0.09781074

Table I conveys a fact that two of the companies we selected had a negative relationship with the market, which means once the market has a positive movement, there will be a loss for the new vehicle companies. On the other hand, the only company with positive β, is lower than average. Specifically, 1% change in the market causes a negative 11% change in LI and negative 21% in NIO.

Once we realize the relationship between stocks and the market, we may choose to invest in LI and NIO when the market is expected to experience a recession in the future; we may choose to invest in XPEV when the market is expected to experience a boom in the future. Hence, investors are not suggested to investing all in new energy vehicle manufacturing.

In conclusion, the three companies are the typical cases of new energy vehicle manufacturing. The results of β indicate that this field is not stable. One firm's loss brings additional effect upon other firms. Thus, new energy vehicle manufacturing is promising but requires more to change.

3.2 Results of Mean-CVaR Model:

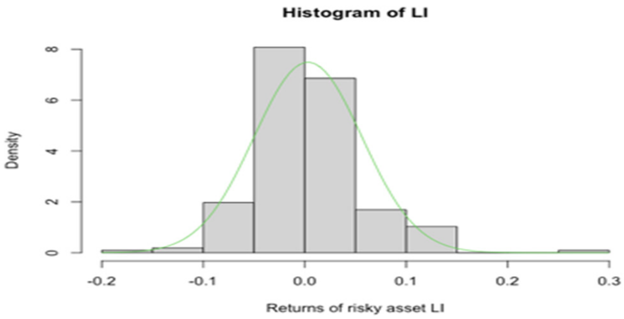

Figure 1: Histogram of LI's Returns vs. Corresponded Normal Distribution

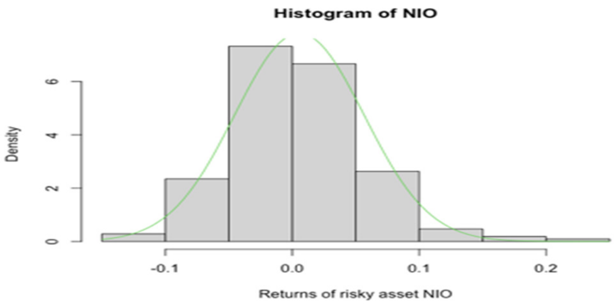

Figure 2: Histogram of NIO's Returns vs. Corresponded Normal Distribution

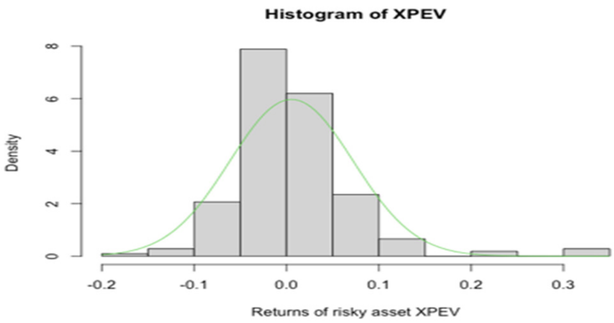

Figure 3: Histogram of XPEV's Returns vs. Corresponded Normal Distribution

According to Figure 1, Figure 2, and Figure 3 above, which illuminate the distributions of returns of risky assets included LI, NIO, and XPEV respectively and curved their corresponded normal distributions, it can be observed that accurate distributions will have a heavier tail than their corresponded distributions which we plan to use to simulate returns of three risky assets. Hence, when we use corresponded normal distributions to compute these three risky assets' VaR values to measure their risk, the accuracy cannot be guaranteed due to the VaR's insufficiency of measuring loss in distribution's tail which we mentioned in the introduction part. VaR values in the following table will only work as a reference instead of playing a decisive role in measuring the risk of these three assets.

TABLE II. UNDER A 95% CONFIDENCE COEFFICIENT RISKY ASSETS' RISK MEASURE VALUES

Risky Assets	**Risk Measure Values**			
	Mean	***Variance***	***VaR***	***CVaR***
LI	0.00323255	0.00283754	0.09085	0.11311
NIO	0.00555881	0.00260644	0.08953	0.11087
XPEV	0.00546291	0.00446404	0.11536	0.14328

TABLE III. UNDER A 99% CONFIDENCE COEFFICIENT RISKY ASSETS' RISK MEASURE VALUES

Risky Assets	**Risk Measure Values**			
	Mean	***Variance***	***VaR***	***CVaR***
LI	0.00323255	0.00283754	0.12715	0.14521
NIO	0.00555881	0.00260644	0.12433	0.14163
XPEV	0.00546291	0.00446404	0.16089	0.18354

TABLE II and TABLE III above show the risk measure values of three risky assets, included mean, variance, VaR, and CVaR under 95% and 99% confidence coefficients, respectively. According to the definitions of VaR and CVaR in the part of methods of risk measures, it can be known that VaR represents the loss that, with probability, at least α (confidence coefficient) will not be exceeded, or equivalent; and CVaR represents the expected loss given that the loss falls in the worst $(1 - \alpha)$ part of the loss distribution. Hence, when we compare these three risky assets, we define an asset to be less risky if this asset has a smaller VaR (or CVaR) than another one.

In the traditional mean-variance model, risky asset NIO has a maximum mean and minimum variance among three risky assets. In both innovative models, mean-VaR and mean-CVaR under 95% and 99% confidence coefficients, risky asset NIO can also be defined as the best asset among three assets since it has the maximum expected return (mean) and minimum risk (evaluated by minimum VaR and CVaR respectively). Even though we treat the results from mean-VaR as only a reference due to VaR's insufficiency, results' consistency from three different models enhances the reliability of our preliminary conclusion that asset NIO is the best choice to invest among these risky assets based on its previous good behaviors in returns. However, we cannot draw our conclusion now, and this conclusion needs to be supported by other results.

3.3 Results of Predictions:

- Predictions by Holt-Winters Filtering:

Due to the definition of Holt-Winters Filtering, which is wholly based on linear decomposition model, the prediction has a strong linearization so that the plot of predictions will be a straight line and do not work in analyzing its trending in a long period (here we choose one month to be the prediction's period). There in this part, we focus on analyzing the prediction's risk measure values in the mean-CVaR model.

TABLE IV. UNDER A 95% CONFIDENCE COEFFICIENT RISK MEASURE VALUES OF ONE-MONTH PREDICTIONS OF RISKY ASSETS

Risky Assets	**Risk Measure Values**		
	Mean	***Variance***	***CVaR***
LI	-0.0327392	0.02959246	0.0283015
NIO	0.0454578	0.01680616	0.0801242
XPEV	-0.1244809	0.07000841	0.0199264

TABLE V. UNDER A 99% CONFIDENCE COEFFICIENT RISK MEASURE VALUES OF ONE-MONTH PREDICTIONS OF RISKY ASSETS

Risky Assets	**Risk Measure Values**		
	Mean	***Variance***	***CVaR***
LI	-0.0327392	0.02959246	0.04613102
NIO	0.0454578	0.01680616	0.09024998
XPEV	-0.1244809	0.07000841	0.06210657

According to the results in Table IV and Table V, we can observe that NIO will be the only asset that has a positive expected return in the following month (in this article, it is beginning on 3rd July 2021) among three risky assets and has a minimum variance at the same time. Even though asset NIO is expected to have the largest CVaR value under both 95% and 99% confidence coefficients among three assets in the following month, it is shown that with the confidence coefficient increasing from 95% to 99% the difference between NIO's CVaR value and others' CVaR value is obviously smaller. Moreover, according to the definition of CVaR (14), it is known that a negative mean would make CVaR value very small so that it is meaningless to compare two assets' CVaR values that one has a positive mean and another has a negative mean to define which one as a less risky asset. Therefore, we choose to use the mean-variance model to compare these three risky assets predictions. In the mean-variance model, assets NIO has a maximum expected mean and a minimum variance among three assets. We can define NIO as the best investment choice in the following month among three assets.

However, in the real-life, the changes of NIO, LI, and XPEV's stock prices will not be strictly linear; that is, our above conclusion is based on an ideal linear model and only work as a reference. We will use an advanced model to simulate these three companies' stock prices and investment returns in the following part.

- Predictions by ARIMA Model:

For forecasting the risky asset LI, we choose $\mathrm{ARIMA}(2,1,2)$ model to simulate its each-day returns in one month. In order to check if this model is fitted, we can plot the acf. and pacf. graphs of predictions' residuals.

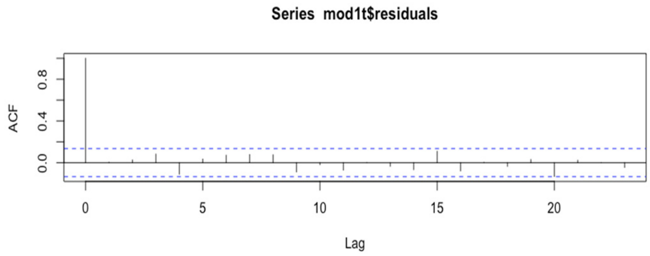

Figure 4: ACF of LI's Prediction's Residuals

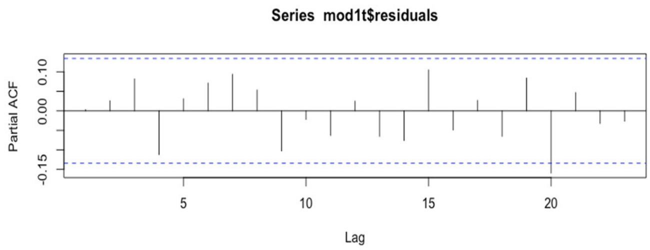

Figure 5: PACF of LI's Prediction's Residuals

According to the Figure 4 and Figure 5 we can observe that over 95% lines are between those blue lines in both figures so that we can define this model as a fitted model to simulate the original data. Then we use the same method to check the following models: ARIMA(1,1,1) for simulating asset NIO and ARIMA(8,1,1) for simulating asset XPEV.

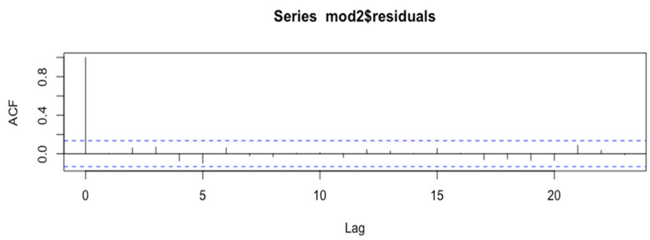

Figure 6: ACF of NIO's Prediction's Residuals

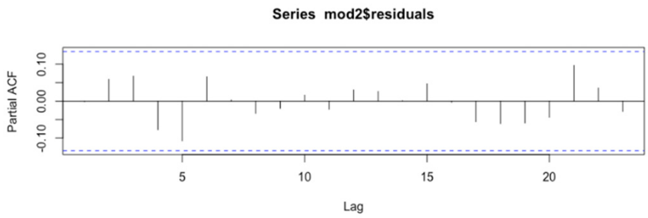

Figure 7: PACF of NIO's Prediction's Residuals

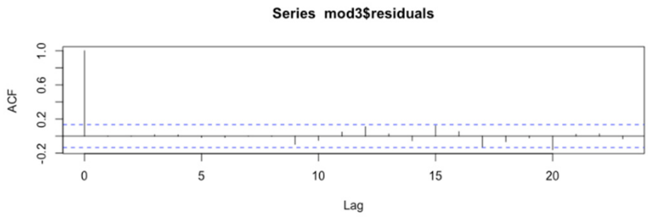

Figure 8: ACF of XPEV's Prediction's Residuals

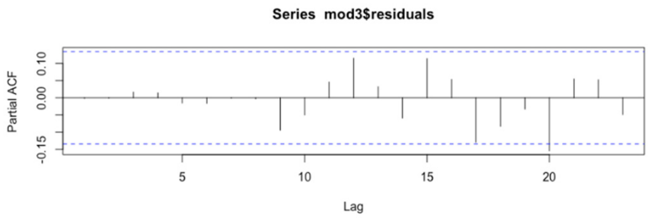

Figure 9: PACF of XPEV's Prediction's Residuals

According to Figure 6, Figure 7, Figure 8, and Figure 9 above, therefore, we can also define $\mathrm{ARIMA}(1,1,1)$ as a fitted model to simulate asset NIO and $\mathrm{ARIMA}(8,1,1)$ as a fitted model to simulate asset XPEV. In the following part, we will focus on the predictions' results and their risk measure.

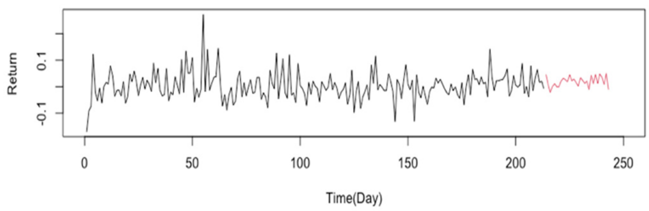

Figure 10: Returns of Risky Asset LI in Days

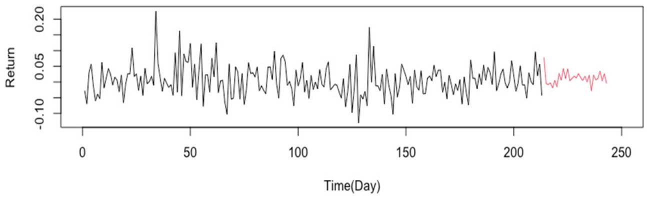

Figure 11: Returns of Risky Asset NIO in Days

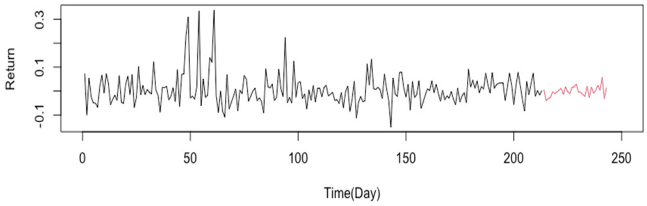

Figure 12: Returns of Risky Asset XPEV in Days

In Figure 10, Figure 11, and Figure 12 above, the black line represents the historical data of each-day returns of risky assets from 28th August 2020 to 2nd July 2021, and the red line represents the forecasting data of each-day returns of risky assets in the following one month (30 days). According to these three figures, we can generally observe that it is predicted that the returns of these three assets will be stable instead of changing sharply in the following month. Moreover, to have more details, we need to analyze these predictions' data in some risk measure values, including mean, variance, VaR, and CVaR.

TABLE VI. UNDER A 95% CONFIDENCE COEFFICIENT FORECASTING RISKY ASSETS' RISK MEASURE VALUES

Risky Assets	**Risk Measure Values**			
	Mean	***Variance***	***VaR***	***CVaR***
LI	0.0190821	0.00036478	0.05050	0.05848
NIO	0.0123072	0.00043661	0.04668	0.05541
XPEV	-0.0006985	0.00044903	0.03416	0.04301

TABLE VII. UNDER A 99% CONFIDENCE FORECASTING COEFFICIENT RISKY ASSETS' RISK MEASURE VALUES

Risky Assets	**Risk Measure Values**			
	Mean	***Variance***	***VaR***	***CVaR***
LI	0.0190821	0.00036478	0.06351	0.06999

Risky Assets	Risk Measure Values			
	Mean	***Variance***	***VaR***	***CVaR***
NIO	0.0123072	0.00043661	0.06092	0.06800
XPEV	-0.0006985	0.00044903	0.04860	0.05578

According to Table VI and Table VII, risky asset XPEV is the only one that is expected to have a negative mean value of each-day return in the following month. Hence, we focus on comparing with risky assets LI and NIO. However, in the mean-variance and mean-CVaR models, there are different results. In the traditional mean-variance model, we can define that the predictions of LI's each-day returns are strictly better than NIO's predictions of each-day return since predictions of LI's returns have a larger mean value and a smaller variance value than NIO's. In mean-CVaR model, although predictions of LI's returns have a larger mean value than NIO's, predictions of LI's returns have a larger CVaR value than NIO's predictions under both 95% and 99% confidence coefficients so that we are only able to define predictions of NIO's returns will be less risky than LI's predictions; that is, one asset is expected to have a better return, but more risk and another one is expected to have a less return but less risk. Hence, it is difficult to define which one is the better asset to invest in general. Therefore, in this part, we can only conclude that both LI and NIO are expected to be worthy investments and that investing one of them depends on investors' aversion to risk.

4 CONCLUSION

According to analyzing data in the CAPM model, we find there exists risk dependence between three sticks' returns; that is, one firm's loss brings additional effect upon other firms. By evaluating three risky assets in the mean-CVaR model and make comparisons with traditional mean-variance model, we view NIO's stock as the worthiest to invest among these three risky assets based on historical data. In considering prospects of three risky assets in the following month, Holt-Winters filtering model shows that NIO's stock is the only one that has a positive average each-day return among three assets; but results ARIMA model show that both NIO and LI's stocks will have a positive average each-day return and are both worthy to invest.

This article measures the risk of new energy vehicle companies' stocks, including LI, NIO, and XPEV, respectively, to analyze the investment prospect of the new energy vehicle company stock market. The domestic new energy vehicle market is in the developing stage. The financial system of the new energy vehicle company's stock market is not accomplished, which causes high systematic risk in the new energy vehicle company's stock market and strengthens risk dependence among risky assets. Hence, for advanced research in constructing investment portfolios to analyze investment prospects of new energy companies' stock market, this article provides the statement of mean-CVaR models for individual new energy vehicle company's stock and confirmation of fitted ARIMA model simulate stock's returns. Moreover, this article provides research methods for resolving complex risk dependence while constructing investment portfolios with different stocks. Putting Copula model may more robustly and accurately predict the CVaR portfolios in constructing complex portfolios. Therefore, conforming to the function to describe complex risk dependence among risky assets will work effectively in measuring the risk of portfolios and construct the optimistic one.

As for investment prospect of new energy vehicle company stock market based on LI, NIO, and XPEV's stocks, we hold the view that as a developing stock market, new energy vehicle company's tocks have a great performance in each-day returns so that it is recommended to invest in new energy vehicle company stock market for individual investors. Also, both LI and NIO's stocks are expected to have a great average each-day return rate, so that we predict that new energy vehicle company stock market will have a large number of capitals poured in; that is, the prospect of new energy vehicle company stock market is well developed. At the national level, accomplishing the financial system of the new energy vehicle company stock market can be helpful for reducing systematic risk and risk dependence among different stocks.

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