Portfolio - Based on US Stock Data

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Abstract. The period 2020-2021 is destined to be one of the most extraordinary periods in China's investment history, having experienced too much "uncertainty". During the past 30 years of sustained economic expansion, both the median household income and the median household standard of living have steadily climbed. People are doing everything they can to protect and grow the value of their disposable income, which is the amount of money left over after covering basic living costs. Therefore, a growing number of individuals are opting for the riskier strategy of investing in stocks to control their personal finances. Our investors frequently confront two stock investment challenges: deciding which of several good stocks to buy to maximize returns, and deciding which of those stocks to buy based on the relative merits of each. Therefore, this article considers four typical companies in the US as examples, analyzes investment ratios using the Markowitz portfolio, and then investigates whether there are better options to aid customers.

Keywords: Markowitz model; Fama-French three-factor model; Fama-French five-factor model; Machine Learning.

1. Introduction

The period 2020-2021 is destined to be one of the most extraordinary periods in China's investment history, having experienced too much "uncertainty". Fluctuations in the Federal Reserve's monetary policy, geopolitical risks, recurring epidemics, and adjustments to epidemic prevention and control policies have all contributed to a steep rise in "uncertainty" and an ever-increasing difficulty factor for investment. To this end, based on Markowitz portfolio theory as used by Hannes Marling and Sara Emanuelsson [1] for portfolio selection. This paper takes four trading records from US stocks and uses the Markowitz portfolio to examine how investors should understand stocks and invest wisely during this period. According to the methodology presented by Martin Širůček [2], a derivation based on the Capital Asset Pricing Model (CAPM) is used to calculate the weights of individual securities in a portfolio. The study found that Tesla, NetEase, and Apple stocks were the better choices as a large percentage of investments during this period. Weibo stocks, on the other hand, have underperformed over this period and should be avoided. Estimates of Markowitz's effective portfolio through J. D. Jobson [3] and extrapolation thereof. Although the Markowitz portfolio is easy to use, it has the disadvantage of being a complex numerical model that is not easy to use in practice. Further research using the Fama-French three-factor model to better understand risk and return led to this conclusion, as described in an essay by Kent L. Womack [4]. For this reason, the fama-french portfolio and the machine learning portfolio are also considered for comparison, and there is a significant improvement in stability, especially in the presence of data volatility, compared to the Markowitz portfolio.

This paper will first detail the business conditions of the four companies selected, present the stock price of each company over the period, analyze them using the Markowitz investment model and then discuss systematically how they compare with other methods. This is followed by a systematic discussion of the comparison with other methods. The strengths and weaknesses of the model currently in use are explained, as well as which method will be used to improve it in the future.

2. Data

(1) AAPL

Apple, formerly Apple Computer Inc. is one of the top five technology juggernauts, ranking alongside Amazon, Google, Microsoft, and Meta, and is a worldwide corporation with its headquarters in Cupertino, California, the United States. Design, development, cellular communications, sales, computer software, internet services, and personal PCs are all a part of its present operations.

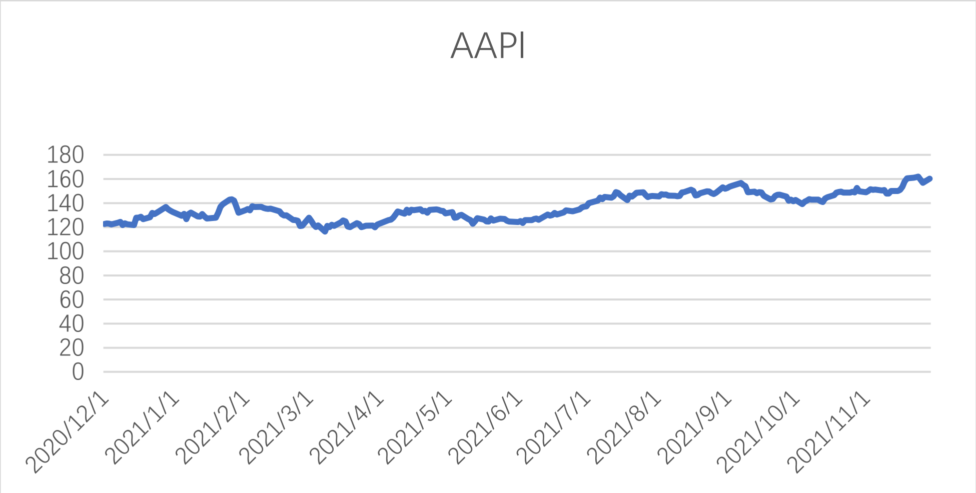

Figure 1. AAPL

As seen in the above chart (Figure 1), Apple's stock price is in the period from the beginning of December 2020 to the end of November 2021, a one-year period. The highest share price was $165.70 and the lowest was $116.21, with an average share price of $136.95 for the year. The highest increase was on March 1, 2021, which was an increase of 5.39%. The highest decline was on March 8, 2021, with a 4.17% drop. The quoted price change is 38.5%.

(2) TSLA

The leading American manufacturer of electric vehicles and solar panels, Tesla, formerly known as Tesla Motors, has teamed up with Panasonic in the battery industry to build and market electric cars, on-board computers (FSD systems), solar panels, and energy storage devices and system solutions. Tesla Motors, the world's best-selling maker of rechargeable vehicles by 2018, was the first business to produce self-driving automobiles. As of October 2021, it was the sixth major corporation with a market value over $1 trillion.

Figure 2. TSLA

As seen in the above chart (Figure 2), Tesla's stock price for the one-year period from early December 2020 to the end of November 2021. The highest share price was $414.50, the lowest was $179.83, and the average share price for the year was $248.94. The highest increase was on March 9, 2021, with an increase of 19.64%. The highest decrease was on November 9, 2021, with a decrease of 11.99%. The quoted price change is 101.68%.

(3) NTES

China's largest email service provider, the leading self-owned quality e-commerce brand, the leading online music platform, the leading online education platform, and the leading information media platform all belong to NetEase, one of the country's top Internet enterprises with a user base of over 1 billion people. NetEase also leads the world in the production and distribution of online games. NetEase's primary strategic businesses are currently online games, e-commerce, online music, online education, and information media.

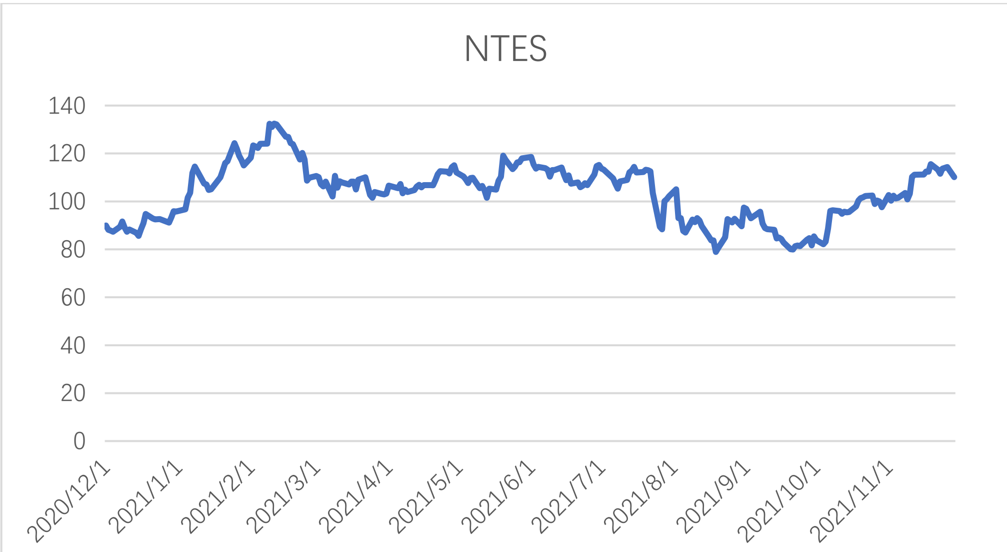

Figure 3. NTES

As you can see from the chart above (Figure 3), NetEase's stock price for the one-year period from early December 2020 to the end of November 2021. The highest share price was $134.33, the lowest was $77.97, and the average share price for the year was $103.81. The highest increase was on March 9, 2021, with an increase of 13.38%. The highest decrease was on November 9, 2021, with a decrease of 13.65%. The quoted price change is 19.21%.

(4) WB

Sina Weibo, a social media site launched by Sina.com, provides micro-blogging. Users can post updates through web pages, WAP pages, mobile apps, etc., and upload pictures and videos or live videos for instant sharing and spreading interaction. Right now, many refer to it as Twitter in Chinese.

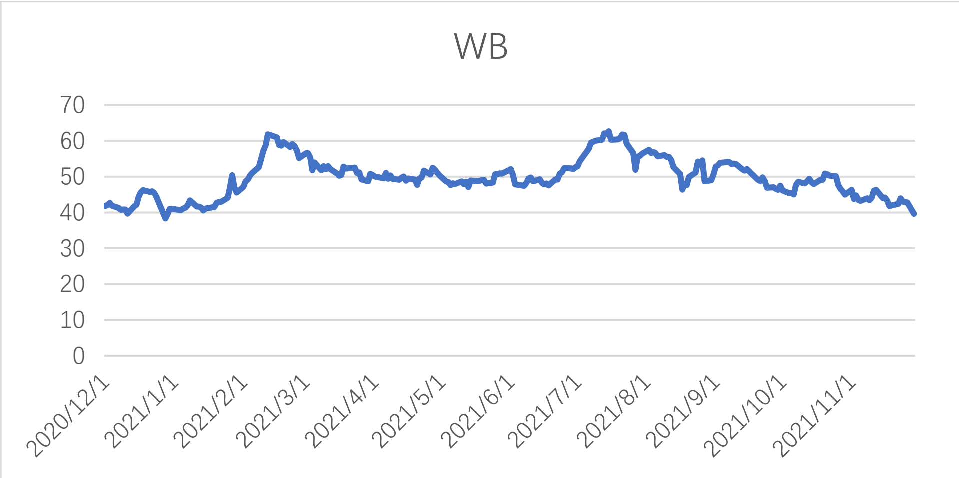

Figure 4. WB

As you can see from the chart above (Figure 4), Weibo's share price for the one-year period from early December 2020 to the end of November 2021. The highest share price was $64.70 and the lowest was $37.30, with an average share price of $49.63 for the year. The highest increase was on March 9, 2021, with an increase of 7.33%. The highest decrease was on November 9, 2021, with a decrease of 13.50%. The quoted price change is -5.78% (Table 1).

Table 1. Descriptive Statistics Tables

	AAPL	*TSLA*	*NTES*	*WB*
Mean	136.8376495	248.4094027	103.7906375	49.66880468
Median	134.720001	235.223328	105.839996	49.27
Standard Deviation	10.89226508	48.15305377	11.71685614	5.318169672
Minimum	116.360001	187.666672	78.919998	38.330002
Maximum	161.940002	409.970001	132.470001	62.66

3. Method

3.1 Markowitz portfolio model

The approach of this article is inspired by the Markowitz model as recognized in this article by Harry Markowitz [5]. In this study, this article selects four stocks and analyzes them according to the efficient frontier surface and the Markowitz portfolio.

This article makes use of the efficient frontier surface, which implies that rational investors favor rewards over risk and are risk-averse. For the same level of risk, they will select the portfolio with the highest projected return; for the same level of expected return, they will select the portfolio with the lowest risk. The efficient set is a portfolio that satisfies these two characteristics, and a portfolio on the efficient frontier is an efficient portfolio.

The Markowitz portfolio model is a squared difference model that includes systematic risk and unsystematic risk when assessing the risk associated with investing in a single stock. Unsystematic risk refers to market risk in general, including macroeconomic or policy changes. Unsystematic risk refers to particular hazards, such as company insolvency, financial fraud, and other singular events. This risk is especially high for individual stocks, although it may be mitigated by diversifying a portfolio among a greater number of stocks.

3.2 Building an optimal portfolio

This article employs the Sharpe ratio, which in finance assesses the performance of an investment (such as security or portfolio) relative to a risk-free asset after correcting for the investment's risk. It is the anticipated value of the difference between the investment return and the risk-free return, divided by the variance of the investment return (i.e., its volatility). It shows the additional yield per unit of risk an investor is willing to assume (Fig 5). Selecting the four stocks mentioned above for the portfolio yields a weight of 57.46% for Apple, 51.17% for Tesla, 7.17% for NetEase, and -15.8% for Weibo (see Table 2 and 3).

Table 2. Investment weighting table

	Weight	ER	W*ER	Min	Max
AAPL	57.46%	0.00118904	0.00068323	-1	1
TSLA	51.17%	0.00325120	0.00166367	-1	1
NTES	7.17%	0.00128335	0.00009200	-1	1
WB	-15.80%	0.00020245	-0.00003199	-1	1

Table 3. Income Statement

Sum	0.999999161
ER(p)	0.002406916
RF	0.000135890
Portfolio Risk	0.022988698
SR	0.098788777

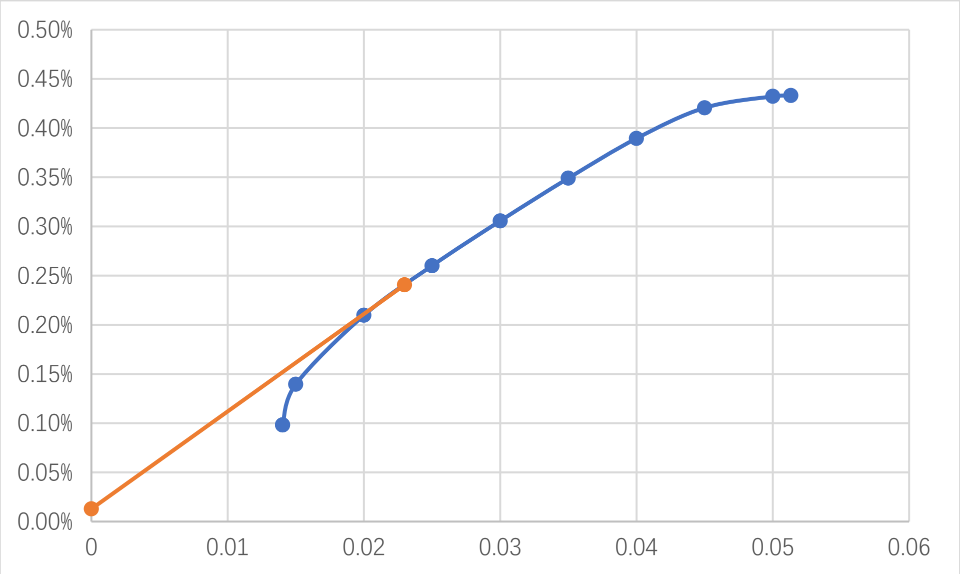

Figure 5. Effective Frontier Surface

4. Discussion

In the course of the study, the advantages of the Markowitz model are demonstrated, which helps new amateur investors to create diversified portfolios. And the theory helps to regulate risk to minimize losses. At the same time, these investments are likely to be highly profitable. Consequently, investors may utilize the model to detect and replace poor assets. The downside of this strategy, however, is that it is not based on current data; instead, the information is derived from past data. Sometimes, the model's underlying assumptions are rendered irrelevant, rendering the model invalid. This is true, especially for stormy markets. It focuses on a variation when it should, ideally, be centered on risk.

When compared to Markowitz's approach to asset pricing and portfolio management, the Fama-French three-factor model was shown to be more effective. It broadens the CAPM by include not only the market risk elements but also the scale risk and value risk aspects. Value stocks and tiny caps are considered due to the model's emphasis on outperformance. Incorporating these two new variables is thought to provide the model with a more accurate gauge of managerial effectiveness by compensating for this emerging pattern of outperformance. An economic regression of past stock prices formed the basis for the model. The conclusion for investors is that they should have the financial wherewithal to withstand more volatility and potential cyclical underperformance in the short term. Investors who can see past the near-term declines will be rewarded in the long run. Based on what I read from R. Sharma's study [6], the model may explain as much as 95% of the variation in stock portfolio performance, investors can fine-tune their holdings to maximize their expected rate of return while minimizing their exposure to any one type of risk. The results of Belen Blanco's research [7], which led to this article, show that portfolios are different depending on how they are put together.

However, Fama and French revised their model in 2014 to incorporate a total of five components. The new model includes a fourth component, profitability, which considers the idea that firms with larger future earnings have better returns on the stock market. The fifth component, "investment," is related to the idea of internal investment and returns, implying that corporations that reinvest their earnings into large-scale expansion initiatives may see their share prices drop.

Many stock investors in Taiwan have adopted machine-learning investment models in order to prevent their stock investments from failing [8]. As a result of the massive amounts of data that the financial sector must process every minute, machine learning has been shown to be useful in improving services and operations in the present. Smart investment advisers are being used by a growing number of banks and other financial institutions to better manage customer portfolios (robot advisors). The services it offers are not carried out by robots, despite the company's name. Instead, it is used as a web-based tool for advising on the administration of client portfolios. Smart advisers and machine-learning-based portfolio management are gaining popularity as an alternative to human investment advisors due to their cheaper cost. When banks and other financial institutions are victimized by fraud, it may have a domino effect throughout all sectors, and the cost of repair will much outweigh the losses incurred. The financial industry may greatly benefit from the use of machine learning to detect and prevent fraud since advanced algorithms can effectively detect and identify fraud trends to prevent fraudulent behavior from occurring. Finally, transaction settlement is a process of transferring payment currencies and equity securities. The process is fully electronic. However, the occurrence of transaction failures still requires manual efforts to resolve them. Machine learning can also be used extensively to avoid transaction failures. As Tejas Mankar [9] says machine learning and artificial intelligence techniques are being used in conjunction with data mining to solve a large number of real-world problems. The article in Ramkrishna Patel [10], leads this article to learn that many stock forecasts now use machine learning techniques as stock prices change daily due to market forces (supply and demand). Machine learning can determine the exact cause of a trade failure within seconds, provide a solution, and predict future trade failures, eliminating the need to spend more time waiting for a human to identify a trade failure.

5. Conclusion

In this paper, four stocks were selected for the study and the dates selected were December 1, 2020, to November 30, 2021. The optimal portfolio approach is sought, and it is confirmed that the capital weight of each stock. The optimal solution was obtained using the Markowitz model, and the efficient frontier surface for graphing.

The study concluded that the best scenario for the past year from December 2020 to November 2021 is to select the four stocks mentioned above for the portfolio, yielding a weighting of 57.46% for Apple, 51.17% for Tesla, 7.17% for NetEase and -15.8% for Weibo. The Markowitz portfolio minimizes risk through diversification. At the same time, the model ensures that overall portfolio returns are maximized. Investors are exposed to two types of stocks - low-risk, low-return and high-risk, high-return stocks.

Markowitz's model has certain flaws, though, including an excessive emphasis on past data, the deployment of a number of unnecessary assumptions, and the preference for mean variance over future risk. It is especially clear that Markowitz's assumptions no longer hold water when dealing with highly volatile markets. However, the Markowitz framework has one major flaw. The strategy favors uncertainty and disregards hazards. Since it is based solely on past performance, it offers no assurance of profitable investment. There are hidden costs that aren't accounted for in the model, such as broker fees, taxes, and other charges. All of the model's assumptions are predicated on the idea that stock prices are independent. The reality of the stock market is that it is volatile and difficult to anticipate. Machine learning, which is the study of creating algorithms and statistical models with which computers can carry out tasks without being explicitly programmed but instead making use of previously discovered patterns and inferences, is the field in which I hope to engage in future research. Machine learning algorithms are employed in the financial sector for a variety of purposes, including the detection of fraud, the automation of trading activities, and the provision of financial advising services to investors. Machine learning allows for rapid analysis of massive datasets with little to no human intervention in the form of explicit programming, yielding better results faster. As the financial sector continues to invest in AI and as AI continues to bring value to services, new applications for machine learning in the financial sector are expected to emerge. With the advent of the AI-powered digital era, machine learning has emerged as a crucial requirement for the banking and investment industries.

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