Stock Price Risk Assessment and Volatility Prediction - Portfolio based in 2020 US Stocks Market

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Author Note

This research does not constitue any form of investment advice or recommendations.

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Abstract

An efficient prediction of stock returns has always been a concern as well as challenge for investors and scholars. The 2020 COVID-19 pandemic has had a significant impact on the US stock market throughout the year, in this article, we performed comparative analysis of the stock performance from difference sectors under the pandemic market crash. And to expand upon past studies on stock price predictions mainly based on machine learning models, we combined Markowitz Mean-Variance Optimization, ARCH and GARCH Models in time series data analysis. The main focus of this research is optimization assessment on the porfolio, followed by volatility coefficiency test. We looked into the daily price data from six securities in three sectors in the whole 2020, and were able to idetify the optimized porfolios under targeted risk levels and to confirm the significant coefficiency for ARCH and GARCH effect within those portfolios. This will provide people with good understanding to how to better strategize investment decisions in dealing with market fluctuations as in 2020, and to more accurately predict portfolio performance in the future.

Keywords: Stocks, Performance, Risks

Word count: 3988

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The efficient prediction of stock returns has always been a concern as well as challenge for investors and scholars. The COVID-19 pandemic has had a significant impact on the US stock market since March 2020 (Mazur, Dang, & Vega, 2020), during which we saw one of the most dramatic crashes in the stock market in all history. Within less than five trading days, Dow Jones Industrial Average plunged almost 6,400 points, a roughly equivalent dropping of 26%. However, different securities from different sectors have had various reactions to the changes and risks that comes with the pandemic and lockdown from the US to global wide. All these factors just make the prediction of stock performance even more challenging. Past research on financial crises has uncovered multiple factors impacting stock returns during and after the market crash (Fung, Lam, Siu, & Wong, 2011). In this article, we would like to conduct evaluation on the performance of the stocks under the background of 2020 market crash so as to achieve an effective stock volatility prediction model and to construct a multi-sector portfolio with a certain level of risk.

Investment Portfolio and Weighting Assumption

Though there are various of ways to measure the return of the stocks, the commonly used methods are based on total price return and total gross return. Total price return is the return on an investment, which can be calculated from the price minus the cost. Total gross returns (Xuan, & Kim, 2020) stand in contrast to total price returns, and it also takes into account dividends and cash payouts etc., which can make a significant difference in the return calculation. The current study is going to explore the returns on portfolios including six securities from three sectors: the finance, information technology, and health care industry. Then I will assess if there will be any significant difference between the total price returns and total gross returns. After that I will further explore the weighting assumption of the portfolio on value-weighted and equal-weighted basis, which is to decide the portion of each one of the securities in the entire portfolio.

Traditional Methods and the Limitations

Traditionally, automated trading architectures are used to build portfolio, and it is a set of rules applied to a group of data to generate outcome for buy/sell decisions. However, the results do not always reflect the reality, so the prediction model is introduced to enhance profitability in addition to accuracy (Chalvatzis, & Hristu-Varsakelis, 2020). Historical estimators from analysis under the Markowitz Mean-Variance Optimization (Markowitz, 1959) dramatically outperformed traditional estimators for both the optimal return and its corresponding allocation (Leung, Ng, & Wong, 2012). Markowitz Mean-Variance Optimization model is a methodology looking to calculate the best return out of a portfolio under a given risk level, and it has been applied in the practice where for each expected return level, the efficiency models will produce optimized strategies of investment portfolio (Deng, Lin, & Lo, 2012). Therefore, in order to generate satisfying results, Markowitz Mean-Variance Optimization models have been implemented in the portfolio formation process in order to maximize the return and minimize the risk (G.-F., W., & Lo, 2012). Based on the Markowitz Mean-Variance Optimization theory, people will evaluate the rate of returns on the securities in the portfolio as random variables, and structure the portfolio weighting factors optimally, i.e. to achieve an acceptable baseline expected rate of return with minimal volatility of risks tolerance. However, there are limitation on the traditional portfolio optimization models when it comes to application in the practical environment. To be more specific, the classic models often refer to mean historical return as expected return of the portfolio, which could result in some inaccurate estimates on short term returns (Freitas, De Souza, & de Almeida, 2009).

Proposed Method for Improvement

Later on from the traditional method, stock predicted returns (Kolm, Tutuncu, & Fabozzi, 2014) are added to the portfolio optimization models in the analysis (Hao, Wang, Xu, & Xiao, 2013). One of the mostly adopted approach is to rely on predicted returns as benchmark return in the portfolio after the optimization models are built (Zhu, 2013). Some researchers also add more predictive variables in the model, such as extended mean–variance–skewness model (Ustun, & Kasimbeyli, 2012) when forming objective functions in portfolio optimization models (Yu, Paul Chiou, W.-J., W.Y., & Lin, 2020) and further improving the performance of initial portfolio optimization models (Yu, & Lee, 2011). Furthermore, researchers who use a combination of machine learning models (Adebiyi, Adewumi, & Ayo, 2014. Hansen, & Nelson, 2002) and deep learning models (M., E.A., Menon, & K.P., 2018. Lu, Lee, & Chiu, 2009) into the return prediction advance traditional portfolio optimization models (Moews, Herrmann, &Ibikunle, 2019). Time series models can also be used in the prediction assessment of stock return and volatility (Subair, & Arewa, 2020), and this research will be using ARCH (autoregressive conditionally heteroscedastic) model and GARCH (generalized autoregressive conditionally heteroscedastic) model in the forecast based on the return of the securities in the optimized portfolio. Both models are going to measure the variance in the time series data setting. The introduction of both models will bring in a moving average component which will allow us to monitor both the change in variance over a period of time and changes within the time-dependent variance.

Purpose and Assumption of the Study

The purpose of the study was to conduct comparative analysis of the stock performance from difference sectors in the background of 2020 market crash from the pandemic, and further advance the portfolio optimization models with two time series models in order to reach an effective risk assessment and return volatility prediction. The current study made the two major contributions to the academic progress: firstly, it assessed the performance and prediction of the stock market in the background of 2020 pandemic, which had some distinguishing differences from other financial crisis in additional to the various reactions of the market participants; secondly, two time series models had been added to the traditional method of portfolio optimization models. The portfolio optimization models benefited from this advancing approach not only by retaining the essences of classic optimization models, but also by adding the usefulness out of time series models to the Markowitz Mean-Variance Optimization model, in order to perform more effective return predictions.

The hypotheses for the study are as below.

H1: There is a significant difference between Total Price Return and Total Gross Return in the same portfolio.

H2: There is a significant difference in terms of portfolio value (return) between Value-Weighted portfolio (VW) and the Equal-Weighted portfolio (EW).

H3: There is an efficient portfolio (yield the highest return for a certain level of risk) based on Markowitz Mean-Variance Optimization.

H4: There is a significant difference in the expected value of all error terms when squared at any given point, and that is to say there is significant estimated coefficient between p lags of squared error and q lags of conditional variance for an ARCH and GARCH effect in the portfolio.

Methods

In this research, we used a daily adjusted closing price of six securities from three sectors: financial services, information technology, and health care industry, which were obtained directly from Yahoo Finance (https://finance.yahoo.com/) to perform the analysis.

First, we used Markowitz Mean-Variance Optimization model in the portfolio formation process. This is a model used to calculate the best return out of a portfolio under a given risk level. In the current study, it was applied in the process of generating an efficient portfolio in order to maximize the return.

Second, we introduced time series models in the prediction assessment of stock returns and volatilities mainly with ARCH (autoregressive conditionally heteroscedastic) model and GARCH (generalized autoregressive conditionally heteroscedastic) model. In the forecast of portfolio returns, we tested if there were any significant differences in the expected value of all error terms when squared at any given point and, in other words, if there were any significant estimated inefficiencies between p lagged squared error terms and q lagged conditional variance terms for an ARCH/GARCH effect in the portfolio. If there is not estimated inefficiency, in other word, the statistical significance (p-value) will be difference from zero, then we can reject the null hypothesis and conclude that there is an ARCH/GARCH effect.

Data

The data were downloaded directly from Yahoo Finance (https://finance.yahoo.com/). The securities were JPMorgan Chase & Co. (JPM), Goldman Sachs Group (GS), Microsoft Corp (MSFT), Apple Inc. (AAPL), Johnson & Johnson (JNJ), and CVS Health Corp. (CVS). These six securities were chosen given that they are the leading companies in their respective industry sectors. Both the market capitalization size of these securities and their underlying business scope made them good samples to represent the whole industry.

The data included daily price of each securities at its open price, highest price, lowest price, close price, adjusted close price (close price plus dividend payment, if any), and trading volume throughout the year of 2020. There were 252 entries for each securities with 6 columns of information, which represented the performance of each securities in 252 business days throughout 2020.

Predictors

The first two predictors of the data were the daily closing price and adjusted closing price of the six securities. Daily closing price was recorded as the price of the securities at the closing time of each trading date. Adjusted closing price was the daily closing price plus any dividends and cash payouts related to that specific trading date. Based on these two predictors, we were able to calculate and identify if there were any significant differences between the total price return and total gross return of the securities as well as within the portfolio. See Table 1 for statistics summary of the securities including mean and standard deviation on the closing price and adjusted closing price.

Table 1

Means and SDs of Closing Price and Adj. Closing Price from Six Securities

Securtiy	M Closing Price	SD Closing Price	M Adj. Closing Price	SD Adj. Closing Price
JPM	106.43	15.84	104.13	15.21
GS	206.31	25.95	203.79	25.84
MSFT	192.91	22.97	191.96	23.34
AAPL	95.2	21.73	94.75	21.84
JNJ	145.77	6.67	143.75	6.9
CVS	64.22	5.23	62.9	5.09

The next predictor was the weight assumption, i.e. the portion of each securities within the portfolio. We tested two assumption approaches - equal-weight assumption and value-weight assumption. Equal-weight assumption means buying the same amount of each securities in the portfolio. Value-weight assumption, which is also know as Cap-weight, refers to the strategy of investing in more securities of companies that have higher market capitalization value. Different assumptions determined the risk level within the portfolio by accumulating the underlying risk of each securities for optimizing, and this way to make sure portfolio formed was efficient enough for further volatility prediction testing.

The last predictor was time in order to account for the impacts of the 2020 market crash as well as the time series analysis we conducted. We used data from the entirety of 2020 to conduct the research in order to assess the effect of V-shape market changes upon the stock volatility prediction.

Outcome

The total price return and total gross return were calculated using the daily closing price and adjusted closing price of each securities. Total price return was calculated as the price of the securities minus their cost. Total gross return was calculated as total price returns plus dividends and cash payouts. By comparing the two types of returns, we were able to see that there were not significant differences between the two return calculation, though price return slightly outperformed the gross return.

Data Analytic Plan

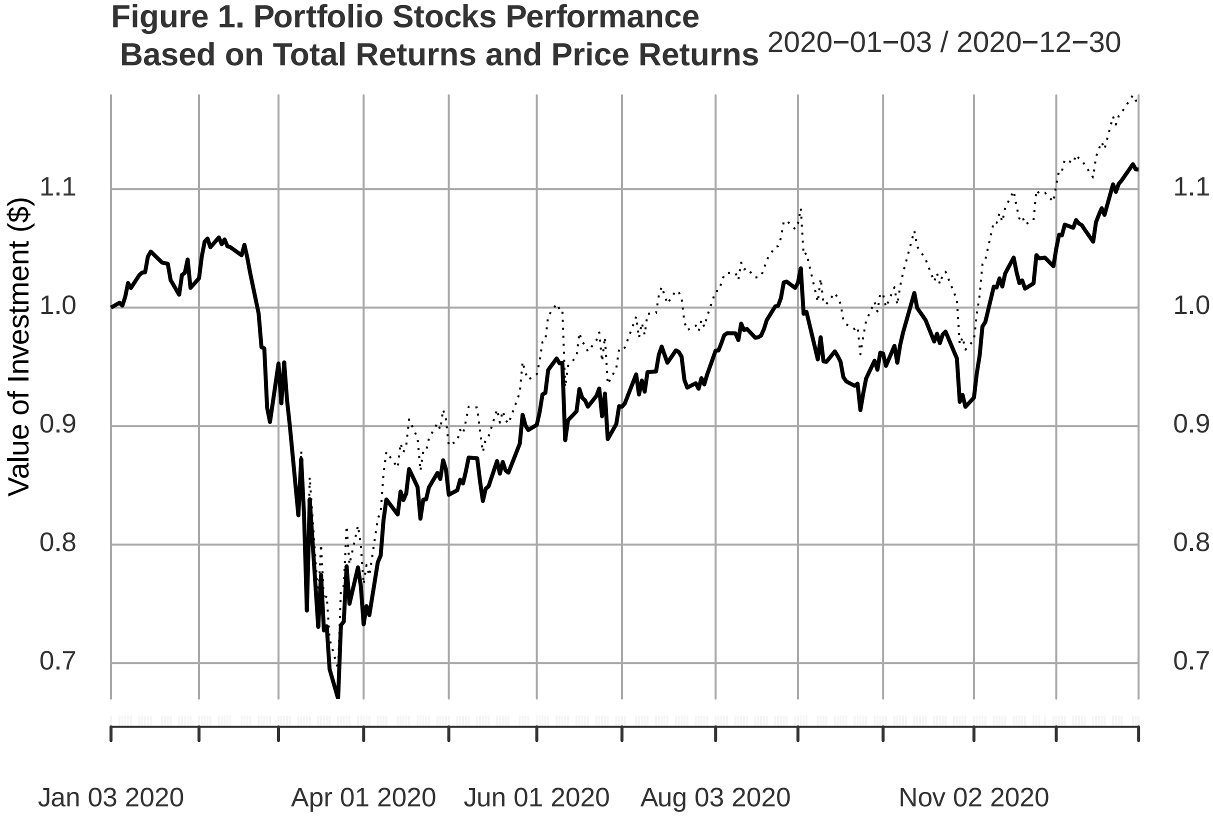
The pre-processing of the data was conducted by using plotting methods mainly to check for any missing values in the dataset, especially with any missing or N/A values. This way we were able to make sure if the time period of the data set covered and only included data for the year of 2020. Based on the plotting, the lines were all consistence for the 6 selected securities. Therefore, we were able to conclude that dataset was complete for the whole year period of 2020 without any missing data. In appendix, we performed plotting of the data on the closing price for each securities to check for missing data.

Results

Portfolio Return Assumptions

The first step of the analysis was to test on difference between Total Price Return and Total Gross Return in the same portfolio. Total price return was calculated as the total of the daily closing price subtracted by the total of the purchase cost of the securities. Total gross return was calculated as the total price return plus any dividends and cash payouts. After the calculation of both returns, we plotted Figure 1 below to demonstrate how much of $1 was going to worth throughout the year of 2020 once invested in the portfolio at the beginning of year. We were not able to identify any significant differences between those two returns though price return (dotted line) has a slightly higher performance than the gross return, which could be related to the divided amount included in the adjusted closing price.

Figure 1. Portfolio Stocks Performance Based on Total Returns and Price Returns



Based on this assumption, we decided to continue our analysis with total price return to count in the dividends and cash payments.

Portfolio Weight Assumption

Once we decided to continue with the total return assumption, we assessed the difference on portfolio value (return) based on Value-weighted assumption and Equal-weighted assumption.

Equal-weight assumption means buying the same amount of each securities in the portfolio. Value-weight assumption, which is also know as Cap-weight, refers to the strategy of investing in more securities of companies that have higher market capitalization value. The market capitalization of each security is calculated as taking the share price multiplying by the number of shares outstanding. To re-balance the portfolio in this analysis, we recorded the numbers of shares outstanding of each securities in the portfolio at the first day of each quarter in 2020: January 01, April 01, July 01, and October 01.

First, we built up the portfolio based on equal weight assumption in which we held each securities for the same amount throughout 2020. The mean and standard deviation of the return of the equal-weighted portfolio were 0.79 and 0.07.

Then, we constructed another portfolio based on value-weight assumption. We re-balanced the weight of each securities at the beginning of each quarter based on the market capitalization size of each security which was calculated as multiplying the stock price by its outstanding number of shares.

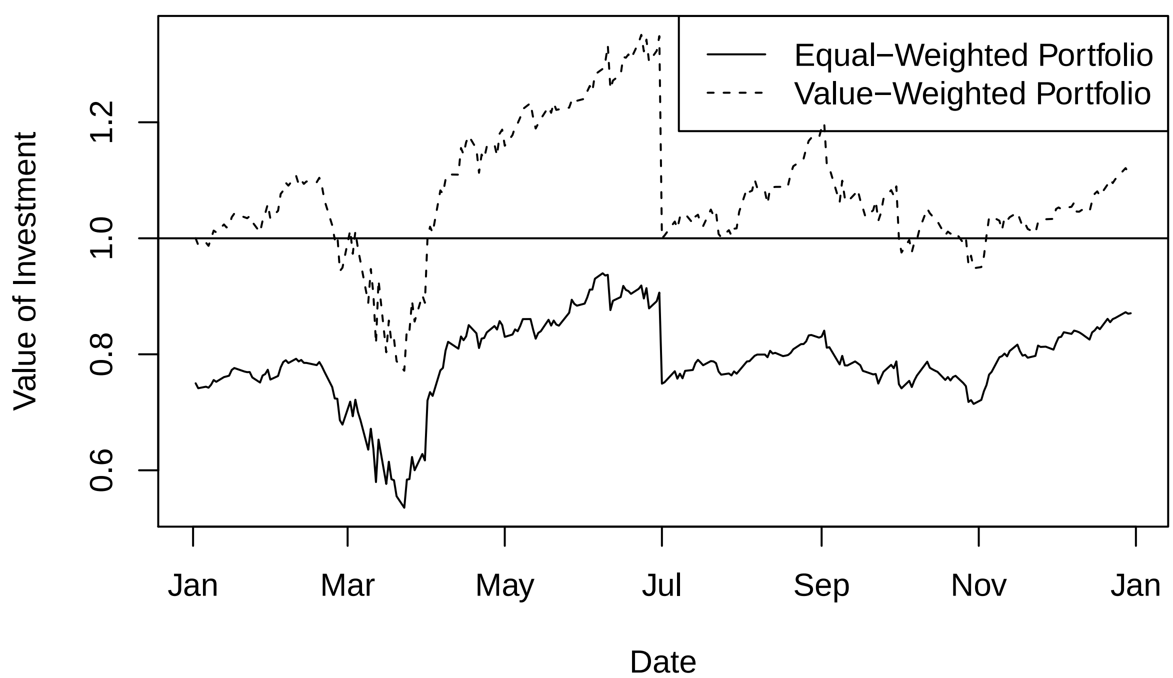
In the analysis, we grouped the number of outstanding shares for the securities grouping by sectors, which were obtained from Yahoo Finance (https://finance.yahoo.com/). For Financial industry, the number of shares outstanding ranges between 3416 to 3394, IT industry for 24920 to 25400, and Healthcare for 3930 to 3940.

Based on the market cap calculation, the portfolio was re-balanced based the cap-weight each quarter. Throughout the market fluctuation in 2020, the weight of IT securities increased from 74% to 82%, while Financial Services and Health Care shirked significantly from almost 15% each to less than 10% each.

Based on the weight assumption changes above, we were able compute the return in the value-weighted portfolio. The means and standard deviations of return in the portfolio were 1.08 and 0.11.

After we calculated the total price return under each assumption, we performed a comparison plotting as Figure 2 below. The results showed an almost 40% significantly higher performance in the value-weighted assumption, which was what we expected and therefore, we decided to construct our portfolio based on value-weighted basis for the following optimization testing.

Figure 2. Value of $1 Investment in Equal−Weighted and Value−Weighted Portfolios Jan. 01, 2020 − Dec. 31, 2020



Markowitz Mean-Variance Optimization

Once we assessed the returns under different weight assumptions, we implemented Markowitz Mean-Variance Optimization model looking to calculate the best return out of a portfolio under value-weighted assumption, and we tested if there such portfolio would be efficient enough to offer highest return for a given level of risk by using mean and variance.

We used 100 increments between the minimum and maximum returns to generate the target returns. The expected return could vary between 0.08% to 5.75%. From there, we identified the minimum variance portfolio that had the lowest portfolio risks as in second portfolio in Table 2 below. This portfolio had a return of 2%, standard deviation of 0.04, and it was made up of three securities: Microsoft (50%), Johnson & Johnson (27%) and CVS (23%).

While running the optimizer, the model looked for a combination of weights of the six securities that generated the target return with the lowest risk. We used the quadprog function in which it looped through the calculations 100 times (increments). There were three constrains included in the algorithm: the total weight in the portfolio must equal to one, the portfolio return has to equal to a target return, and the weights for each security has to be or greater than zero. The Sharpe Ratio calculation asked for a risk-free rate for which we use the 3-Month Constant Maturity Treasury as a proxy (https://fred.stlouisfed.org/series/DGS3MO). Since the annual yield rate as of December 31, 2020 was 0.09%, we converted this to a monthly yield by dividing the rate by 12, and that gave us 0.0075%. Then we calculated the Sharpe Ratio for each of the portfolios constructed based on the risk-free value above. The portfolio that gave us the highest Sharpe Ratio would be the Tangency Portfolio (as third portfolio in Table 2 below). The tangency portfolio had a return of 6%, standard deviation of 0.09, and it was made up of just one securities: Apple. The sharpe rate of 0.67 indicated a market-beating performance.

Following on in Table 2, we also demonstrated two more portfolios with the highest return (fourth) portfolio) and lowest return (first portfolio).

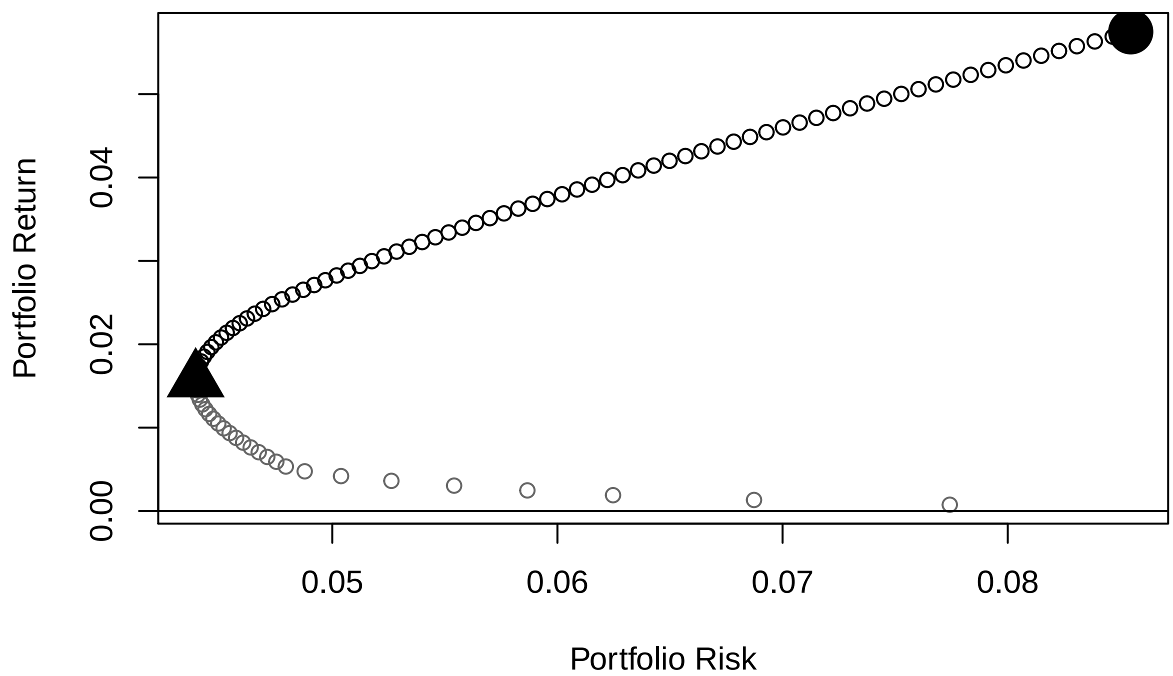
Table 2

Porfolio Optimization

tgt.ret	tgt.sd	wgt.JPM	wgt.GS	wgt.MSFT	wgt.AAPL	wgt.JNJ	wgt.CVS	Sharpe
0.00	0.08	1.00	0.00	0.00	0.00	0.00	0.00	0.01
0.02	0.04	0.00	0.00	0.50	0.00	0.27	0.23	0.35
0.06	0.09	0.00	0.00	0.00	1.00	0.00	0.00	0.67
0.06	0.09	0.00	0.00	0.00	1.00	0.00	0.00	0.67

We ended up with the Figure 3 below as the Mean-Variance Efficient Frontier of three sections based on the Quadratic programming approach. It marked the portfolio return under different portfolio risk. From the figure, we could confirm that there is an efficient portfolio based on the Markowitz Mean-Variance Optimization which yielded the highest return under a targeted risk. The Triangles identified the minimum variance portfolio, which marked the return from the portfolio if we set the risk to its lowest possibility. On the other hand, the solid dot marked the tangency portfolio, which represented the highest return we can expect, and accordingly represented a relatively highest risk in the portfolio.

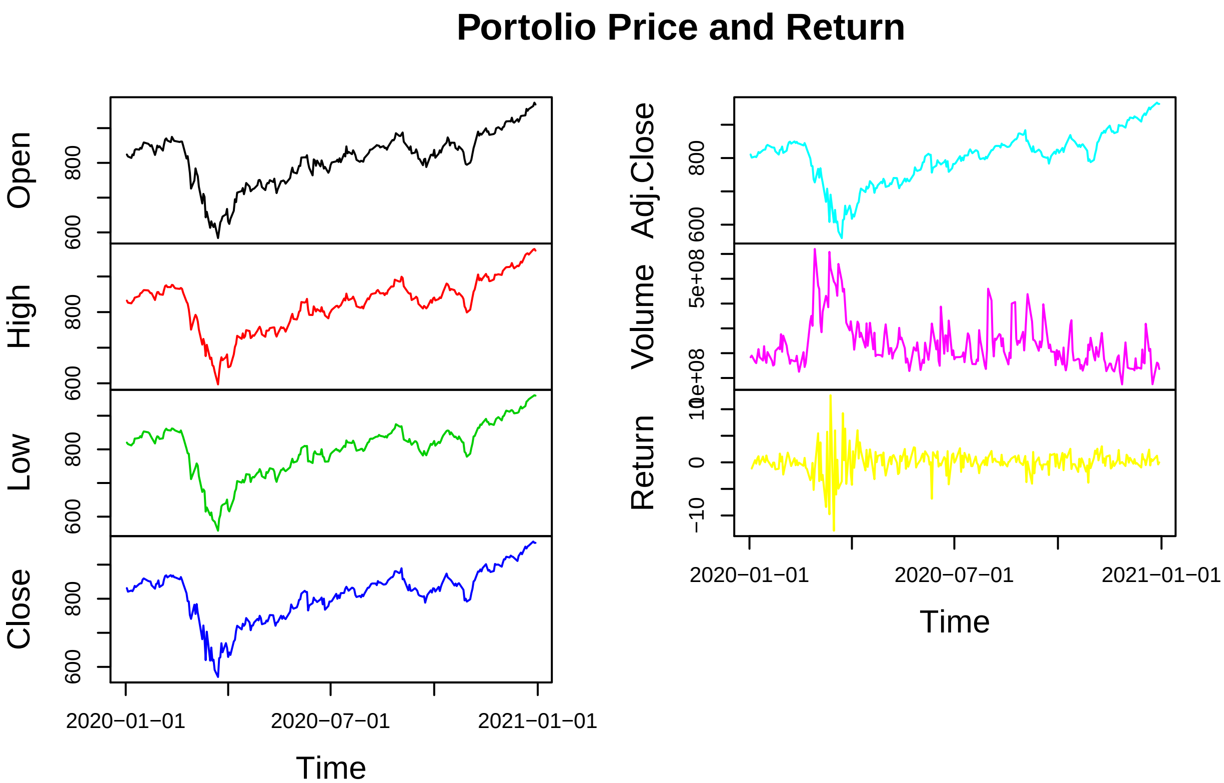
Figure 3. Mean−Variance Efficient Frontier of Three Sections Based on the Quadratic Programming Approach



ARCH And GARCH Models

In this section, we introduced time series models in the prediction assessment of stock return and volatility mainly with ARCH (autoregressive conditionally heteroscedastic) model and GARCH (generalized autoregressive conditionally heteroscedastic) model. In the forecast of portfolio returns, we tested if there were any significant differences in the expected value of all error terms when squared at any given point and, in other words, if there were any significance for us to reject the an ARCH/GARCH effect in the portfolio.

To start with, we plotted the data for an overview as below.



ACF and PCF were used to understand the influence of historical values on the current value. The function ACF computed estimates of the autocorrelation, and PACF was used for the partial autocorrelations. Results of the ACF and PCF plotting can be located in the appendix.

We used a significance level of 0.05 for our null hypothesis test. The ARCH LM-test was statistically significant (chi-squared = 1306, p $<$ 0.001), so we would reject the null hypothesis and conclude that there was a significant coefficiency in the testing, and there was ARCH effect in the portfolio.

Since ARCH model required estimation of the coefficients of p-value terms, which could potentially consume some certain degrees of freedom, sometimes it could be difficult to interpret all the coefficients, especially for those that were negative. Therefore, we introduced GARCH model here so the conditional variance depended not only on past squared errors but also on lagged conditional variances. Detailed results of the GARCH test can be located in the appendix. The results also indicated a strong coefficient from which we concluded that there was GARCH effect in the porfolio as well.

Discussion

The impact of COVID-19 has been expanded to various aspects of our daily lives, including the capital market. This analysis aimed at extending the existing research on time series optimization and projection. We applied Markowitz Mean-Variance Optimization, plus two time series models - ARCH and GARCH models in the risk assessment and volatility testing, covering the entire year of 2020 with the focus of the V-shaped price fluctuation on six securities from three sectors in the market.

The research started with the testing on the difference between total price return and total gross return in which we did not identified significant difference, therefore we cannot reject the first null hypothese but we decided to continue our research based on total price return to include the dividends and cash payout. Then we assessed the returned based on two different portfolio weight assumptions - value-weighted assumption and equal-weighted assumption. The research indicted that a significantly higher return can be expected from the portfolio structured based on value-weight assumption, so we rejected the second null hypothese and chose value weight assumption as the structural basis of our portfolio. After that, we applied Markowitz Mean-Variance Optimization model on different combinations of portfolio risks and returns , and were able to reject the third null hypothese as we were able to identify efficient portfolios including the minimum variance portfolio (lowest risks) and tangency portfolio (highest returns). Last but not the least, we tested the ARCH and GARCH effect in the portfolio for coefficiancy assessment, and both testing results suggested significant effect in the portfolio. Therefore, we rejected the fourth null hypothese as the portfolio is ARCH and GARCH effective.

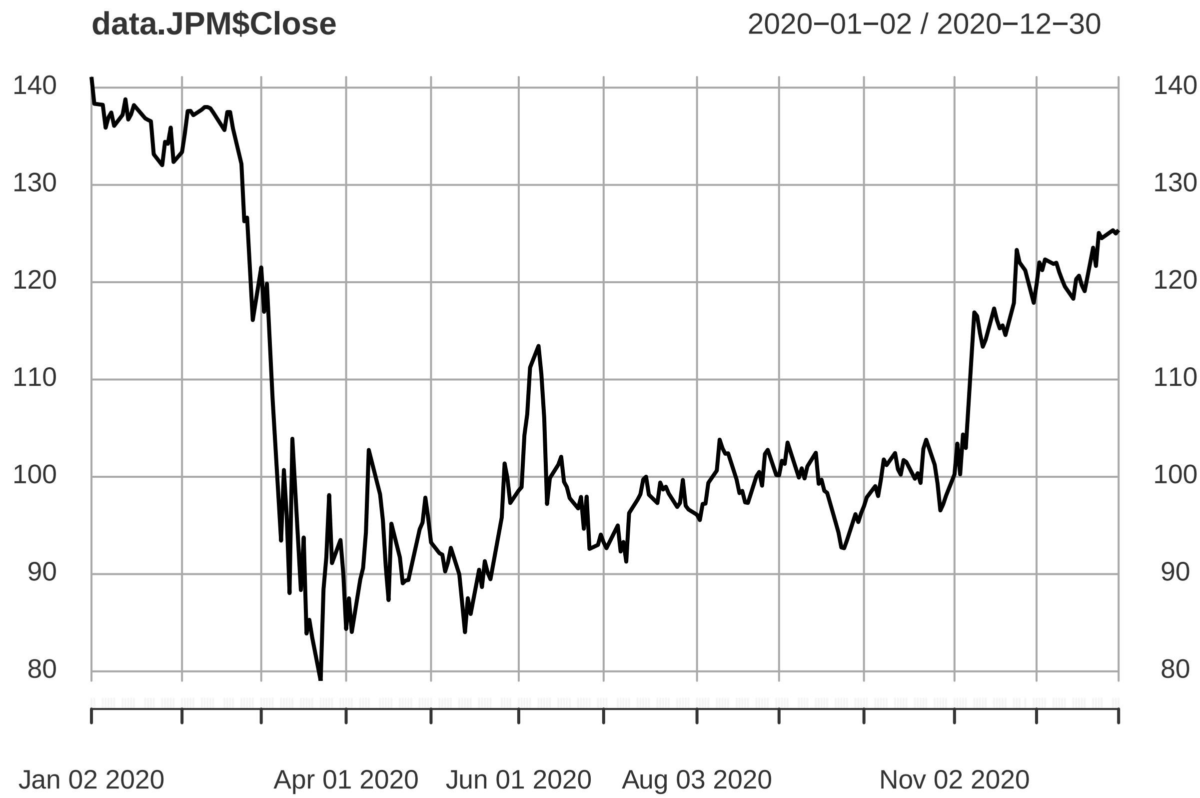
The limitation of the research can be the time variance of the data as we mainly focused on the 2020 pandemic impact which might not be happening on a regular basis. Though there are various of contributions affecting the performance of the stock market, the COVID can be one of the most significant impacts on the market throughout 2020.

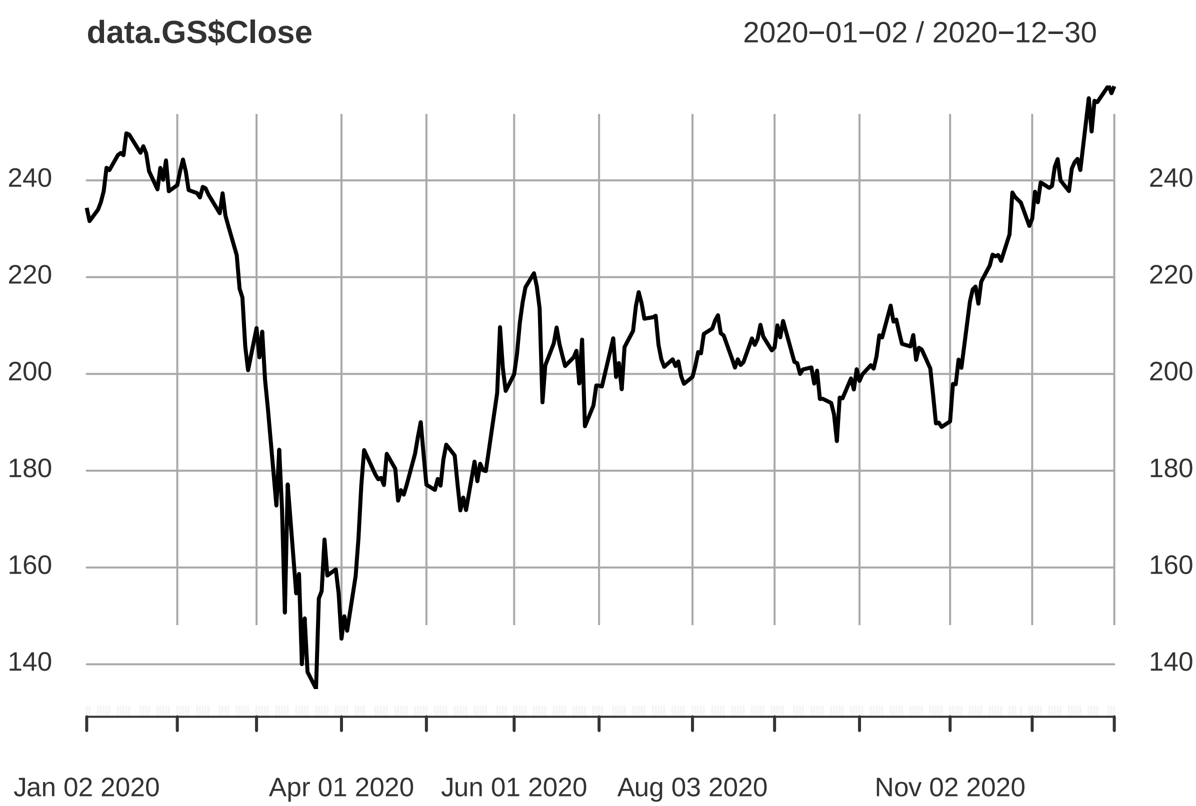
Therefore, the current study does not provide evidence about the efficiency of the portfolios under the regular market conditions (without COVID) from this research. In order to solve this, a randomly selected time series data can be considered in order to get a better picture of the market behaviors. Thus, further research can be conducted to extend the duration of data range, ideally 12 more months either before or after March 2020 market crash. The potential hypotheses can be considered as: first, there is significant difference from the return calculations based on equal and value weight assumptions pre and post COVID; second, the optimization and coefficiency testing are both effective within the portfolios pre and post COVID.

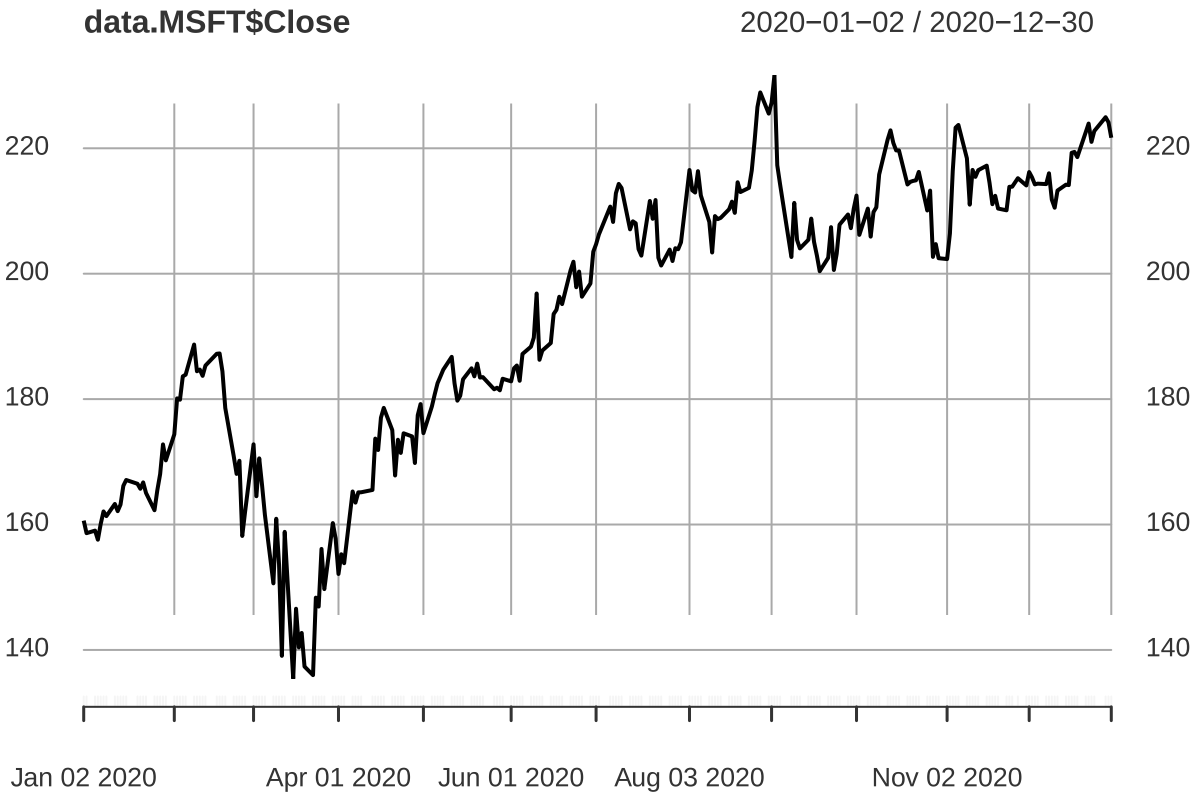
In all, this research enriched the current studies on stock market optimization and risk assessment mainly in the following three aspects. Firstly, we assessed the return calculation and were able to identify that price return calculations is a more accurate measurement of stock performance. Secondly, we found that value weighted portfolios have better performance than the equal weight portfolios, and this provided a practical investing strategy for stock market investors. Thirdly, we applied both optimization and time series models in the particular project, and the combination of these models filled the research gap in the existing literature as this approach brought in a moving average component to monitor both the change in variance over a period of time, as well as changes within the time-dependent variance, and this feature enhanced the efficiency of the predicted portfolios. This can provide the investors with a much more effective forecast model when they are trying to assess the stock market volatility based on the historical performance of the market, from which investors will receive the return forecasts to be expected based on the risk tolerance level they set.

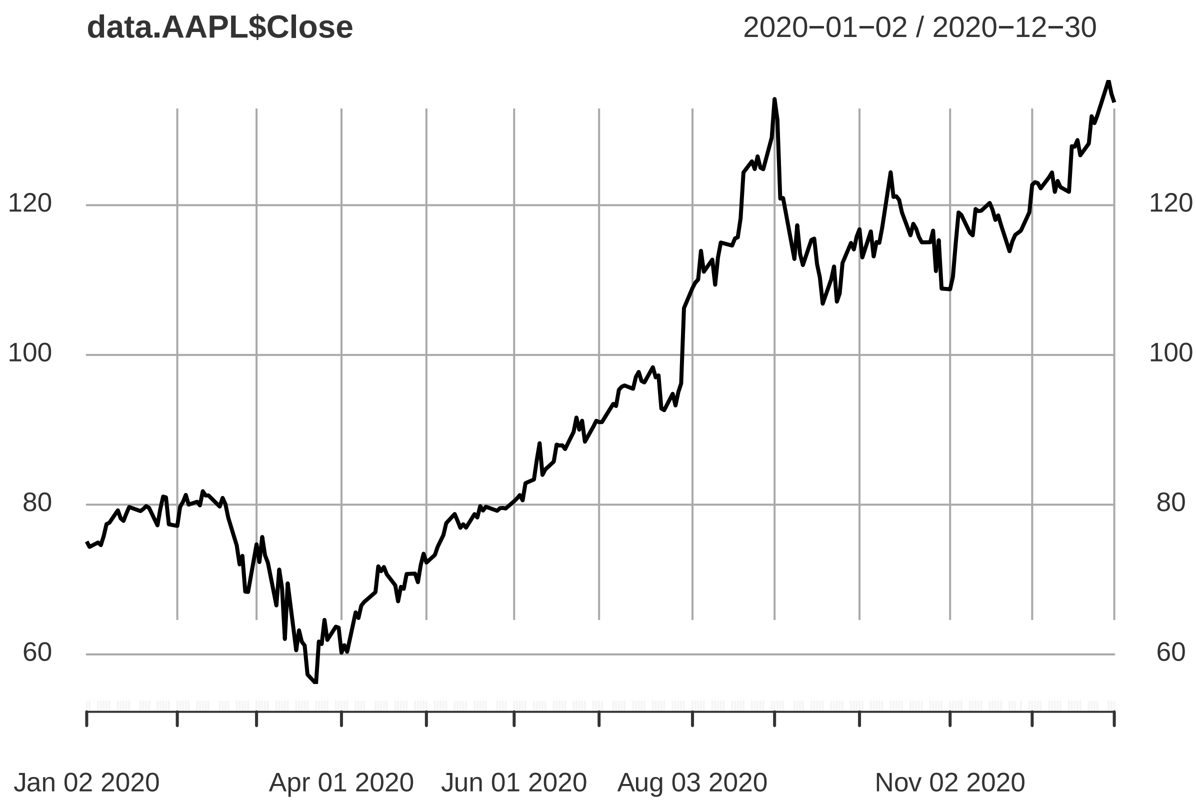
Appendix

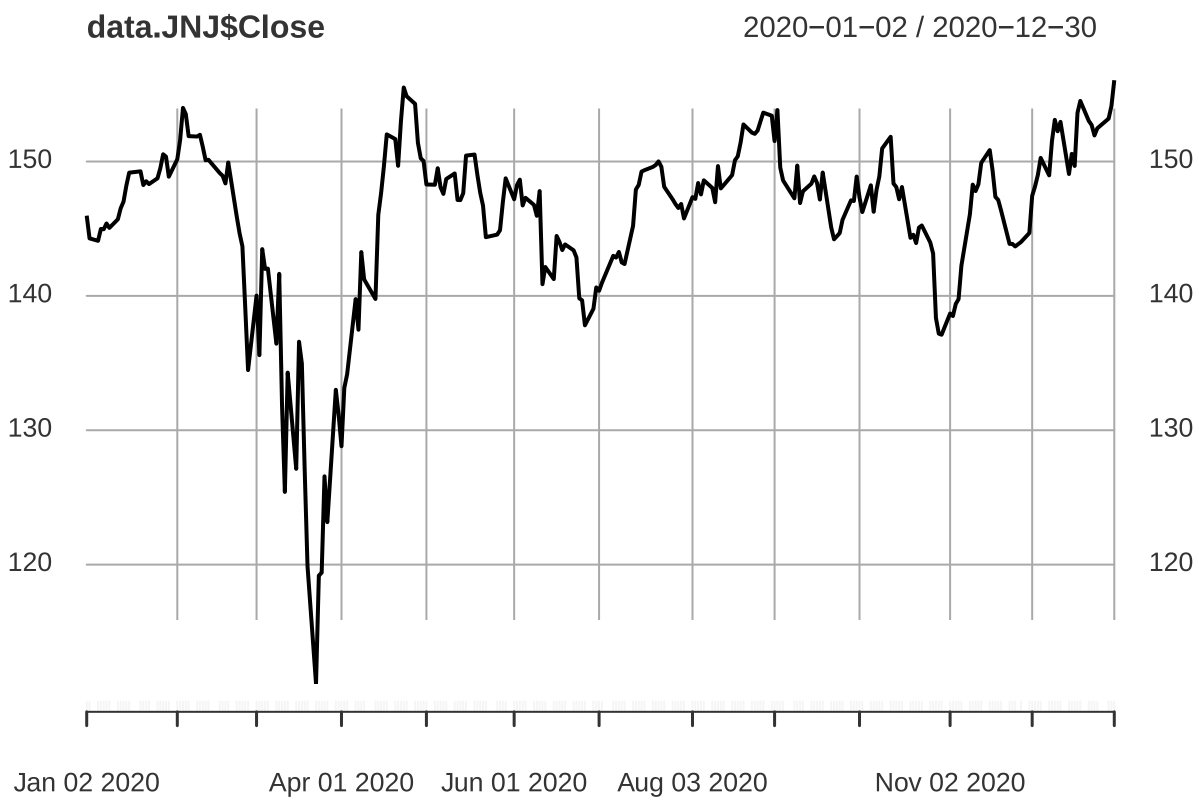
1. Plotting of the data for each security to check for missing data as below:



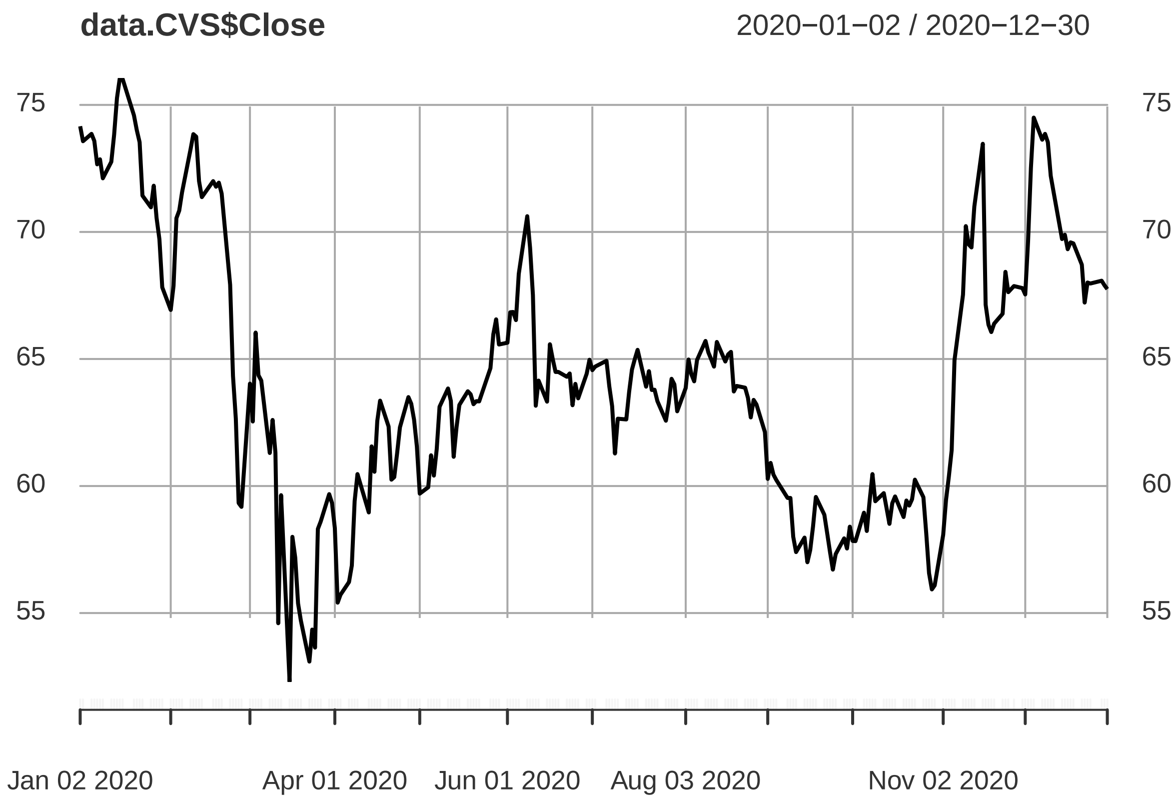



data.MSFT$Close
2020−01−02 / 2020−12−30
220
200
180
160
140
Jan 02 2020
Apr 01 2020
Jun 01 2020
Aug 03 2020
Nov 02 2020

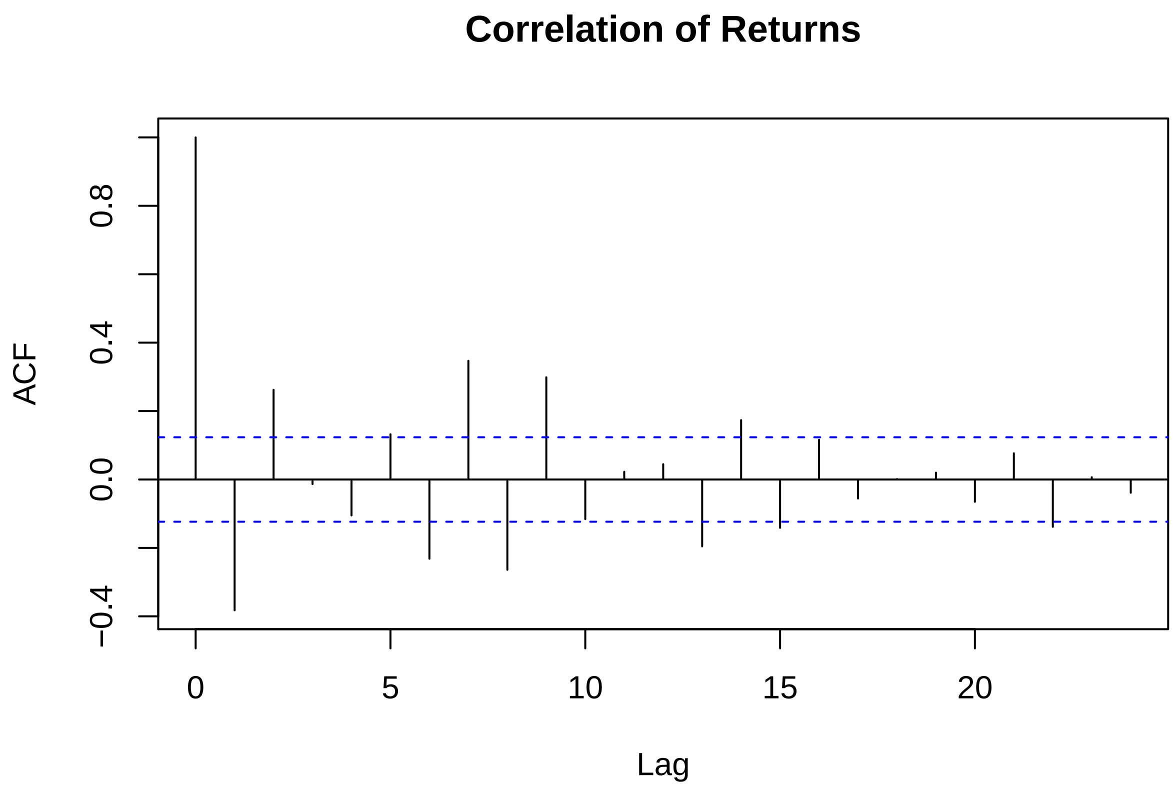

data.AAPL$Close
2020−01−02 / 2020−12−30
120
100
80
60
Jan 02 2020
Apr 01 2020
Jun 01 2020
Aug 03 2020
Nov 02 2020

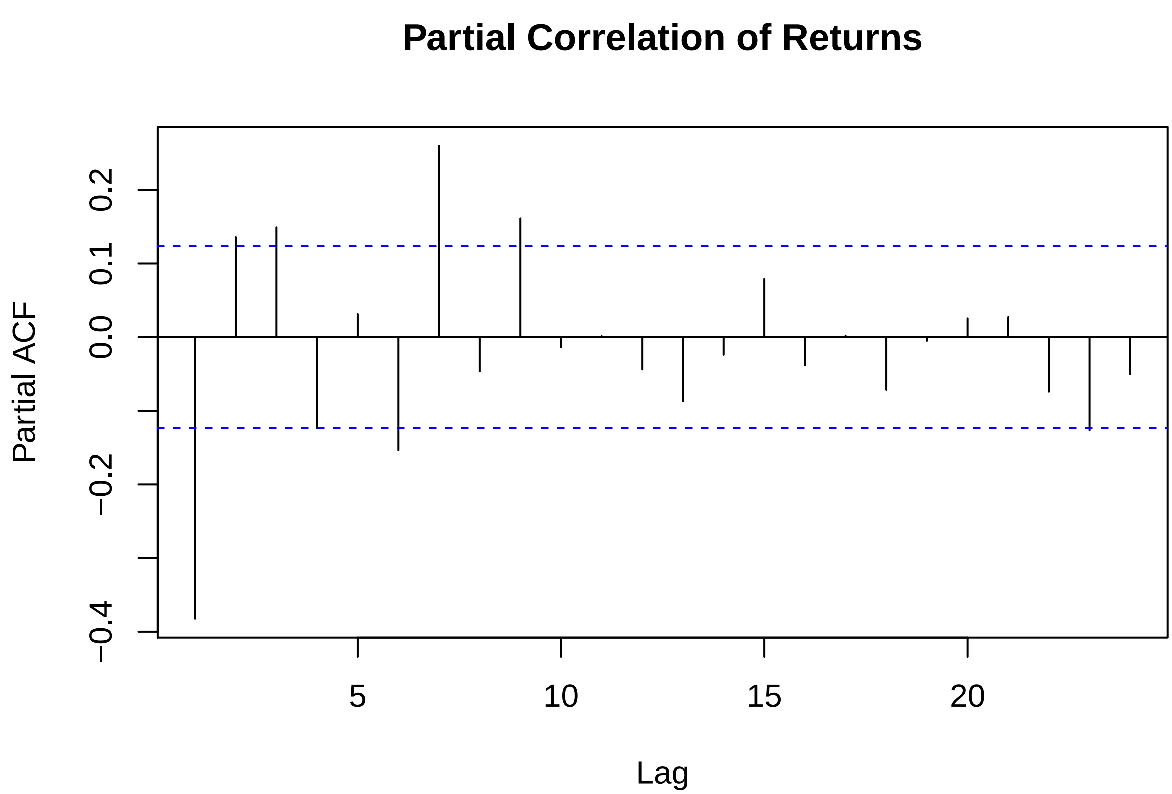

data.JNJ$Close
2020−01−02 / 2020−12−30
150
140
130
120
150
140
130
120
Jan 02 2020
Apr 01 2020
Jun 01 2020
Aug 03 2020
Nov 02 2020

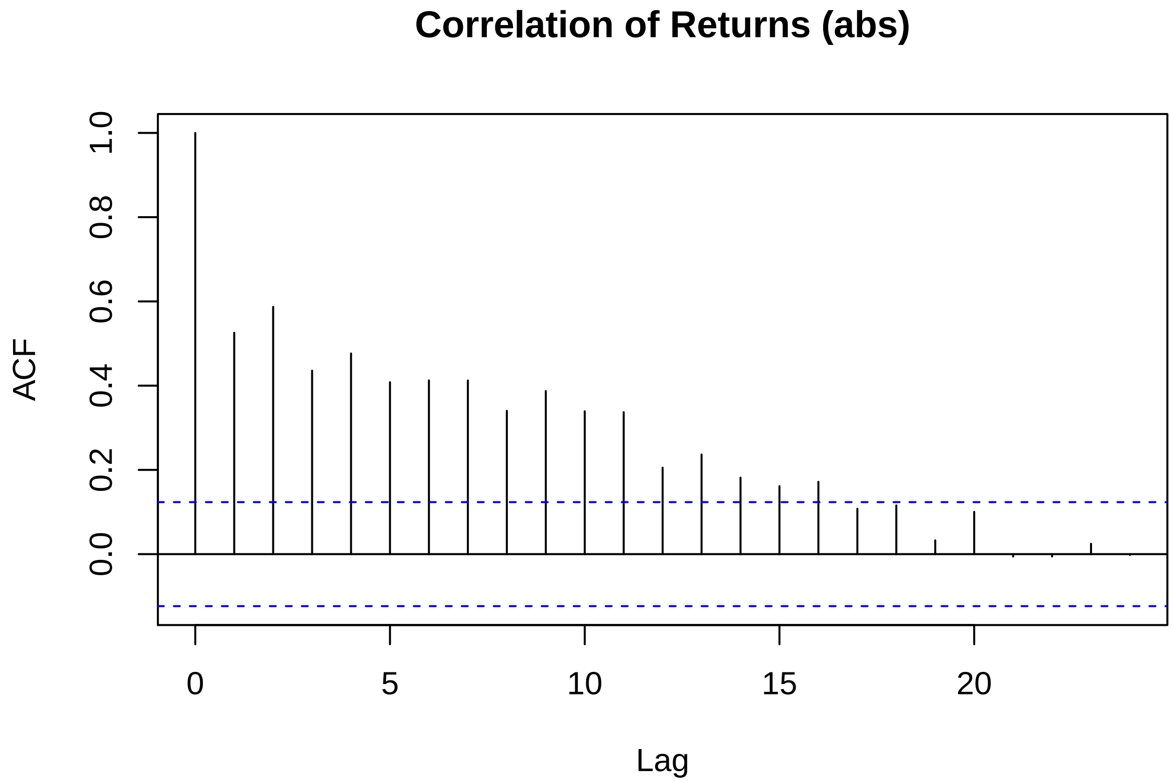
354

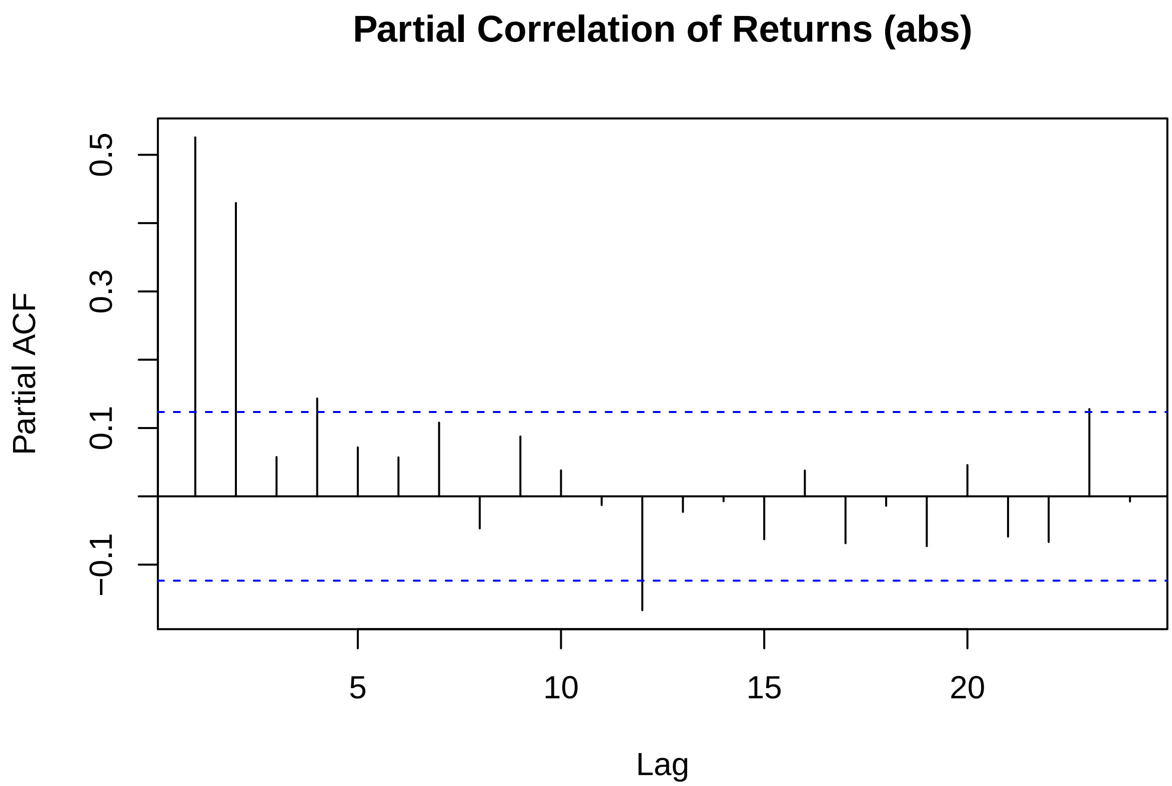

data.CVS$Close
2020−01−02 / 2020−12−30
75
70
65
60
55
Jan 02 2020
Apr 01 2020
Jun 01 2020
Aug 03 2020
Nov 02 2020

2. ACF and PCF function






Correlation of Returns (abs)
ACF
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20
Lag



3. GARCH test

```
##
## Title:
##  GARCH Modelling
##
## Call:
##  garchFit(formula = ~garch(1, 1), data = TSComp[, 7], trace = FALSE)
##
## Mean and Variance Equation:
##  data ~ garch(1, 1)
## <environment: 0x000000001348bc38>
##  [data = TSComp[, 7]]
```

```
##
## Conditional Distribution:
##  norm
##
## Coefficient(s):
##       mu    omega   alpha1    beta1
## 0.11503  0.29182  0.20938  0.71259
##
## Std. Errors:
##  based on Hessian
##
## Error Analysis:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu       0.11503     0.09306    1.236 0.216401
## omega    0.29182     0.11774    2.479 0.013192 *
## alpha1   0.20938     0.05686    3.682 0.000231 ***
## beta1    0.71259     0.06568   10.849  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
##  -493    normalized:  -1.96
##
## Description:
##  Wed Apr 21 22:36:14 2021 by user: xingc
```

References

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