The Key To Portfolio Success

With Monte Carlos Simulation and Fibonacci Retracement

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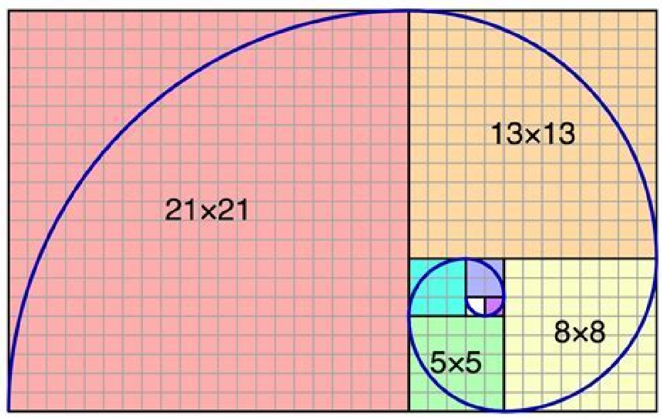
Abstract

The objective of this paper is to obtain a stock portfolio with the optimal result. Samples were taken from Virginia Tech SEED's real energy portfolio. The chosen equities were tested through the Monte Carlos Simulation in order to obtain the most successful portfolio. Success of the portfolio was determined by having the highest percentage return and Sharpe Ratio. Traditionally, themes of portfolio success can be achieved through: diversification, risk-management, setting a goal, and establishing a time horizon. Through trials from the Monte Carlos Simulation, these themes prove accurate. Patterns of the optimal portfolio can be seen through diversifying one's portfolio and being overweight in companies that have historically performed well.

Introduction



The Fibonacci Retracement is named after Italian mathematician, Leonardo Pisano. Fibonacci Retracement levels are horizontal lines that are based off of the Fibonacci sequence. The Fibonacci Sequence (FS) is a mathematical sequence that the whole world follows. The FS follows the rule that each number in a series follows the sum of 2 numbers before it. The Golden Ratio (φ) (figure above) also derived from the FS which is a special ratio between two quantities in which the ratio between the two quantities is equal to the ratio of their sum to the larger of the two quantities $\frac{a+b}{b} = \frac{a}{b}$. The Golden Ratio is theorized that each number is ~1.618 times larger than the previous number. The Fibonacci sequence can be seen in many things on Earth such as sunflowers, shells, tornados, animals, etc. Continuing, by using the Fibonacci Retracement through FS, The horizontal lines established indicate support and resistance levels. Support and resistance levels are tools often used in technical analysis by using historical price patterns to potentially forecast a security's future price. Support levels show increase in demands at a certain price while resistance levels show selloff. Based on the Golden Ratio (figure above), The Fibonacci Retracement levels are **23.6%, 38.2%, 50%, 61.8%, and 78.6%**. These percentages are the Golden Ratio in Fibonacci Retracement. By understanding and applying the Fibonacci Retracement to securities, investors can mediate risk by understanding support and resistance levels.

Moving on, the Monte Carlo Simulation is named after a famous gambling location in Europe called Monaco, this method/algorithm was created and used during WWII to improve decision making under unknown conditions. Essentially, the Monte Carlo simulation is a tool that is used to predict the probability of a variety of outcomes when random variables are present. The algorithm runs trials and forecasts results. The simulation can be used for a variety of things such as gambling, investing, experiments, etc. The structure of a MCS consists of t*he predictive model*, *specifying probability distribution*, and the simulation itself. The predictive model establishes dependent and independent variables, the probability distribution uses historical data to create a range of an unknown variable from happening, and the simulation generates and presents the results. In the context of portfolios, we will be testing the theory of if being overweight in high performance portfolios will generate one that is the most optimal.

More on Fibonacci Sequence
More Info on Monte Carlos Simulation

Literature Review

Based on the Fibonacci Retracement levels, we will establish and visually graph these support and resistance levels. We will then apply these Retracement levels to our sample portfolio. Recalling, the Retracement levels are 23.6%, 38.2%, 50%, 61.8%, and 78.6%. These metrics will be judged based on historical price patterns such as the 52 - week range. Finally, the sample portfolio will be visualized in a graph to determine the potential support and resistance levels based on historical data.

Additionally, this report will also review the Monte Carlos Simulation in order to design the optimal stock portfolio from SEED's Energy Sector. The MCS will generate the best portfolio based on the current portfolio weight. The most successful portfolio will be one that has the highest rate of return as well as Sharpe Ratio. Before the simulation, however, the model must establish variables and conditions such as the different stocks and parameters required for the simulation. The simulation also requires information based on historical data. For example, it will randomly generate portfolio weights and determine financial metrics. Finally, the Monte Carlos simulation will be conducted 5 times in order to remove any potential outliers. For each simulation, the trials will be conducted 10,000 times, each trial will be stored and plotted in the form of a scatter plot. Finally, the optimal portfolio will be shaded in black with its rate of return and Sharpe Ratio listed.

Data Samples

The data for our portfolio will be Retrieved from [Yahoo Finance]() using the Panda datareader function.The equities used in the simulation are based on SEED's real energy portfolio: *ExxonMobil* (XOM), *Chevron (CVX), Kinder Morgan (KMI)*, *Constellation Energy Corporation* (CEG), Dominion (D), *Duke* (DUK), Energy ETF (XLE). The sectors that are exposed in the SEED's portfolio are both Energy and Utilities. The reason for choosing SEED's energy portfolio is due to the fact it is an ongoing portfolio. Thus, it will be interesting testing how one should allocate it in order to optimize it. Additionally, the share distribution of the portfolio can be seen in the figure on the right. The time horizon for the sample portfolio was from January 19st, 2020 to December 1st, 2022. This is shy of a three year time horizon. Thus, the portfolio has been exposed to numerous macro events like Covid-19 (March 2020), increase of the federal funds rate, and

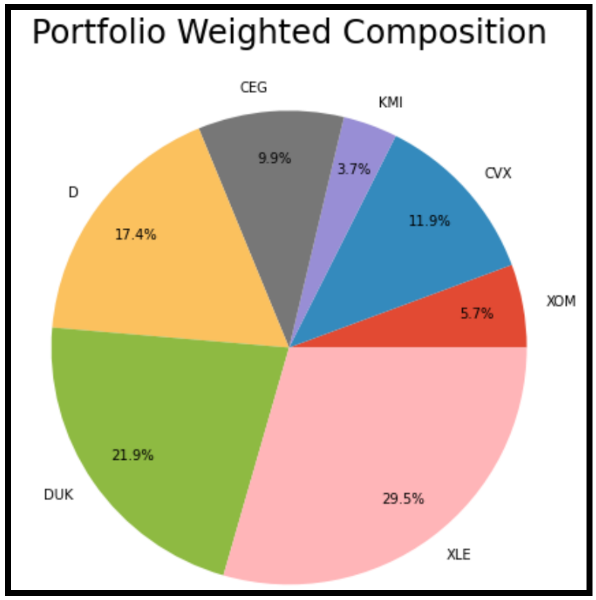
Stock	Shares
ExxonMobil (XOM)	198
Chevron (CVX)	252
Kinder Morgan(KMI)	747
Constellation Energy Corporation (CEG)	405
Dominion (D)	1116
Duke (DUK)	843
Energy ETF (XLE)	1252

Symbols	Cumulative Returns
XOM	86.474416
CVX	81.963206
KMI	32.840422
CEG	84.857470
D	-6.013617
DUK	34.562301
XLE	83.549885

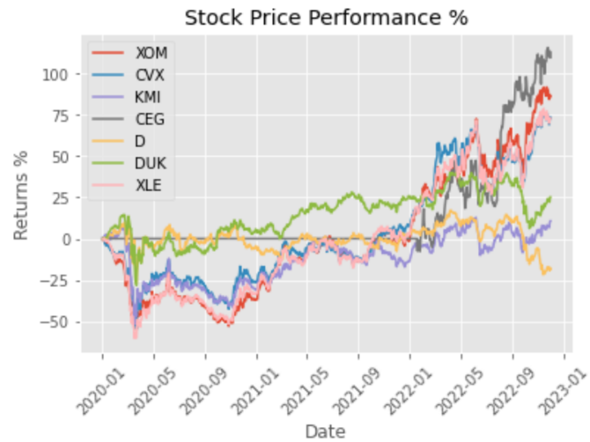
expansionary monetary policy. Based on the dataset, it can be seen that the current portfolio value is roughly over $380 thousand dollars. Additionally, the top performers are in order: *XOM, CEG, XLE, CVX, DUK, KMI, and D*.

Methods

From the timeline (2020 - 2022) of the portfolio, it can be seen that the cumulative performance of the portfolio has been roughly 37.33%. This is an overperformance of the market that is approximately over 25%. The weighted portfolio allocation can be seen on the right. Additionally, returns of each equity can be seen in the dataframe below. Though there may be variability due to CEG not being a publicly traded company until January 20 of this year. In order to learn more about portfolio allocation, we will apply the fundamental portfolio formula $Returns = \Sigma(Weight_i * Returns_i)$.



Symbols	XOM	CVX	KMI	CEG	D	DUK	XLE
Date							
2020-01-03	-0.803938	-0.345883	0.760464	0.000000	-0.244006	0.066403	-0.297130
2020-01-06	-0.042313	-0.683528	1.140696	0.000000	0.524634	0.553467	0.478707
2020-01-07	-0.860364	-1.951756	1.378332	0.000000	0.305021	-0.077478	0.214580
2020-01-08	-2.355427	-3.071737	0.570354	0.000000	-0.329435	0.066403	-1.436135
2020-01-09	-1.607902	-3.228193	2.423968	0.000000	-0.048807	0.309940	-0.709822
...	...	...	...	...	...	...	...
2022-11-25	90.291330	74.290943	7.702692	115.911119	-16.991724	24.343441	74.728767
2022-11-28	84.576368	69.224459	6.719897	110.688883	-18.219377	23.082779	69.935938
2022-11-29	85.803409	71.757701	9.147978	109.844445	-19.366085	22.246502	72.503518
2022-11-30	87.148098	73.920919	10.535462	113.600006	-17.558331	24.730373	73.359387
2022-12-01	86.240439	73.142927	10.708889	109.933336	-18.556645	25.204677	72.788808



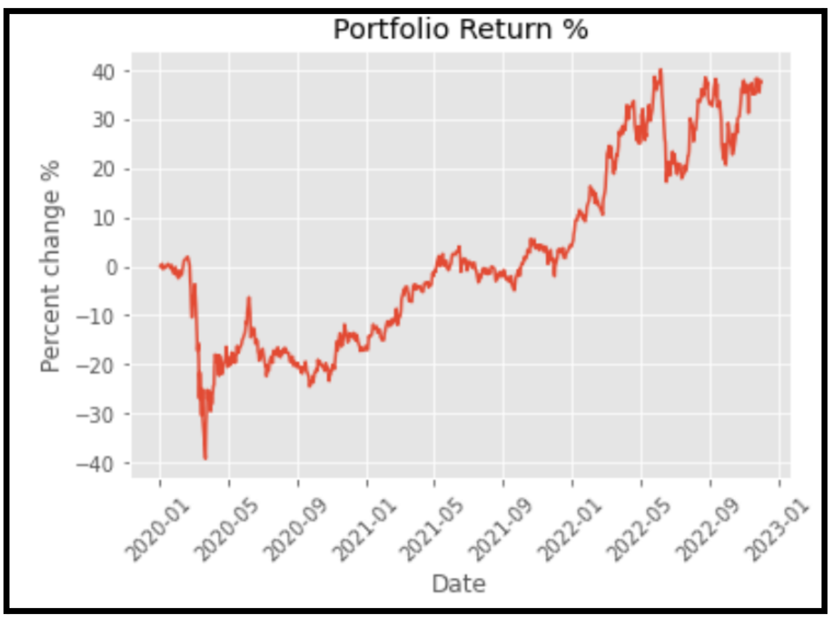
In order to test our dataset, the Fibonacci Retracement will be applied to the portfolio line graph. The support and resistance levels will be established and evaluated if they do in fact apply to the dataset. The current hypothesis is that macroeconomic factors will lead to increased demand or high levels of selloff which in return will affect the entire portfolio. This can be seen in 2020 when Covid-19 cases first appeared in the United States and the global stock market took a dive. The theory is that the selloff of March 2020 can be correlated to be a line of resistance from the Fibonacci Retracement.

Next, the Monte Carlo simulation will be tested to see the variability of weights within the portfolio. The simulation will be tested thousands of times and an optimal weighting will be established and determine how it applies to the current portfolio. The best result in the simulation will have the greatest ratio of returns to volatility. The Sharpe ratio ($\frac{Return - Risk\ Free}{SD\ (\sigma)}$). The hypothesis will test if there's an interval in which the perfect portfolio can be consistently replicated. If the theory stands true, there will be a bound in which portfolio weight allocation will no longer matter. The simulation will be conducted 5 times, to ensure the data is consistent. The more trials the simulation is backtested, the more consistent the results will be. These criterias will be the primary measure for success in the experiment.

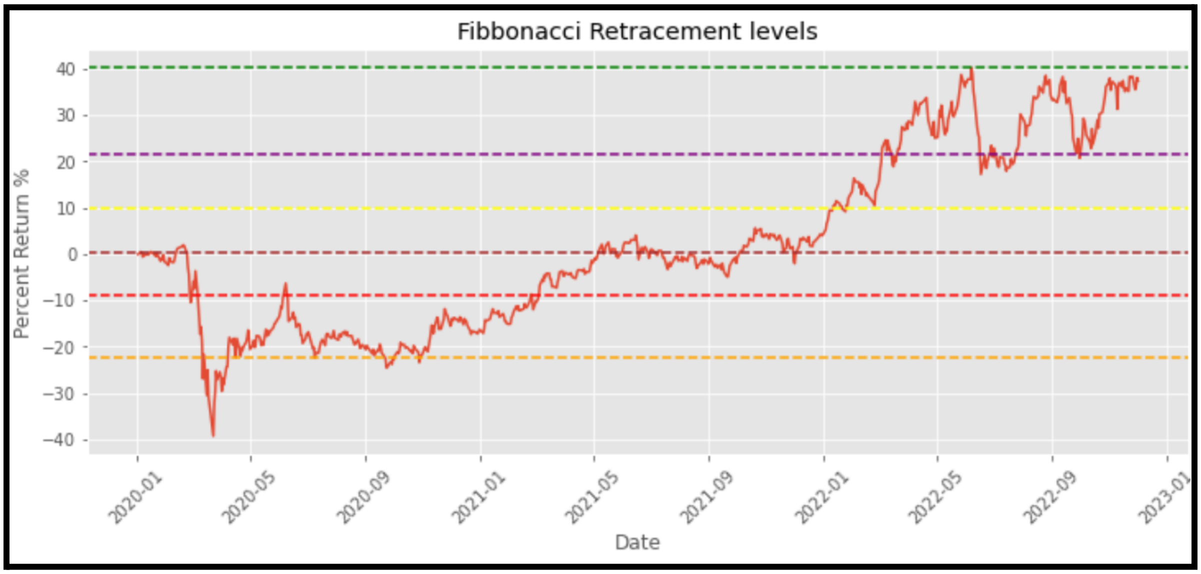
Experiment

Below is a Sensitivity analysis of all securities and their correlations. Companies within similar industries have higher correlations. For example, there is a high correlation with U.S integrated supermajors (CVX and XOM). The least correlated company is CEG. This may be due to its uniqueness of being a primary nuclear energy company. The energy ETF (XLE) has the highest correlation with other companies since it is a mix of various companies.

Symbols	XOM	CVX	KMI	CEG	D	DUK	XLE
Symbols							
XOM	1.000000	0.867057	0.746797	0.145690	0.341417	0.414946	0.944028
CVX	0.867057	1.000000	0.828977	0.140008	0.394706	0.472968	0.936444
KMI	0.746797	0.828977	1.000000	0.157740	0.368967	0.459315	0.852747
CEG	0.145690	0.140008	0.157740	1.000000	0.153294	0.167067	0.150194
D	0.341417	0.394706	0.368967	0.153294	1.000000	0.843860	0.347477
DUK	0.414946	0.472968	0.459315	0.167067	0.843860	1.000000	0.422796
XLE	0.944028	0.936444	0.852747	0.150194	0.347477	0.422796	1.000000



In order to analyze the Fibonacci Retracement, the cumulative returns of the portfolio must be graphed (figure above). The visual represents a weighted portfolio of returns from 2020 to 2022. Besides the sharp decline in 2020, the overall portfolio return remains relatively positive. After applying the Fibonacci levels to the graph, the figure below shows potential support and resistance levels. The levels are as follows: Orange: 23.6%, Red: 38.2%, Brown: 50%, Yellow: 61.8%, and Green: 78.6%. Overall, there does seem to be a correlation between returns of the portfolio and the Fibonacci levels.



As mentioned before, the predictive model of the MCS establishes various parameters. In total, fifty thousand different portfolio weights are generated and plotted in a scatterplot. The simulation will be run five times to ensure that there is a correlation between the results. In the visualization section of the report, the optimal portfolio weight of the various equities are determined. The scatterplot resembles that of the efficient frontier. With more trials run, the shape of the efficient frontier can be easily identified. The results of the optimal portfolio are shown below:

Trial 1 Summary Statistics (#8965):
Highest Rate of Return: 39.09%
Lowest Rate of Return: 26.23%
Highest Sharpe Ratio: 0.81
Lowest Sharpe Ratio: 0.23

Trial 2 Summary Statistics (#4123):
Highest Rate of Return: 39.50%
Lowest Rate of Return: 26.70%
Highest Sharpe Ratio: 0.81
Lowest Sharpe Ratio: 0.31

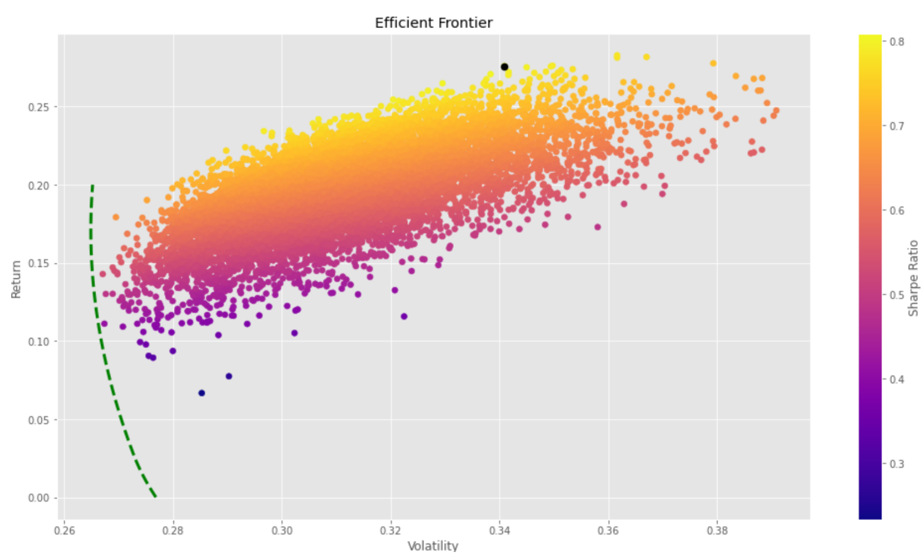
<u>Trial 3 Summary Statistics *(#5867):*</u>
Highest Rate of Return: 39.49%
Lowest Rate of Return: 26.84%
Highest Sharpe Ratio: 0.81
Lowest Sharpe Ratio: 0.27

<u>Trial 4 Summary Statistics *(#9993)*:</u>
Highest Rate of Return: 40.36%
Lowest Rate of Return: 26.74%
Highest Sharpe Ratio: 0.82
Lowest Sharpe Ratio: 0.32

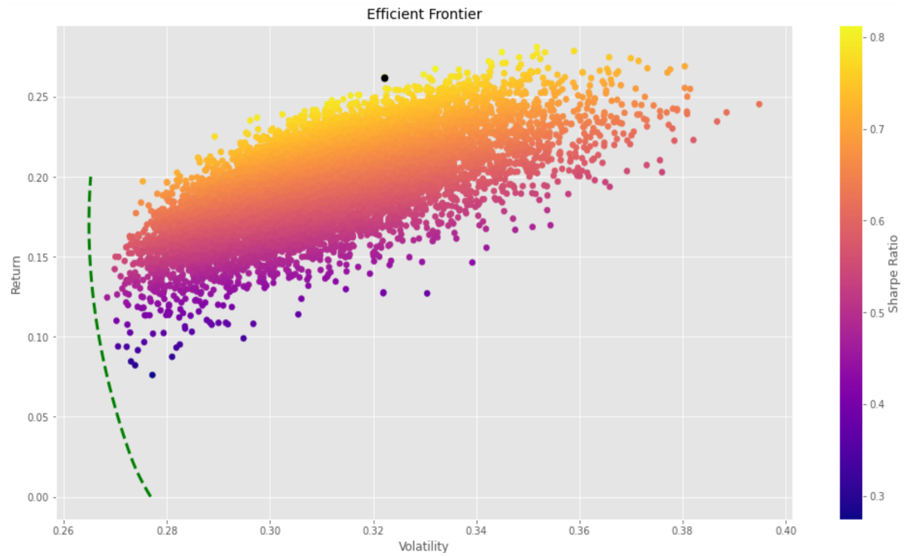
<u>Trial 5 Summary Statistics *(#4343)*:</u>
Highest Rate of Return: 40.41%
Lowest Rate of Return: 26.86%
Highest Sharpe Ratio: 0.82
Lowest Sharpe Ratio: 0.22

<u>Visualization</u>

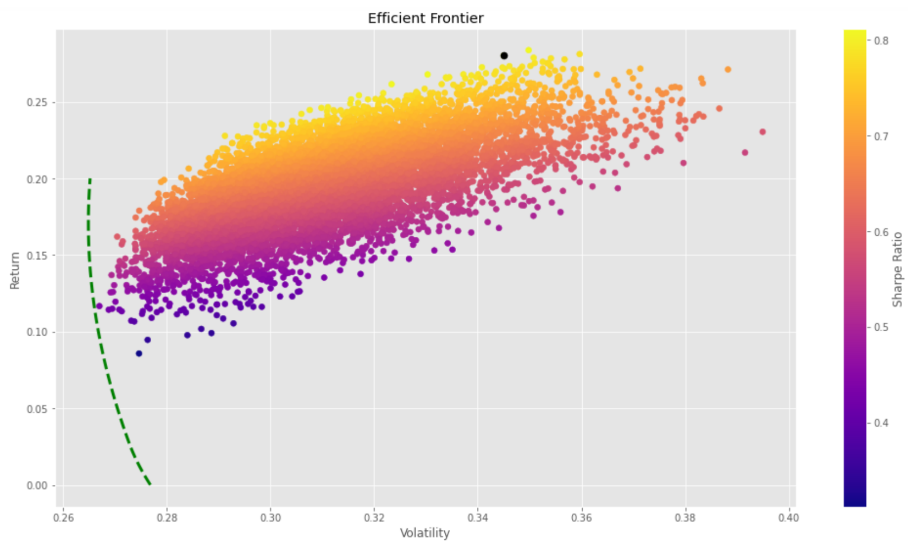
Optimal Portfolio Weight (#8965)	
ExxonMobil (XOM)	27.07%
Chevron (CVX)	2.76%
Kinder Morgan (KMI)	0.48%
Constellation Energy Corp (CEG)	43.41%
Dominion (D)	0.67%
Duke (DUK)	7.27%
Energy ETF *(XLE)*	18.34%



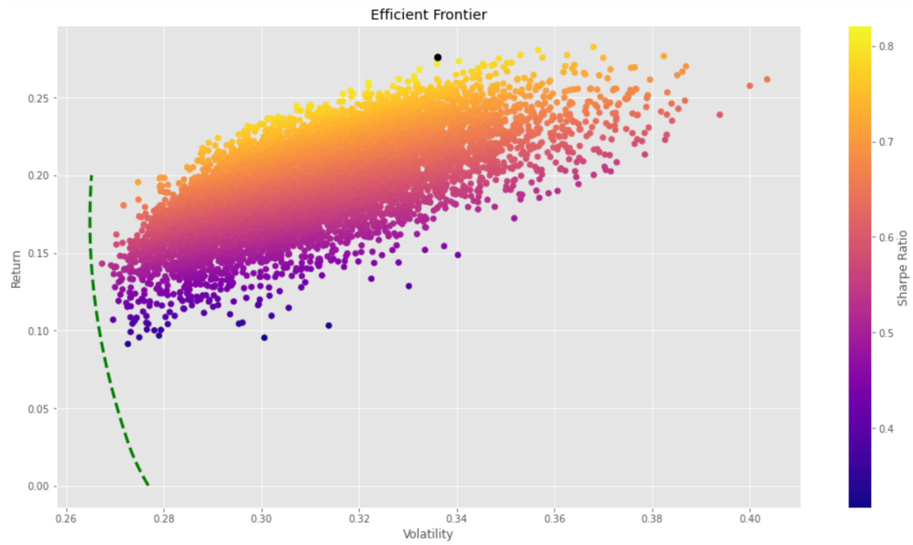
Optimal Portfolio Weight (#4123)	
ExxonMobil (XOM)	39.38%
Chevron (CVX)	28.34%
Kinder Morgan (KMI)	0.85%
Constellation Energy Corp (CEG)	26.65%
Dominion (D)	1.45%
Duke (DUK)	2.42%
Energy ETF *(XLE)*	0.91%



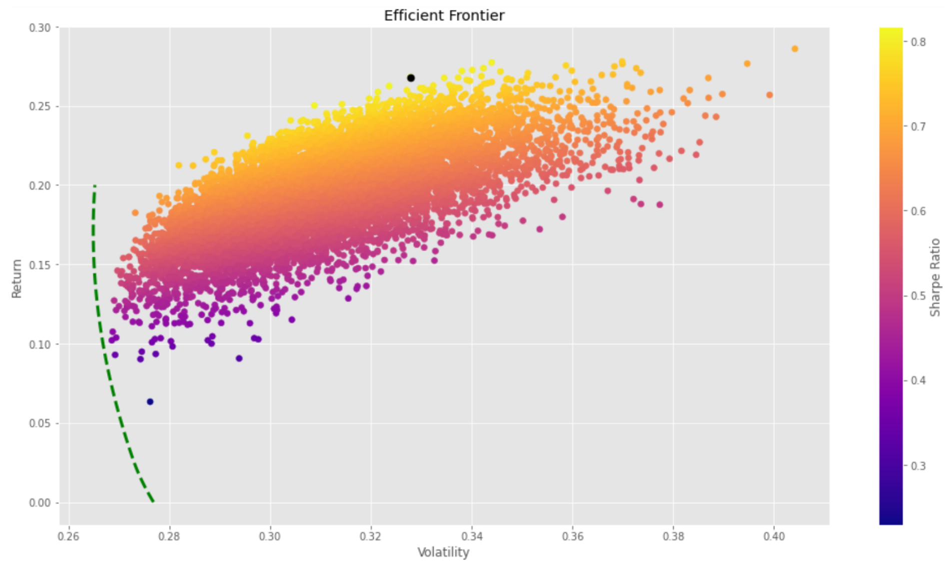
Optimal Portfolio Weight *(#5867)*	
ExxonMobil (XOM)	29.74%
Chevron (CVX)	1.82%
Kinder Morgan (KMI)	0.76%
Constellation Energy Corp (CEG)	34.81%
Dominion (D)	0.12%
Duke (DUK)	16.14%
Energy ETF *(XLE)*	16.61%



Optimal Portfolio Weight (#9993)	
ExxonMobil (XOM)	34.83%
Chevron (CVX)	24.94%
Kinder Morgan (KMI)	1.34%
Constellation Energy Corp (CEG)	31.71%
Dominion (D)	0.27%
Duke (DUK)	6.27%
Energy ETF *(XLE)*	0.60%



Optimal Portfolio Weight (#4343)	
ExxonMobil (XOM)	34.56%
Chevron (CVX)	21.38%
Kinder Morgan (KMI)	0.82%
Constellation Energy Corp (CEG)	26.98%
Dominion (D)	0.05%
Duke (DUK)	12.13%
Energy ETF *(XLE)*	4.07%



Results

The initial hypothesis proves to be true in that there may be a correlation between support and resistance levels and an asset's historical price. After applying the Fibonacci Retracement to the portfolio, it can be seen that a security's market price reacts to Fibonacci Retracement levels and the model of supply and demand comes into play. The scenarios that these support and resistance levels appear tend to be large scale macroeconomic events. For example, during March of 2020, there was an enormous market selloff due fear of the Coronavirus. Another instance of a market selloff occurred in June of 2022. This is primarily due to the escalation of the Russia vs Ukr war, China's zero Covid policy, and the effect of inflation. This ultimately turned the economy to a bear market. The 61.8% FR line experienced high levels of sensitivity from 2020 to 2022. Overall, performance of historical data does seem to be impacted by the Fibonacci Retracement level.

When running the Monte Carlos Simulation, it showed that the optimal portfolio within the five simulations occurred in trials: 8965, 4123, 5867, and 9993. Of all the trials, the maximum rate of return was 40.41%, the minimum return was 26.23%, a maximum sharpe ratio of 0.82, and a minimum of 0.22. The allocation of the portfolio in order to maximize the rate of return was to be overweight in the top performing companies: XOM, CVX, and CEG. In the same manner, the optimal portfolio was underweight in both Dominion and Kinder Morgan. The visual graph showed that the optimal portfolio always was plotted in the top middle region of each scatterplot.

Discussions

From the experiment and data collected, it can be concluded that the Fibonacci Retracement level does indeed have an impact on portfolio performance. This can be applied to further projects such as using these support and resistance levels to predict the future price of any type of securities. Additionally, the Monte Carlos simulation did show that there is a range in which diversification would no longer aid one's portfolio. In SEED's portfolio, there seems to be an opportunity to increase returns by 3% (37% to 40%). Additionally, the Sharpe Ratio range fell between 0.22 and 0.82. When looking into portfolio weights, our hypothesis seems to prove that being overweight in high performing companies leads to the best result (Chevron, ExxonMobil, and Constellation Energy Corporation). However, the biggest constraint with this theory goes about assessing historical data. Like what many investors believe, "past performance is not indicative of the future". The simulation is completely built around the performance of historical data. In the future, the Monte Carlos simulation could also be tested on different sectors in the markets to ensure that this strategy does in fact work.