A Comparative Study on the Impact of Portfolio Diversity.

MSc Research Project

MSc Fintech

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MSc Project Submission Sheet

School of Computing

Student Name:	Nachiket Kaore
Student ID:	19107978
Programme:	MSc Fintech **Year:** 2020
Module:	Research Project
Supervisor:	Noel Cosgrave
Submission Due Date:	28th September 2020
Project Title:	A Comparative Study on the Impact of Portfolio Diversity.
Word Count:	5985 **Page Count** 23

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A Comparative Study on the Impact of Portfolio Diversity.

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Abstract

The Modern portfolio theory is considered to be one of the most significant approaches for portfolio management. The theory suggests using diversity for optimal investment opportunities and to minimize specific risk. Portfolio diversification reduces the impact of market fluctuations, improves the risk-adjusted returns and provides stability. On the contrary, too much diversification can lead to difficulties in keeping track of the stocks, unwanted tax complications and reduced gains during sudden spikes. Due to these factors, it is necessary to quantify the impact of diversification on portfolios. This paper is aimed at identifying and quantifying the impact of diversity on portfolios. For conducting this research, 2 portfolios have been developed with varying degrees of diversification. Performance indicators such as Beta, Jensen's Alpha, Sharpe ratio, Sortino ratio, annualized returns, Value at Risk and Conditional Value at risk have been used in this research. The findings of this analysis show that in all aspects, the diversified portfolio outperforms the other. The diversified portfolio provides better returns per unit risk, higher overall returns, considerably lower risk in terms of volatility and lower value at risk. The comparative analysis illustrates that a diverse portfolio is substantially more favourable than an undiversified portfolio. The results of this study can help investors make decisions based on quantitative analytics and not based solely on advice. However, it should be noted that the stocks selected for this research are profitable on their own and additional research can be done for stock selection which has been addressed in concluding section.

1 Introduction

In 1938, John Burr Williams introduced the 'Dividend Discount Model' which helped to calculate a firm's stock valuation. This enabled investors to buy stocks based on mathematical predictions, rather than relying on trust and fiscal information. Using the work of Williams (1938), additional developments were made by Markowitz (1952) and thus the modern portfolio theory was formed. A portfolio is a financial instrument consisting of multiple income generating assets which are expected to grow in value such as stocks, bonds, debentures, real estate, mutual funds, cryptocurrencies, foreign exchange, credit default swaps, etc. The composition of a portfolio can be equated to the risk-taking appetite and the market position of the investor. Consider an investor seeking to purchase low risk assets as he believes the market is bearish, would opt for safer assets such as government issued bonds, treasury bills or in some cases gold. In comparison, if the investor sentiment suggests a bullish market, there will be a higher risk tolerance and the investor will go for risky assets such as IPOs, stocks, CDS, etc. A well-diversified portfolio consists of a mix of risky assets whose risk is mitigated using low-risk or risk-free assets.

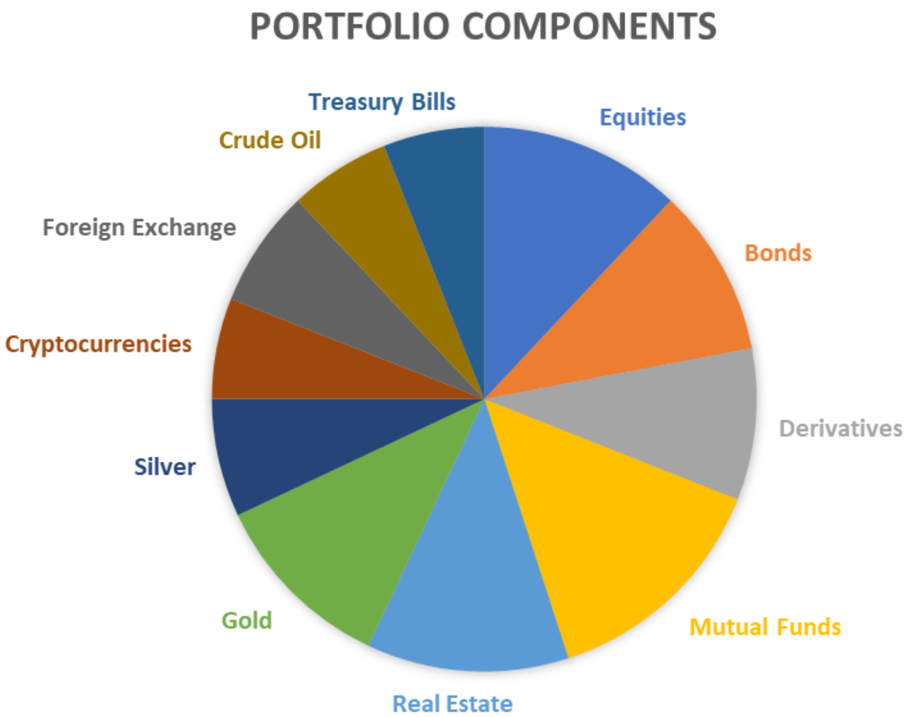

Figure 1: Sample Components of a diversified portfolio.

As illustrated in figure 1, a portfolio can consist of multiple financial instruments, however, the invested amount for each asset is different. The expected return is directly impacted whenever the amount of investment is changed for individual assets. By carefully adjusting the weights of the portfolio, the investor can maximize the returns with minimal risk. However, diversification has its own flaws. Over diversification will minimize the effect of major stock price rises due to the inclusion of other stocks that intend to mitigate portfolio volatility. In simplest terms, consider portfolio consisting of a risky asset and a risk-free asset with equal weights. If the risky asset jumps in value, the expected return for that asset would also increase, however, the expected return of the portfolio would not show the same increase as the risk-free asset would bring down the expected return of the portfolio. If the weights are adjusted to increase the investment in the risky asset, the portfolio returns would also increase.

"Diversification is protection against ignorance. It makes little sense if you know what you are doing." – Warren Buffet

Warren Buffet's statement clearly asserts his sentiments against diversification. In 1996, during the Berkshire Hathaway Annual meeting, he argued that diversification is for those investors who are not confident in their portfolio and those who aim at achieving average returns. Charlie Munger in the same meeting suggested that the modern portfolio theory introduced by Markowitz (1952) provides limited utility. It can be argued that investing in a portfolio with low diversity is a rich man's game because not all investors will have the same risk tolerance and would prefer to invest safely, and would be satisfied with lower returns but with improved stability and continuity. These polarising arguments have motivated the work in this research.

1.1 Research Question and Motivation

Can an investor rely on portfolio diversity to achieve better yields and reduce the overall risk?

This question is targeted towards analysing the benefits of a diversified portfolio over a non-diversified portfolio. Because of the controversial statements made by one of the most prominent investors of this period, there have been mixed reactions and, to say the least, some confusion about portfolio diversification. The aim of this research is to evaluate and review the effect of diversity on portfolio and provide outcome-based recommendations. The first section includes a literature review followed by the research methodology used in this study. The latter half of this paper consists of the design specification, implementation, and evaluation followed by a critical analysis of the results. The result of this study is a conclusive response to the research question and recommendations for future studies.

2 Literature Review

Markowitz (1952) is known for developing the portfolio theory which has become a cornerstone for portfolio selection, management, and optimization. The main purpose of the portfolio theory is to maximize the return while reducing the total risk of the portfolio. (Sharpe, 1964) added in this theory and developed the Capital Asset Pricing Model (CAPM) which is used for calculating the expected returns of the portfolio. Later on, Sharpe (1994) developed the 'Sharpe Ratio' which helps in understanding the risk-returns of the portfolio while considering the volatility. In 1990, they both received a Nobel Prize for the contributions.

Zhifeng (2020) in his research has focused on the prediction of the stock market volatility for safer investments. The two predictors used in this paper are the oil prices and the stock market returns of the S & P 500 index from January 1990 to December 2018. Additionally, the VIX index spanning the same time period has been utilized. The research relies on the Autoregressive model as a standard benchmark and for comparison, the recursive estimation model and rolling estimation model have been utilized. This kind of analysis is beneficial for macroeconomic understanding.

Zevallos (2019) suggests using quantile regression models for predicting the realised volatility. The researcher used the 5-minute intraday pattern of the IGBVL index for VaR prediction with a sample size of 1 year. Using small sample sizes is useful for short term prediction, however, might fail if long term forecasts are required.

Choi (2020) suggests managing the portfolio weights by carefully understanding the relationship between the oil price fluctuations with the optimal hedge ratios. The research utilized the Autoregressive Distributed Lag, Bekk Garch with casualty tests such as Toda-Yamamoto Granger. This research also utilized the VIX volatility index along with the VKOSPI volatility index derived from S&P 500 and KOSPI 200 index.

Rahimi et al. (2017) proposed using the Ant Colony algorithm for determination of stocks in a portfolio and optimization is based on entropy. A similar approach using entropy has been applied by Pala (2020). The main model used for optimization in the latter research is the particle swarm optimiser.

Konovalova et al. (2019), focuses towards the application of VaR (Value at Risk) for portfolio management consisting of a plethora of mutual funds. Using mathematical and statistical analysis the researchers calculated the possible losses while considering their probability, the VaR for each asset in the portfolio along with their weights by using a universal indicator. The mix of stocks have been considered on the basis of their yield, risk of investment, the average and median daily yield from 2010-2017 from the MICEX index. With optimization, the portfolio's annual was yield was calculated at being 29.6% with a fairly high risk at 23.4% (Standard Deviation). Even though this research is focused on the risk aspect of the portfolio, it also provides emphasises on the optimization of the portfolio.

Chavalle (2019) focuses on portfolio optimization while considering the optimization costs. He performs 12 simulations in his research with incremental investments for 4 portfolios of 15 stocks each to determine the best weights possible for the stocks. The 4 portfolios consist of stocks of similar industries which can reduce the portfolio diversity.

Banholzer (2019) suggests using sentiment analysis for portfolio optimization. In his study, the sentiment values for 4 foreign markets were determined using the PCA model. The researcher attempts to quantify the influence of investor sentiment on the portfolio returns and volatility. In order to do so, the less weights have been allocated the assets with a higher sentiment value and high weights to the assets with lower sentiment value.

Oliinyk (2019) relies on the Pontryagin Maximum Principle and Markowitz' portfolio theory for portfolio management. In his research, the primary indicators of the risk factor of the portfolio are the VaR and CVaR (Conditional Value at Risk) while the performance of the portfolio would be determined by the NPV. In order to mitigate the risk by diversification, Alexeev et al. (2015) uses portfolios with different combination of sizes. The study suggests using high frequency data (5-minute intervals) for calculating the conditional correlation between the stocks of the portfolio. The study uses portfolios consisting of 5, 10, 20, 30 and 40 stocks.

Dixit (2020) also suggests using CVaR as a performance indicator for a portfolio. In her research 3 distinct portfolios have been suggested based on their risk returns. These portfolios are (a) risk-neutral (for investors with higher risk appetite (b) risk-aversion (for investors with low risk appetite (c) combined compromise (for investors with adequate risk appetite. This study is directed towards portfolio diversification for achieving optimum risk mitigation.

The importance of portfolio diversification has been inspected by Mensi et al. (2017) where the research conducted by team is based upon the comparative study between the stock markets of developed countries with the stock markets of developing countries. The researchers suggest mitigating the high-risk high yield stocks of the developing markets such as the BRICS countries (Brazil, Russia, India, China and South Africa), with the low- risk low yield stocks from developed markets such as US, Japan and a few European countries. The study further concluded that increasing the weights of the stocks from developed countries is a better option for controlling the VaR rather than investing in risk free assets of the developed markets. A similar study conducted by Chulia et al. (2017), suggests portfolio diversification where the co-dependency among the stocks is minimal to ensure the portfolio can manage market shocks much more efficiently.

Bhutto et al. (2020) suggests portfolio diversification using international markets, namely the BRICS group of indexes. The study also identifies the short-term and long-term benefits of such portfolio diversification using the ARDL model (Auto- Regressive Distributed Lag) for predictive analytics. Gruszka et al. (2020) suggests portfolio management is about investing at the right time. The study uses the Polish stock market data to test the theory of time sensitive investments in the portfolio. The study confirms that rebalancing portfolios over a period can provide better returns.

Beckmann et al. (2019) suggests using the SGE (Shanghai Gold Exchange) quoted gold as a primary diversifier, particularly when the portfolio consists of telecommunications, information, materials, and energy assets. The study also uses oil as a possible diversifier, but the findings suggest that gold is a better choice as much as the portfolio's optimum weight leans towards gold.

Constantin (2011) suggests investing in catastrophe bonds for leveraging risk of the portfolio. The study utilized 2 portfolios, one with European stocks and other with international stocks (Barring USA). The findings of the study suggest investing in catastrophe bonds during economic crises is more lucrative than using traditional risk-free assets as the main mitigator.

Gilber et al. (2019) focuses on the comparative analysis of the different risk metrics used for optimizing portfolios. The primary risk metrics used are the VaR, CVaR, Wang Transform measure and the omega ratio. These metrics have been tested by a portfolio consisting of assets whose weights have been adjusted by using SAA and DAA (Static Asset Allocation & Dynamic Asset Allocation). It is suggested that the omega ratio is a better identifier of risk, however, it considers volatility as a risk (positive or negative variation).

In a similar research, Bujack et al. (2018) suggests diversification after analysing the CDS (Credit Default Swaps) and of the global market and credit risk of the individual stocks. With a portfolio consisting of 11 stocks, the research shows higher returns after diversification based on credit risk and optimization. In a similar study Andrea Consiglio et al. (2018) suggests using CDS as the main diversifiers in the portfolio. The study runs 3 simulations with different investor positions to calculate the results which show lower risk factors when diversified by CDSs. Both researchers have used CVaR as the primary risk indicator upon which further strategies are developed.

Bierman (1978) suggests, the ideal method of diversification is to use assets with lower correlation to the existing assets for better results in terms of risk mitigation. Using assets with greater correlation would result in amplifying the risk instead of reducing. For the best results, negatively correlated assets are ideal, however, such assets are rare and difficult to identify.

Since Markowitz introduced the portfolio theory, various papers have been published which support his work and add on it. Portfolio diversification is used for risk mitigation however, a lot of research has not been done for differentiating between a diverse portfolio and a portfolio consisting of assets from the same domain. The core benefit which a diverse portfolio provides is that it attempts to hedge the risk of a few risky assets with less risky or risk-free assets. This paper aims at performing comparative analysis among portfolios on the basis of diversification.

3 Research Methodology

Since the aim of this research is to identify the impact of diversity in portfolios, 2 portfolios have been developed. Among the 2, one portfolio was diversified by the use of 10 separate stocks, and the other was not diversified. Following the creation of portfolios, individual stock prices have been collecting using yahoo finance from 1st Jan 2017 to 29th July 2020. The diversified portfolio was created using Markowitz's Modern Portfolio Theory (1952), and the non-diversified portfolio was created using the high-risk, high-reward strategy. As most stocks used in this research are from the United States, the market indicator considered is the S&P 500.

3.1 Data and Tools

The diversified portfolio consisting of 10 stocks include Vanguard, Amazon, Alphabet, Facebook, United Rentals, Nvidia, Netflix, Walt Disney, Shopify, and Microsoft. The undiversified portfolio consists of only 2 stocks, Nvidia and United Rentals. The financial analytics has been carried out using the programming language R. The volatility of Vanguard, Facebook United Rentals and Nvidia can be observed from figure 4,5,6, and 7. The remainder of the stocks are comparatively less volatile; however, visual representation is not the sole determinant of a portfolio’s volatility and performance.

Tangible evidence is required for determining the performance of the portfolio. In order to identify the advantages of a diversified portfolio, this research utilizes various techniques. In most cases, the overall returns of the portfolio determine the performance of the portfolio, however there are additional performance indicators as well. This study relies on Beta, Jensen's Alpha, Sharpe Ratio, Sortino Ratio, Value at Risk and Conditional Value at Risk for assessing the performance of the portfolios.

Figure 2: Amazon Trend

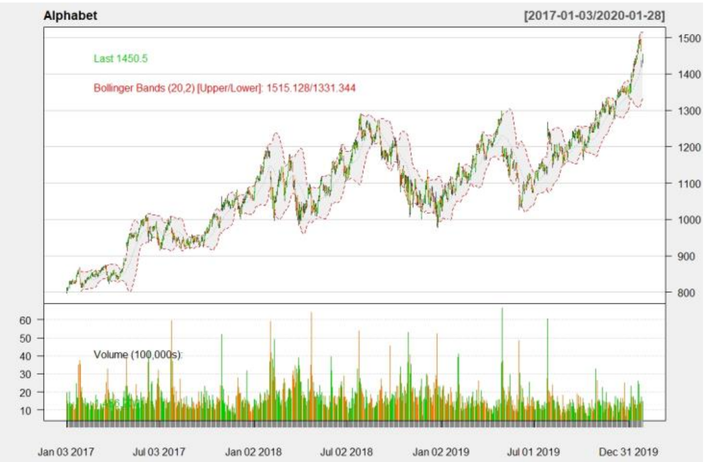

Figure 3: Alphabet Trend

Figure 4: Vanguard Trend

Figure 5: Facebook Trend

Figure 6: United Rentals Trend

Figure 7: Nvidia Trend

Figure 8: Netflix Trend

Figure 9: Walt Disney Trend

Figure 10: Shopify Trend

Figure 11: Microsoft Trend

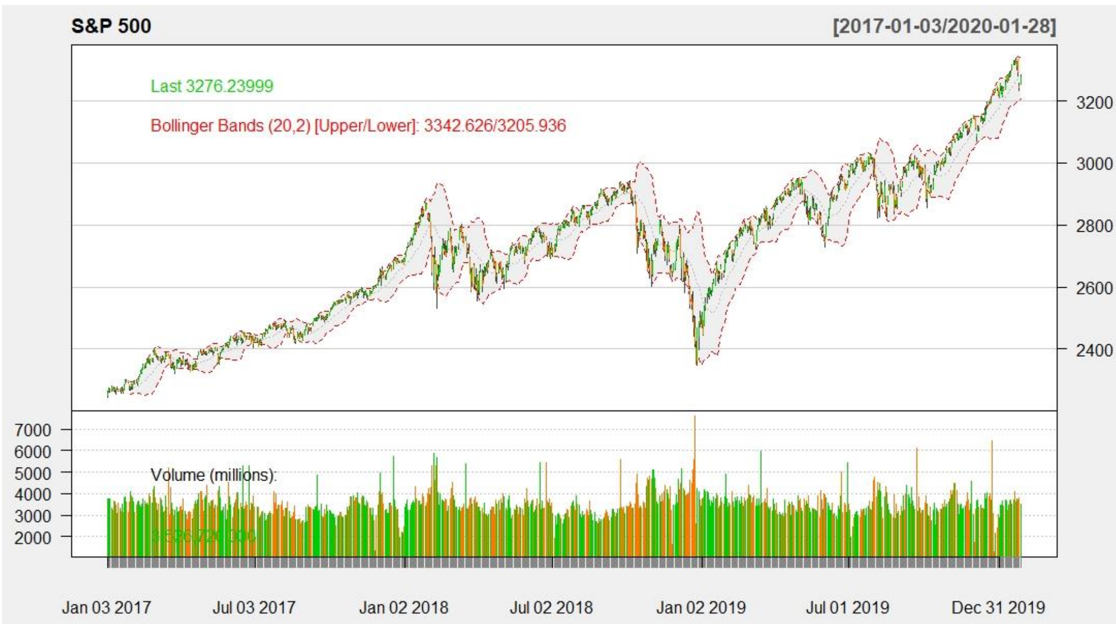

Figure 12: The trend of S&P 500

3.2 Portfolio Justification

Careful selection for stocks is necessary to gain returns and to mitigate risks. The correlation function is used in this research for stock selection. Usually, stocks with lower correlation are used in a portfolio as it offsets the risk of other stocks in the portfolio. For example, as seen from table 1, the correlation of Vanguard with the Market is 0.99 which can be reduced by Netflix or Shopify. Negatively correlated stocks are crucial to achieving the best possible outcome in terms of correlation-based diversification, but these kinds of stocks are rare and hard to find as suggested by Bierman (1978). Assets belonging to the same industry make similar movements and respond similarly to fluctuations in the market. Portfolios of assets belonging to similar sectors are highly vulnerable to market volatility as they have no other assets to reduce the aggregate effect of such volatility.

Table 1: Correlation of stocks against the Market.

Stock	S&P 500
Vanguard	0.996313
Amazon	0.6157997
Alphabet	0.7935255
Facebook	0.6546907
United Rentals	0.7165753
Nvidia	0.667198
Netflix	0.5162172
Walt Disney	0.7200487
Shopify	0.5168794
Microsoft	0.8610947

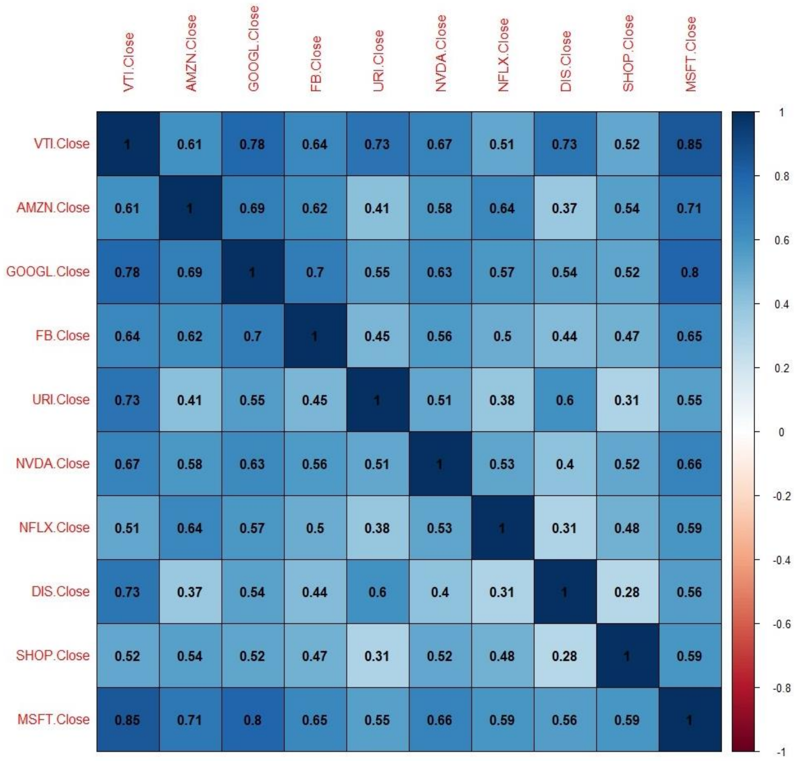

Figure 13 : Correlation of Stocks.

4 Design Specification

Using monthly or annualised returns is not enough to assess the performance of the portfolio. It is not advisable to invest in a portfolio solely on the basis of its returns, as there are numerous other performance indicators that can provide critical information about the volatility, risk, excess returns, optimal weights, etc. This research attempts to use 7 different performance measures for determining the performance of the portfolio. Each method provides a different insight and can change the viewpoint and strategy of the investors depending upon their ultimate goals. For example, if the investors are aiming for larger returns, they might focus on the Jensen's Alpha and if they prefer stability then the ideal performance metric would be the Beta.

4.1 Beta

The 'Beta' coefficient is a measure of a portfolio's volatility or risk when compared to the market index. This metric was introduced along with the CAPM which provides insights to investors for understanding the direction of the stock when compared to the market. For example, if the Beta is 1, then the stock's volatility is equal to market. When it exceeds 1, then it is assumed that the stock is more volatile than the market and if it is below 1, then the volatility is lower than the market. In certain cases, the beta could be negative, indicating inverse correlation of the stock with the market index.

$$\beta = \frac{Cov\ (R_p\ , R_m)}{Var\ (\ R_m)} \tag{1}$$

Mathematically, Beta can be represented using the equation (1) where –

a. R_p and R_m represent the returns of induvial stock / portfolio and the market index respectively.
b. Cov (R_p, R_m) is the covariance between the stock / portfolio and the market.
c. Var (R_m) is the Variance of the Market.

4.2 Jensen's Alpha

This metric represents the excess returns of a portfolio calculated by using the CAPM. Achieving alpha returns is not an easy task as market outperformance takes a great deal of expertise and understanding of the market.

$$\propto = R_p - (R_f + \beta(\ R_m - R_f)) \tag{2}$$

Mathematically, Jensen's Alpha is represented by equation (2) where -

a. R_p and R_m represent the returns of induvial stock / portfolio and the market index respectively.
b. R_f is the risk-free rate.
c. B is the beta.

4.3 Sharpe Ratio

The Sharpe Ratio is used to understand the relationship between a portfolio's returns against its risk. The portfolio is said to be performing well if the Sharpe ratio is above 1. Increasing the number of stocks in a portfolio can potentially increase the Sharpe Value as well, however, does not guarantee increased returns.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{3}$$

Mathematically, the Sharpe ratio is represented by equation (3) where -

a. R_p and R_f represent the returns of induvial stock / portfolio and the risk-free rate.
b. σ_p is the standard deviation of the portfolio's alpha.

4.4 Sortino Ratio

The Sortino Ratio is derived from the Sharpe Ratio with one key difference; instead of using the standard deviation (Positive and Negative), it relies on the standard deviation of the downside risk (negative) ensuring that it focuses on losses and not just the volatility. On account of this distinction between the two ratios, investors tend to rely on Sortino ratio for making investments.

$$Sortino\ Ratio = \frac{R_p - R_f}{\sigma_d} \tag{4}$$

Mathematically, the Sortino Ratio is represented by equation (4) where σ_d is the standard deviation of the downside risk.

4.5 Annualized Returns.

Annualised returns are the total amount of returns which a portfolio can generate each year over a period of time. This is the most common technique used by investors before making investments. Calculating annualised returns does not provide information regarding the volatility or the risk of the portfolio.

$$Annualized\ Returns = ((1 + R_1) \times (1 + R_2) \times (1 + R_3) \times \dots (1 + R_n))^{\frac{1}{n}} - 1 \tag{5}$$

Mathematically, Annualized returns is represented by equation (5) where *n* is the number of years.

4.6 Value at Risk and Conditional Value at Risk

The VaR of a portfolio is the maximum amount of loss expected by a portfolio for a given period of time. In essence, the VaR of a portfolio represents the worst-case scenario. The CVaR is the expected loss of the portfolio if it crosses the VaR threshold. The benefit of CVaR over VaR is that it offers the predicted average loss, rather than a wide range of potential losses that can be difficult to account for.

$$VaR_{1-\alpha} = P \times Z_{\alpha} \sqrt{\begin{bmatrix} W_1 & \dots & W_1 \end{bmatrix} \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1n} \\ \dots & \dots & \dots \\ \sigma_{n1} & \dots & \sigma_{nn} \end{bmatrix} \begin{bmatrix} W_1 \\ \dots \\ W_n \end{bmatrix}} \tag{6}$$

$$CVaR_{\alpha} = \frac{1}{\alpha} \int_0^{\alpha} VaR_{\gamma}(R) d_{\gamma} \tag{7}$$

Mathematically, VaR and CVaR are represented by the equations (6) and (7) where,

a. α is the confidence level.
b. P is the amount invested.
c. Z_{α} is the Z-Score.
d. W is the weight assigned to the asset.

5 Implementation

This section provides and overview of the tools and key datapoints used in this research. For this research, the CRISP-DM model of data processing has been followed. The stock market data has been sourced from 'Yahoo Finance' which is an open repository for financial data. For the purpose of this research, the closing values of 10 stocks and the market index has been collected from 1st January 2017 to 29th July 2020. The 'quantmod' package in R was used for data collection. As only the daily closing values are required for this research, the remainder of the data has been removed. In total, the data from 3 years and 7 months has been used for research. The concerned data does not have any missing values hence there is no requirement of data imputation or substitution. All performance metrics were calculated using the 'Performance Analytics' package in R. These metrics have been applied to both portfolios as a measure to identify the portfolio which is better performing. Both portfolios are then optimized for calculating the VaR and CVaR and the efficient frontier plot for visualization. The results obtained by utilizing these metrics have been described and analysed in the following section.

6 Evaluation

The purpose of this research is to identify the impact of diversity on portfolios and accordingly 7 performance metrics have been selected. For simplification, the diversified portfolio will be referred to as Portfolio A and the non-diversified portfolio as portfolio B. The rubric specifying the parameters for measurement is set out in table 2. Using this table as a grading scheme, the results have been discussed in this section.

Table 2: Evaluation Criteria.

Sr. No	Performance Metric	Evaluation Criteria
1	Beta	Lower is better
2	Alpha	Higher is better
3	Sharpe Ratio	Higher is better
4	Sortino Ratio	Higher is better
5	Annualized returns	Higher is Better
6	VaR	Lower is better
7	CVaR	Lower is better

6.1 Experiment 1 – Beta

For the first metric, the beta of portfolio A is 1.14 suggesting it is moving with the market and is lower than portfolio B whose beta is 1.54. Volatility is expressed in terms of Beta, which is significantly higher for portfolio B. Table 3 illustrates the beta values of individual stocks against S&P 500.

Table 3: Individual Beta Values

Stock	VTI	AMZN	GOOGL	FB	URI	NVDA	NFLX	DIS	SHOP	MSFT
Beta	0.99	0.88	1.04	1.05	1.60	1.54	0.96	0.98	1.30	1.18

6.2 Experiment 2 – Jensen's Alpha

In case of Jensen's Alpha, the value for portfolio A stands at 0.30 which is significantly higher than the alpha of portfolio B which is 0.06. Although both portfolios delivered positive alphas, portfolio A outperforms portfolio B. Table 4 illustrates the individual Alpha values.

Table 4: Individual Alpha Values

Stock	VTI	AMZN	GOOGL	FB	URI	NVDA	NFLX	DIS	SHOP	MSFT
Alpha	0.00	0.35	0.05	0.07	-0.13	0.21	0.27	-0.08	1.03	0.24

6.3 Experiment 3 – Sharpe Ratio

In the case of the Sharpe ratio, portfolio A shows a higher value at 1.37 than portfolio B which exhibits a poor value at 0.48. The Sharpe ratio of portfolio B is lower due to the absence of diversification.

6.4 Experiment 4 – Sortino Ratio

The Sortino ratio provides a stronger view on a portfolio's risk-return as it only considers the downside risk. Portfolio A had a higher ratio of 0.11 than portfolio B, which gave a ratio of 0.05 suggesting that the first portfolio is gaining larger returns when compared to its risk.

6.5 Experiment 5 – Annualized Returns

The overall annualized returns for Portfolio A is projected to be 41.42 % which is significantly higher than portfolio B which stands at 20.79%. Table 5 and 6 represent the calendar returns of both portfolios.

Table 5: Calendar returns of Portfolio A

Portfolio A	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
2017	-0.5	-0.8	-0.1	1	-0.2	0	-1.1	1	0.7	-1.7	0.7	-0.9	-1.9
2018	0.4	-0.7	2.7	0.1	0.3	-0.5	-0.7	-0.1	-0.1	4	1.1	1.7	8.4
2019	2.1	-0.4	0.9	0.8	-1.8	0.1	-1	-0.7	1	-0.8	-0.8	0.2	-0.4
2020	-1.3	2.8	-1.1	0.3	1.6	2.5	-0.3	1.1	NA	NA	NA	NA	5.6

Table 6: Calendar returns of Portfolio B

Portfolio B	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
2017	-1.3	-1.4	0.2	-0.6	-0.9	0.3	-0.9	0.9	1.2	0.3	1.7	-1.5	-2.1
2018	0.5	-1.8	3.5	-1.8	-0.9	-1	1	0.5	1.8	3.8	2.6	0.4	8.8
2019	1.3	-0.8	1.4	0.5	-3.5	0.6	-3.4	0.6	0.7	-1.3	-1.3	0.3	-4.9
2020	-4	5.1	1.5	-1.4	3.5	2.5	-0.3	1.7	NA	NA	NA	NA	8.8

6.6 Experiment 5 – Value at Risk and Conditional Value at Risk.

The total VaR for portfolio A using optimal weights was 3.5%. Due to the volatile nature of Shopify, it was the highest contributor of VaR for the portfolio followed by Nvidia and United rentals. The VaR was 4.4% owing primarily to Nvidia for portfolio B. This research uses the historical, gaussian and modified methods of calculating VaR as seen from figure 14 and 15. Similar results are observed for CVaR as the total value at risk for Portfolio A is 7.8% and for portfolio B it is 9.3%.

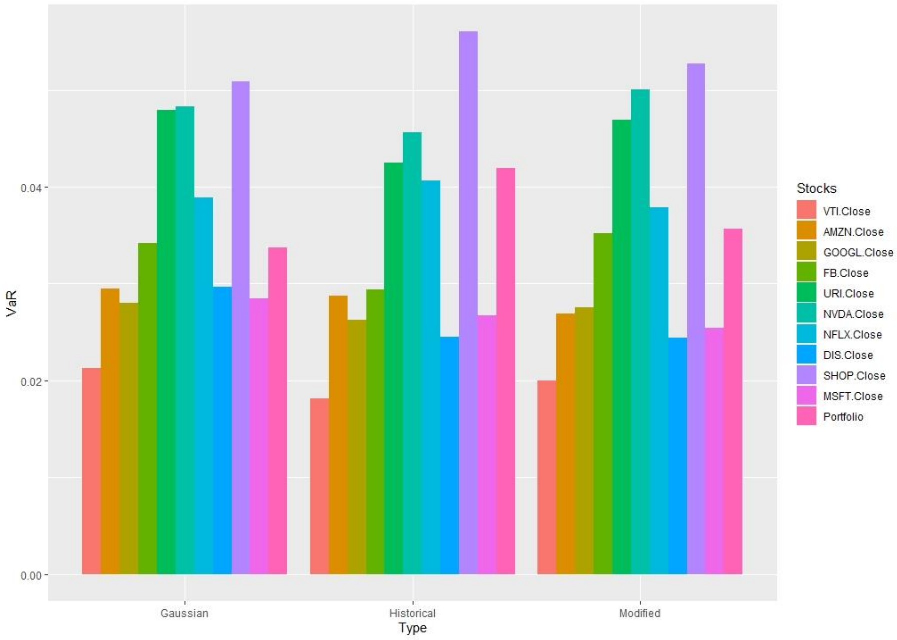

Figure 14: VaR Comparison of Portfolio A

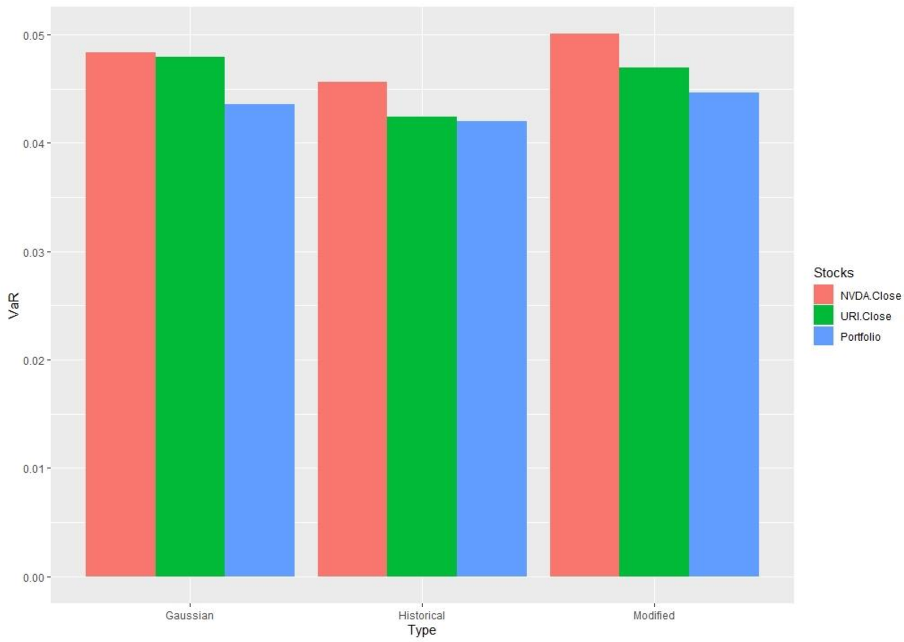

Figure 15 : The VaR comparison of Portfolio B

6.7 Discussion

In every simulation, portfolio A outperforms portfolio B as seen from the experiments above. The key benefit of diversification is that the balance of other stocks in the portfolio cushions the risk of individual stock. Portfolio A provides better returns with lower risk and volatility. The risk of highly volatile stocks in the portfolio such as Nvidia, Shopify and United Rentals is mitigated by the safer and less volatile stocks such as Amazon, Vanguard and Disney. This is only possible of the portfolio has been diversified using the stocks which have low correlation among them. As seen from the figure 13, Nvidia has lower correlation with

Disney and Facebook, therefore the excess risk carried by Nvidia is lowered by them. The Sharpe ratio and Sortino ratio are directly affected by diversification as efficient diversification can improve the return per unit risk undertaken by the portfolio. In case of returns, the results suggest that portfolio A would provide double the returns annually as compared to Portfolio B.

Table 7 : Performance Matrix

Performance Metric	Portfolio A	Portfolio B	Evaluation Criteria
Beta	1.14	1.54	Lower is better
Jensen's Alpha	0.30	0.06	Higher is better
Sharpe Ratio	1.37	0.48	Higher is better
Sortino Ratio	0.11	0.05	Higher is better
Annualized Returns	41.42%	20.79%	Higher is Better
VaR	3.5%	4.4%	Lower is better
CVaR	7.8%	9.3%	Lower is better

With a wider range of available stocks, it becomes easier to manage the risk of Portfolio A by adjusting the weights of each asset. For portfolio optimization, 2 constraints and 2 objectives were incorporated for each portfolio as mentioned below.

- The total sum of weights should be 100%
- Minimum and Maximum Weights.
    - Portfolio A – Minimum can be 5% and Maximum can be 30%
    - Portfolio B – Minimum can be 5% and Maximum can be 75%
- The output should maximize returns.
- The risk considered is the Standard Deviation (Volatility).

Using these constraints, the weight distribution for portfolio A was maximum for United Rentals and Shopify at 30% each. For Portfolio B the maximum weight was allocated to Nvidia which was at 70%. However, when the weight distribution restriction was removed, the model allocated equal weights to each asset for portfolio A, however, for portfolio B it completely omitted United Rentals suggesting that it was a bad investment. This can be attributed to the lack of diversification and quantity of stocks as cushioning stocks are missing in portfolio B.

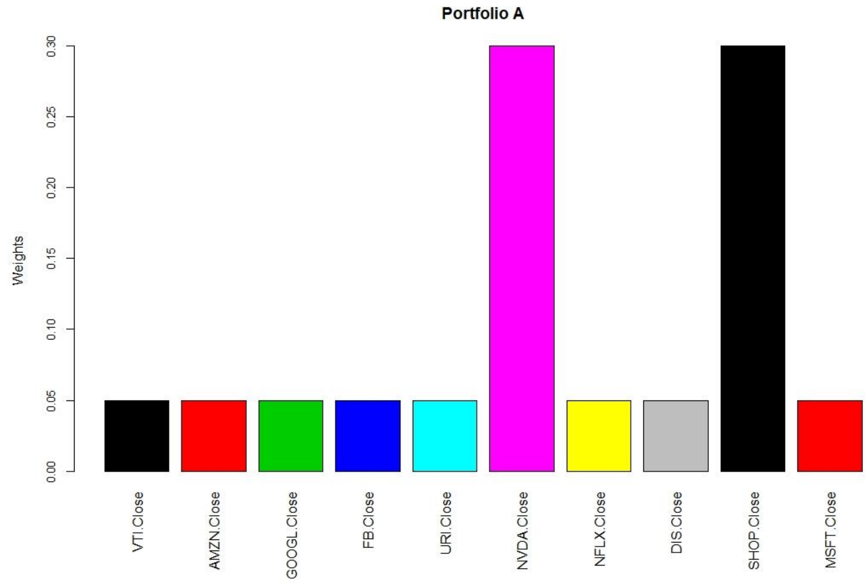

Figure 16: Weight Distribution for portfolio A

As observed from figure 17, Shopify carries the highest risk but can also earn the highest return unlike United Rentals which only carries the risk without earning considerable gains. Nvidia is next in line in terms of earnings per unit risk. Rest of the stocks have lower risk and lower returns which are being used to mitigate the risk of Shopify and Nvidia.

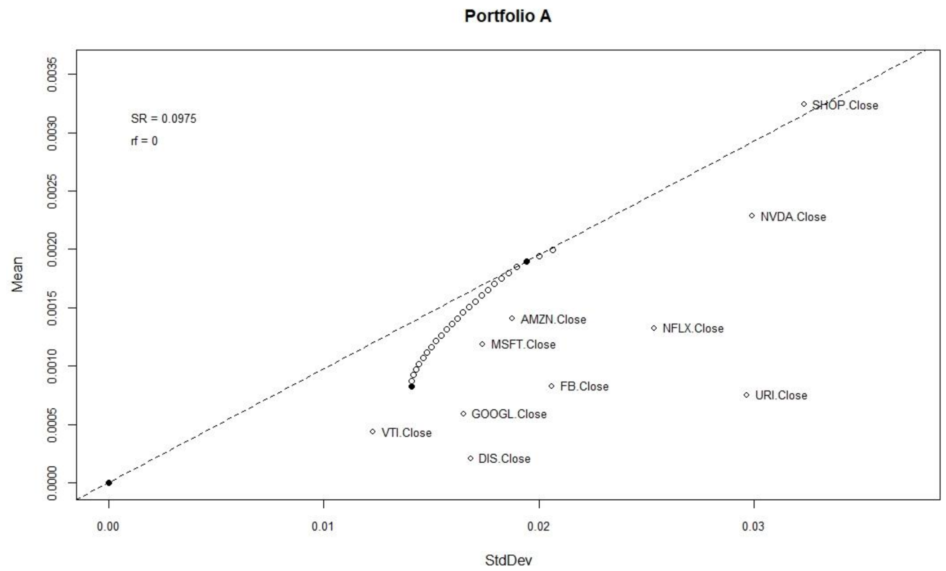

Figure 17: Efficient Frontier Plot for Portfolio A

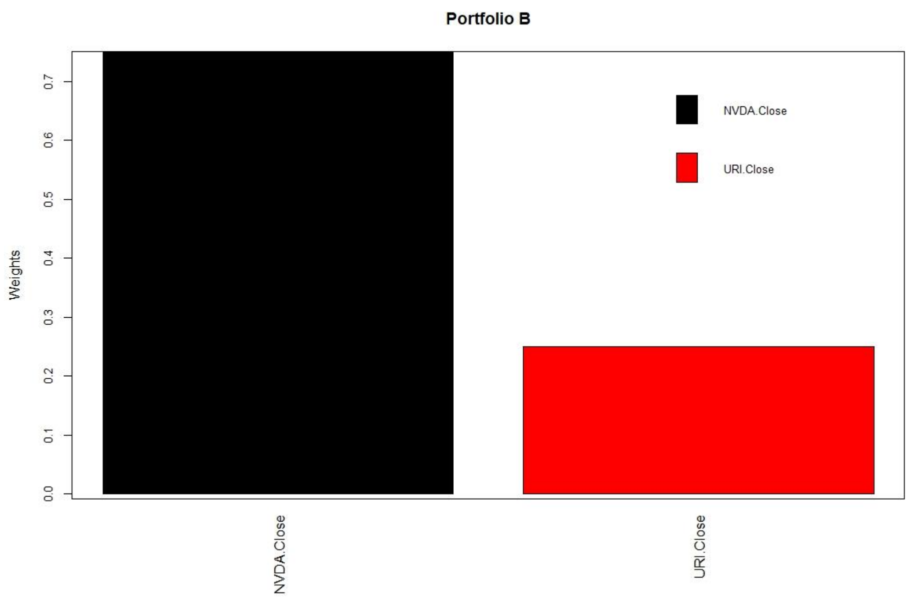

Figure 17: Weight Distribution for portfolio B

Nvidia can earn the highest return per unit risk for portfolio B, but they are reduced due to the lower returns of United Rentals. United Rental carries similar risk but with drastically low returns, hence falling back on United Rentals is not advisable. This is common issue faced when portfolio diversification is absent or very low. The ability of a portfolio to balance itself using clever weight distribution is lost and thus increases its overall risk.

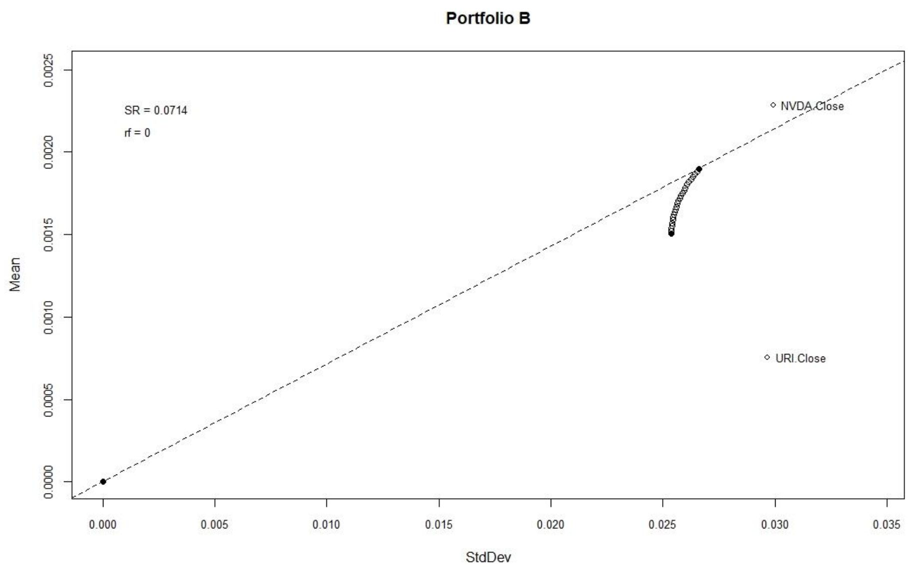

Figure 18: Efficient Frontier Plot

The results of this research agree with the proposed method of diversification and stock selection by Markowitz (1952). By following Konovalova et al. (2019) and Dixit (2020) this research also applies VaR can CVaR as a performance indicator after optimization. The portfolio has been selected using the correlation technique suggested by Bierman (1978) and Chulia et al. (2017). This research does not consider the transaction and optimization costs as suggested by Chavelle (2019) and omits other diversification options such as CDS, gold, bonds, etc. as suggested by Constantin (2011), Bujack et al. (2018) and Beckmann et al. (2019). This research utilized 7 different performance metrics for determining the strength and efficiency of the portfolio covering various areas such as the risk, volatility, returns, optimization, weight distribution, risk-return ratio and the value at risk.

7 Conclusion and Future Work

Financial companies across the globe are advising their clients to diversify their portfolios due to the benefits such as reduced risk and manageability. However, few influential investors such as Warren Buffet, Charlie Munger, Mark Twain and others are against the idea of diversification. This research is aimed towards understanding the impact of portfolio diversification on the performance of the portfolio. For understanding the key differences, this research uses 2 portfolios with varying degrees of diversification and runs 7 performance measurement metrics on each. The performance metrics used in this research are the Beta, Jensen's Alpha, Sharpe Ratio, Sortino Ratio, annualized Returns, Value at Risk and Conditional Value at risk. The results of this study suggest that a diversified portfolio can outperform a non-diversified portfolio in all metrics. The risk of the diversified portfolio was significantly lower than the other without compromising on the returns. The overall value at risk for the diversified portfolio was lower as well. This study is limited to a set of stocks which were selected on the basis of their performance over the years and correlation between them and the market. With additional market research, highly lucrative portfolios could have been created for both scenarios. The advantages of a non-diverse portfolio have not been discussed in this research as it is mainly focused on the diversification impact.

For future studies, it is recommended to use a different pair of portfolios or increase the degree of diversification by including additional assets such as gold, international markets, CDS, etc. Machine language algorithms for risk and market analysis can be run on volatility indexes. Additional performance metrics can be utilized for further analysis. Instead of using correlation as the primary source for stock selection, it is possible to use complex structures such as sentiment analysis.

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