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1. Introduction

Constructing an investment portfolio is a task in balancing the pursuit of returns with the management of risk. Equity markets offer a wide range of opportunities across sectors and asset classes, but with those opportunities come varying level of volatility and correlation. Focusing on a single high performing stock, such as Amazon (AMZN), can yield impressive gains during favorable periods, but exposes the investor to significant idiosyncratic risk when conditions turn adverse.

Morden portfolio management requires a robust quantitative framework to balance risk and return. Markowitz's mean variance theory provides a foundation, practical implementation involves complex data engineering, exploratory analysis and simulation to understand uncertainty and model risk.

This seminar paper applies a structured, data driven workflow to ten large-cap equities from multiple sectors, including technology, industrials, healthcare, financials, and consumer staples. Using Python's data analysis and visualization ecosystem, I converted the raw price data to derive daily returns, portfolio construction, and risk assessment. The analysis has both an equal weighted portfolio and a Monte Carlo simulation of 1000 random portfolios to find the feasible risk-return combinations.

By including the Value-at-Risk (VaR) at the 5% significance level alongside traditional measures like expected annual return, volatility, and Sharpe ratio, this paper provides a more comprehensive view of the portfolio performance, capturing not only the average outcomes but also the potential strength of adverse scenarios. This paper points out the importance of diversification, correlation analysis, and risk adjusted optimization in modern portfolio management.

2. Theoretical Review

2.1 Modern Portfolio Theory (MPT)

Modern Portfolio Theory, introduced by **Harry Markowitz (1952)**, is the foundation of quantitative portfolio construction. It says that the risk and return of a portfolio are determined by not just the characteristics of single assets, but also by the correlations between them. By combining assets with imperfect correlations, investors can reduce portfolio volatility without proportionally reducing expected returns the principle of diversification (Markowitz, 1952).

The expected portfolio return is:

$$\boldsymbol{E[R_p] = \sum_{i=1}^{n} w_i E[R_i]}$$

The portfolio variance is:

$$\boldsymbol{\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}}$$

where σ_{ij} is the covariance between returns of assets i and j (Elton et al., 2014)

An efficient portfolio maximizes return for a given level of risk forming the efficient frontier.

2.2 Volatility

Volatility is the statistical measure of the dispersion of returns, typically stated as the standard deviation of returns over a given period.

For portfolio returns R_p, the volatility is:

$$\boldsymbol{\sigma_p = \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} \left(R_{p,t} - E[R_p]\right)^2}}$$

Annualized term, volatility is computed by the square root of the number of trading days in a year (e.g., $\sqrt{252}$ for daily returns).

2.3 Sharpe Ratio

The Sharpe Ratio, introduced by William F. Sharpe (1966), measures excess return per unit of risk (standard deviation). The Sharpe ratio is unaffected by the addition of cash or leverage in the portfolio.

$$\boldsymbol{SR = \frac{E[R_p] - R_f}{\sigma_p}}$$

where R_f is the risk-free rate and σ_p is portfolio volatility. A higher Sharpe ratio indicates better return per unit of risk.

2.4 Value at Risk (VaR)

Value at Risk (VaR) measures downside risk of the portfolio. It has three components: the lose size, the probability and a time frame. For example, 5% VaR of 3%, meaning there is a 5% chance of losing 3% in a single day.

2.5 Expected Shortfall

Expected Shortfall also called as Conditional Value at Risk (CVaR), is a risk measure calculate the average loss in the worst-case scenario. Value at Risk (VaR) indicates the maximum expected loss at a particular confidence interval, Expected Shortfall goes a step further by computing the mean loss beyond that VaR threshold.

$$\boldsymbol{ES_\alpha = E[L \mid L \geq VaR_\alpha]}$$

3. Empirical Analysis

3.1 Introduction of the Data

The data includes daily adjusted closing prices for ten large-cap equity stocks from January 2014 to December 2022. Daily returns were calculated as percentage changes in adjusted prices.

Ticker	Company	Sector	Industry	Index
AMZN	Amazon	Consumer Discretionary	Internet Retail	S&P 100, Nasdaq 100
CAT	Caterpillar	Industrials	Industrial Machinery & Equipment	S&P 100
DE	Deere & Company	Industrials	Agricultural & Construction Machinery & Equipment	S&P 100
EXC	Exelon	Utilities	Multi-Utilities	S&P 100 / Russell 1000
GOOGL	Alphabet	Communication	Internet Services	S&P 100
JNJ	Johnson & Johnson	Health Care	Pharmaceuticals	S&P 100
JPM	JPMorgan Chase	Financials	Diversified Banks	S&P 100
META	Meta Platforms	Communication	Interactive Media & Services	S&P 100
PFE	Pfizer	Health Care	Pharmaceuticals	S&P 100
PG	Procter & Gamble	Consumer Staples	Household & Personal Product	S&P 100

Table 1: Introduction of the companies

3.2 Descriptive Statistics of Daily Return

Ticker	Mean	Std	Min	25%	Median	75%	Max	CV
AMZN	0.0876	2.0891	-14.0494	-0.8547	0.1084	1.0875	14.1311	23.84
CAT	0.0707	1.8513	-14.2822	-0.8282	0.0545	1.0102	10.3321	26.17
DE	0.0941	1.8386	-14.0722	-0.7453	0.0660	0.9339	13.4910	19.54
EXC	0.0607	1.5805	-16.0891	-0.6714	0.1166	0.8126	17.9941	26.03
GOOGL	0.0672	1.7379	-11.6341	-0.7180	0.0950	0.9206	16.2584	25.85
JNJ	0.0464	1.1455	-10.0379	-0.4792	0.0437	0.6053	7.9977	24.67
JPM	0.0612	1.7373	-14.9649	-0.7407	0.0295	0.8610	18.0125	28.39
META	0.0625	2.3353	-26.3901	-0.9474	0.1001	1.1985	17.5936	37.38
PFE	0.0500	1.4216	-7.7346	-0.6270	0.0181	0.7063	10.8552	28.43
PG	0.0462	1.1708	-8.7373	-0.4804	0.0618	0.6085	12.0090	25.35

Table 2: Descriptive Statistics

The data covers 2,257 observations for each stock, several years of historical price movements. The highest average prices are observed for DE (0.0941%) and AMZN (0.0876%). Lowest average return was for JNJ (0.0464%) and PG (0.0462%). The highest volatility is observed in META (2.3353%) and AMZN (2.0891%), showing greater price fluctuations. The lowest volatility is seen in JNJ (1.1455%) and PG (1.1708. Maximum daily gain was for JPM (18.0125%) and EXC (17.9941%). Maximum daily loss was for META (-26.3901%). Interquartile range shows that most stock return fall within ±1% for defensive stocks like JNJ and PG but it exceeds ±2% for high growth tech stocks.

3.3 Correlation Matrix

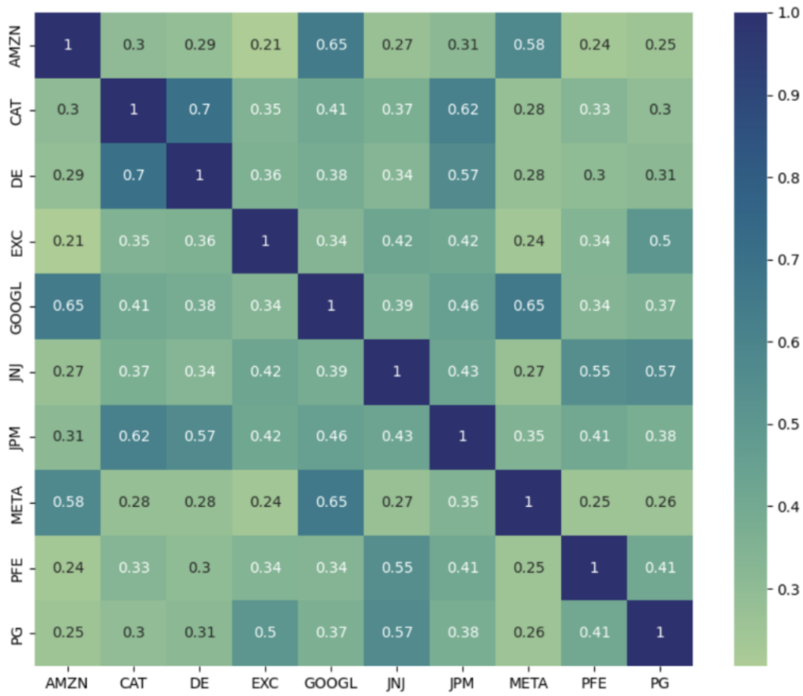

Figure 1: Correlation Matrix

The highest correlation is observed between CAT and DE (0.70), stating they responds similarly to market conditions. Other notable high correlation includes GOOGL – AMZN (0.65) and META – GOOGL (0.65). The lowest correlation is seen between META and EXC (0.24), as well as PFE and META (0.25), indicating diversification benefits.

3.4 Volatility

Volatility is an indicator if risk, it measures the degree of variation in stock returns. Higher volatility states that return fluctuate more, implying greater uncertainty and risk for investors, while lower volatility suggest stable returns. The dispersion between the lowest and highest standard deviation values (1.1455% JNJ vs. 2.3353% META) indicates a wide range of risk levels in the portfolio. This diversification offers benefits in terms of risk reduction.

3.5 Coefficient of Variation

The Coefficient of Variation (CV) measures risk per unit of return by dividing standard deviation of return by the mean return. It helps to compare the risk-return profiles across different assets. A lower CV states that the stock gives more return for each unit of risk. DE (19.54) and AMZN (23.84) indicates they provide higher return than the risk taken.

3.6 Value at Risk

5% confidence level, the historical VaR accords to 5th percentile of the historical daily returns. The 5% Historical VaR indicates a one-day loss of approximately 2.52%. High volatility stocks like META and AMZN shows greater historical losses, that leads to a large individual stock VaR values. Defensive stocks like PG and JNJ have smaller historical values, which is consistent with their lower volatility.

3.7 Monte Carlo Simulation

The Monte Carlo Simulation was used to generate a wide range of potential portfolio weights combinations and evaluate their risk return trade off. 1000 simulations were run with initial investment of 1,000,000 Euro, randomly assigning weights to the ten stocks while making sure that the sum of weights equaled to one. For each simulated portfolio, following metrics were calculated:

- Expected Annual Return
- Portfolio Volatility (Standard Deviation)
- Sharpe Ratio
- Final Portfolio value over the investment horizon
- Return on Investment

The simulation results were plotted in a risk-return scatter plot. The color and size correspond to the Sharpe Ratio. The optimal portfolio was defined as the one with the highest Sharpe Ratio. The results of one of the simulations runed are as follows:

- Portfolio Expected Annual Return = 17.74%
- Portfolio Standard Deviation (Volatility) = 18.08%
- Sharpe Ratio = 0.83

- Portfolio Final Value = $3719710.60
- Return on Investment = 271.97%

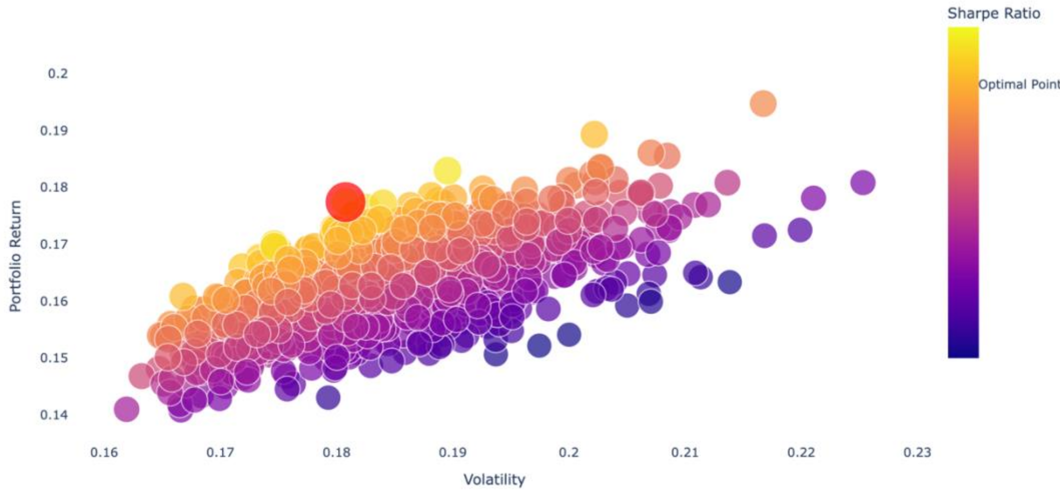

Figure 2: Efficient Frontier

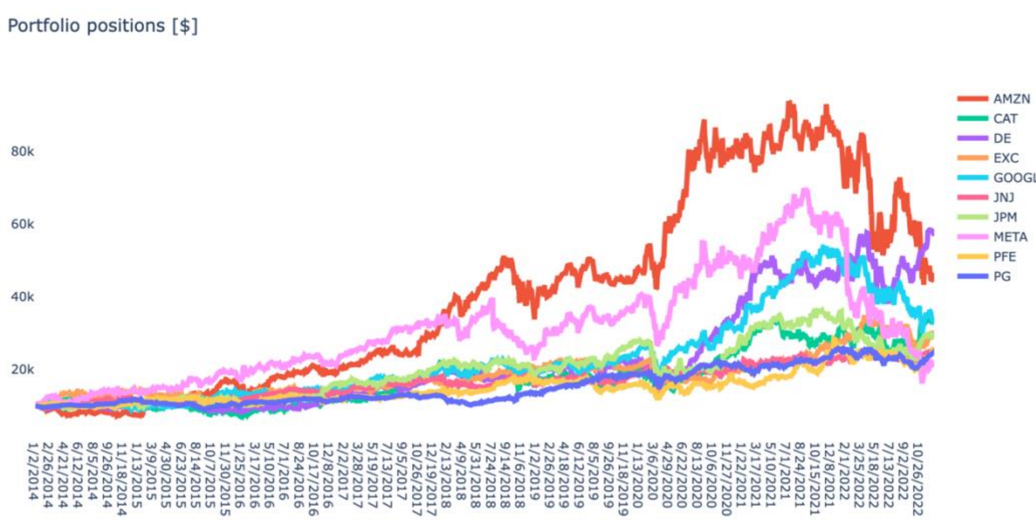

Figure 3:Portfolio Position over time

When compared to an equal weighted portfolio 10% to each stock. The result are as follows:

- Portfolio Expected Annual Return = 16.30%
- Portfolio Standard Deviation (Volatility) = 18.02%
- Sharpe Ratio = 0.76
- Portfolio Final Value = $320387.48
- Return on Investment = 220.39%

Figure 4: Total Portfolio Value

Advantage of Monte Carlo Simulation lies in the ability to explore large set and to identify combinations that maximize the risk-adjusted return. The equal weighted portfolio is robust in some cases, the portfolio optimization process demonstrated that proper asset allocation can yield superior performance without increasing volatility.

4. Conclusion

This paper studies the risk-return analysis and the construction of a diversified portfolio consisting of ten large cap equites from different sectors. Using historical prices from January 2014 to December 2022, we computed descriptive statistics, correlation matrix, Value at Risk (VaR), Expected Shortfall and ran Monte Carlo Simulation to find the optimal portfolio.

Several key principles of Morden Portfolio Theory (Markowitz, 1952) were confirmed by the empirical analysis. First, diversification across sectors reduce overall portfolio risk without declining the return. The correlation matrix showed low correlations between several assets, emphasizing the benefits of holding heterogeneous securities.

Risk Measures such as VaR and ES pointed significant differences between high growth technology stocks and defensive stocks.

Monte Carlo Simulation results showed that an optimized portfolio attain a higher Sharpe Ratio (0.83) and higher returns compared to that of an equal weighted portfolio (Sharpe Ratio of 0.76), maintaining similar level of volatility.

Overall, the findings indicates that while an equal weighted portfolios offer simplicity, systematic optimization and quantitative methods can yield superior results. Although, all results are based on the historical performance of the stock and assume that the past relationship to hold , while that are not the case in the dynamic markets.

5. References

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- Python libraries: NumPy, seaborn, matplotlib, plotly, cufflinks, SciPy

6. Appendix

Sample of Adjusted closing Prices Dataset (first 10 rows)

Data Source: Yahoo Finance

Date	AMZN	CAT	DE	EXC	GOOGL	JNJ	JPM	META	PFE	PG
2014-01-02	398.79	89.20	88.25	26.94	556.91	93.54	58.31	54.71	29.86	75.68
2014-01-03	396.44	88.81	87.84	26.95	556.91	93.47	57.97	54.56	29.64	75.50
2014-01-06	392.13	88.13	87.30	26.79	554.92	93.37	57.30	54.05	29.44	74.88
2014-01-07	398.03	88.73	88.40	26.89	556.18	93.99	57.90	54.63	29.79	75.20
2014-01-08	401.92	89.78	89.70	27.06	561.11	94.40	58.48	55.15	30.03	75.84
2014-01-09	397.97	88.94	88.64	26.90	556.95	94.06	57.85	54.78	29.94	75.54
2014-01-10	397.66	89.54	89.03	27.02	558.20	94.24	58.16	55.25	30.14	75.99
2014-01-13	392.55	88.12	88.38	26.84	553.66	93.86	57.40	54.20	29.63	75.25
2014-01-14	398.84	89.77	89.67	27.12	561.49	94.51	58.54	55.45	30.16	76.05
2014-01-15	401.01	90.12	90.80	27.20	563.16	94.76	58.80	55.73	30.28	76.28

Note: Full file is available as supplementary material.