Analyzing PLTR Stock Performance and Portfolio Diversification with AAPL, SPY, and Gold

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Abstract

In the midst of rapid technological development, Palantir Technologies (PLTR) has emerged as an important investment opportunity, attracting attention from both institutional and individual investors. This study provides a comprehensive analysis of PLTR's performance and explores how diversification with other asset classes, namely Apple (AAPL), the S&P 500 index (SPY), and Gold (GLD), can optimize returns while mitigating risks. The analysis begins by evaluating individual risks through mean returns, standard deviations, correlations, and covariances, and then extends to portfolio diversification and risk management strategies. Using multiple regression, results indicate that SPY significantly explains variations in PLTR returns, with an R^2 of 0.285 and RMSE of 0.038 on test data. The model achieved a moderate level of directional accuracy, highlighting both the potential and limitations of linear models in financial prediction.

Keywords

Computational finance; Portfolio optimization; Python; Stock data analysis; Financial technology

Chapter 1 : Introduction

1.1 Background

Financial technology's (FinTech) explosive expansion has revolutionized investing methods by facilitating sophisticated analytical techniques and data-driven decision-making. Today, academics and practitioners may effectively assess asset allocation, predict returns, and apply risk management measures thanks to algorithmic techniques in portfolio management, which makes investment analysis more methodical and accurate.

Over the last five years, Palantir Technologies (PLTR) has been a well-known stock due to its strong growth potential and creative contributions to data analytics. It is a fascinating topic for risk-return analysis, though, because it is also linked to significant volatility and increased investment risk. Apple Inc. (AAPL), on the other hand, is commonly recognized as a reliable, high-performing stock that provides steady returns and reduced relative volatility, setting the standard for more predictable performance.

This analysis now includes gold (GLD) as a safe-haven asset and the S&P 500 index (SPY) as a market benchmark to give a more comprehensive view of diversification. By looking at these assets collectively, the study hopes to examine how risk and return interact across various asset classes and offer useful advice on how to diversify a portfolio and use efficient risk management techniques over a five-year period.

1.2 Problem Statement

In increasingly unpredictable financial markets, investors must balance risk and return. High-growth equities, such as Palantir Technologies (PLTR), have the potential to yield large profits, but they also have a high risk of market volatility and investment loss. Stable equities, such as Apple Inc. (AAPL), on the other hand, gives more consistent returns but can have less room for expansion. Furthermore, while alternative assets like gold (GLD) and conventional benchmarks like the S&P 500 index (SPY) are crucial for portfolio stabilization, their relationships with companies that are both highly volatile and highly stable are not always clear-cut.

1.4 Project Purpose

The purpose of this study is to :

1. Evaluate the performance of Palantir Technologies (PLTR) and investigate how portfolio diversification with Apple (AAPL), the S&P 500 index (SPY), and Gold (GLD) can optimize returns while mitigating investment risks.
2. Assessing individual risk measures, analyzing correlations, and constructing diversified portfolios which aims to provide practical insights for investors seeking to balance risk and return.
3. The study seeks to demonstrate the applicability of regression-based models for financial prediction and portfolio optimization in a computational finance context.

1.5 Methods

This study employs a quantitative approach to analyze stock performance and portfolio diversification. The methodology consists of the following steps:

1. Data Collection: Historical daily adjusted closing prices for PLTR, AAPL, SPY, and GLD over a five-year period were obtained using Python libraries such as yfinance.
2. Data Preprocessing: The data were cleaned to remove missing values and aligned to ensure consistent timeframes across all assets.
3. Descriptive Analysis: Individual asset performance was evaluated using mean returns, standard deviations, and visualizations to assess volatility and trends.
4. Correlation and Covariance Analysis: Pairwise correlations and covariances were computed to examine interdependencies among the assets, providing insight into diversification potential.
5. Portfolio Construction: Several portfolio combinations were simulated to analyze risk–return trade-offs, incorporating different weightings of PLTR, AAPL, SPY, and GLD.
6. Risk Assessment: Portfolio risk was quantified using standard deviation and Value at Risk (VaR) measures to assess potential losses under adverse market conditions.
7. Regression Analysis: A multiple linear regression model was applied to determine the extent to which SPY, AAPL, and GLD explain variations in PLTR returns. Model performance was evaluated using R^2, RMSE, and directional accuracy metrics.

Chapter 2 : Theory and Formula

The author of this research examines stock performance and portfolio diversification using basic concepts from computational finance and financial economics. Regression-based predictive modeling, asset correlation, risk measurement, and portfolio optimization are important ideas that together offer a framework for assessing the trade-off between risk and return.

2.1 Financial Market

Investors trade a variety of financial instruments on the financial market, where supply, demand, and group expectations all affect pricing. Shiller (2011, Yale University Financial Markets) asserts that financial markets assist investors in assessing and controlling risk in addition to compiling data about the state of the economy. Statistical metrics like variance, standard deviation, and mean returns can be used to quantify the systematic and idiosyncratic risks that investors face.

According to Shiller, diversity is an essential investing tactic that enables people to optimize profits while lowering their exposure to risk. Investors can create safer and more lucrative portfolios by distributing their money among assets with varying risk profiles and correlations. Asset correlations and covariances shed light on how combined holdings respond to changing market circumstances. This idea serves as the foundation for the justification of incorporating safe-haven assets like gold (GLD), broad-market benchmarks like SPY, stable equities like AAPL, and high-growth stocks like PLTR into a diversified portfolio.

2.2 Classes of Stocks

Stocks can be classified into different categories based on factors such as growth potential, stability, and risk profile, which helps investors make informed portfolio decisions:

1. Growth Stocks: Shares of companies expected to grow faster than the overall market. They typically reinvest earnings for expansion rather than paying dividends. Growth stocks, such as Palantir Technologies (PLTR), often exhibit high volatility and potential for substantial returns but carry elevated risk.

2. Value Stocks: Shares considered undervalued relative to fundamental metrics like earnings or book value. These stocks provide moderate returns and lower volatility, appealing to risk-conscious investors seeking steady growth.

3. Blue-Chip Stocks: Well-established companies with stable performance, consistent dividends, and reliable growth. Apple Inc. (AAPL) exemplifies this category, offering lower risk and predictable returns compared to high-growth stocks.

4. Index Funds and Market ETFs: Instruments like the S&P 500 (SPY) represent a diversified basket of stocks. They allow investors to track overall market performance while mitigating company-specific risk.

5. Safe-Haven Assets: Assets such as Gold (GLD) are often included in portfolios to hedge against market volatility. While not technically stocks, they help stabilize portfolios during downturns.

By mixing high-growth, stable, and protective assets, investors may create portfolios that balance risk and return and maximize performance in a variety of market scenarios.

2.3 Regression Analysis in Finance

Regression analysis is a statistical method used to examine the relationship between a dependent variable and one or more independent variables. In finance, it helps understand how asset returns are influenced by other factors such as market indices, related stocks, or macroeconomic indicators.

In this project, regression analysis is applied to study how Palantir Technologies (PLTR) returns are affected by Apple (AAPL), the S&P 500 index (SPY), and Gold (GLD). Modeling PLTR returns as a function of these assets allows investors to:

- Assess the degree to which each asset explains PLTR’s performance.
- Quantify sensitivities and co-movements.
- Identify systematic patterns for predictive insights.

Key regression metrics include:

- **R-squared (R^2):** Proportion of variance in the dependent variable explained by independent variables.
- **Root Mean Square Error (RMSE):** Average magnitude of prediction errors.
- **Directional Accuracy:** Ability of the model to predict the direction of returns, important for practical investment decisions.

By offering a quantitative technique to assess correlations, co-movements, and possible hedging techniques, regression analysis enhances portfolio theory and facilitates data-driven choices when mixing high-volatility assets with steady and secure investments.

2.4 Python for Finance

Python has become a widely used programming language in finance due to its simplicity, versatility, and powerful data analysis libraries. For stock performance analysis and portfolio optimization, Python offers tools such as:

- **Pandas:** Efficient data manipulation and time-series analysis.
- **NumPy:** High-performance numerical computing for calculations like returns, variances, and covariances.
- **Matplotlib and Seaborn:** Data visualization for trends, correlations, and portfolio analysis.
- **yfinance:** Access to historical stock and market data from Yahoo Finance.
- **SciPy and statsmodels:** Advanced statistical analysis, including regression modeling.

Investors and academics may effectively visualize financial data, automate data gathering, compute risk metrics, and model portfolio combinations with Python. Python is used in this project to collect daily stock prices for five years, compute returns, assess risk factors, do regression analysis, and model diversified portfolios of PLTR, AAPL, SPY, and gold (GLD).

2.5. Formula in Financial Market and Python as Tools for Finance

2.5.1 Formula for Daily Returns, Mean Return, Standard Deviation, Covariance, and Correlation Coefficient

Financial markets rely on quantitative measures to evaluate risk, return, and relationships between assets. The key formulas used in this project include:

1. Daily Returns

$$Rt = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where:

R_t = daily return at time t
P_t = closing price at time t
P_{t-1} = closing price at time t-1

2. Mean Return

$$\mu_x = \frac{1}{n}\sum_{i=n}^{n} prob\ (x = x_i)\ x_i$$

Where:

μ_x = average return over n periods
x_i = individual period return

3. Variance and Standard Deviation

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \mu_x\right)^2$$

$$\sigma = \sqrt{\sigma^2}$$

Where:

σ^2 = variance of returns
σ = standard deviation (risk)
4. Covariance

To measure how assets move together. If **Cov(X, Y) > 0**, the assets tend to move in the same direction (positive relationship).

$$Cov\,(X, Y) \;=\; \frac{1}{n-1}\sum_{i=1}^{n}\left(x_1 - \overline{x}\right)\left(y_1 - \overline{y}\right)$$

Where:

- X_i, Y_i = individual returns of assets X and Y at time i
- $\overline{X}$ = mean returns of X
- $\overline{Y}$ = mean returns of Y
- n = number of observations

5. Correlation Coefficient

Normalizes covariance to a value between -1 and 1, indicating strength and direction of linear relationship.

$$\rho(x, y) \;=\; \frac{Cov\,(x,y)}{\sigma_x \sigma_y}$$

2.5.2 Python as a Tool for Finance

Python served as the primary computational tool in this study, enabling efficient handling of large financial datasets and application of statistical models. The platform facilitated a range of tasks, including data collection, transformation, and visualization, as well as the implementation of portfolio optimization and predictive modeling techniques.

Python was specifically used to assess inter-asset linkages, calculate asset returns, and quantify risk using correlation and volatility structures. Additionally, it encouraged the creation of regression-based models to assess explanatory factors and produce forecasts. In order to improve the interpretability of the results, visualization tools were incorporated to show statistical findings, portfolio trade-offs, and market trends..

Python supported both empirical research and useful investment decision-making by combining these features to create a methodical framework for applying financial theories to actual market data.

2.6 Methodology

1. Data Collection
   Historical price data for PLTR, AAPL, SPY, and GLD were obtained from a reliable financial database. The dataset was cleaned and validated to ensure accuracy and consistency before further analysis.
2. Preprocessing and Initial Analysis
   The data was transformed into standardized return measures and examined through descriptive statistics to capture price behavior, volatility, and underlying patterns.
3. Feature Construction
   Key market indicators, such as moving averages, directional signals, and momentum measures, were developed to evaluate market trends and potential trading signals.

4. Risk and Return Estimation
   Statistical models were applied to estimate expected returns, volatility, and downside risk through probability-based measures, providing insight into potential loss scenarios.
5. Portfolio Construction
   Multiple portfolio allocation scenarios were designed to compare diversification strategies and evaluate trade-offs between risk and return.
6. Regression and Predictive Analysis
   A regression framework was employed to assess the relationship between PLTR and other assets, with predictive insights derived from directional trends and risk-adjusted measures.

Chapter 3: Result & Data

3.1 Overview

This chapter presents the results of the quantitative analysis conducted using Python, with libraries such as NumPy, Pandas, Matplotlib, and data retrieved from Yahoo Finance (yfinance). After checking and cleaning the raw data, the study evaluates price movements, return distributions, moving averages, and trend signals. Further analysis includes log return properties, Value at Risk (VaR), covariance and correlation across assets, portfolio construction, and regression modeling with PLTR as the dependent variable.

3.2 Preprocessing and Initial Analysis

The analysis began with summary statistics of PLTR, AAPL, SPY, and GLD to ensure data quality and interpret basic return properties. This step revealed how volatile each stock is by comparing mean returns against standard deviations, as well as identifying price ranges and typical trading behavior. Absolute price differences highlighted that PLTR experiences larger raw movements than other assets, while daily return distributions confirmed its higher volatility. Transforming price differences into standardized daily log returns allowed comparability across assets, forming the foundation for risk modeling.

Price	Close	High	Low	Open	Volume
Ticker	PLTR	PLTR	PLTR	PLTR	PLTR
count	1243.000000	1243.000000	1243.000000	1243.000000	1.243000e+03
mean	33.856750	34.685122	32.900661	33.785121	6.007956e+07
std	38.245751	39.008125	37.232074	38.147665	4.240285e+07
min	6.000000	6.170000	5.920000	5.980000	9.126400e+06
25%	11.845000	12.145000	11.390000	11.930000	3.394220e+07
50%	21.400000	21.790001	20.930000	21.340000	4.731400e+07
75%	27.920000	28.845000	26.889999	28.045000	7.146630e+07
max	186.970001	190.000000	184.410004	189.000000	4.502905e+08

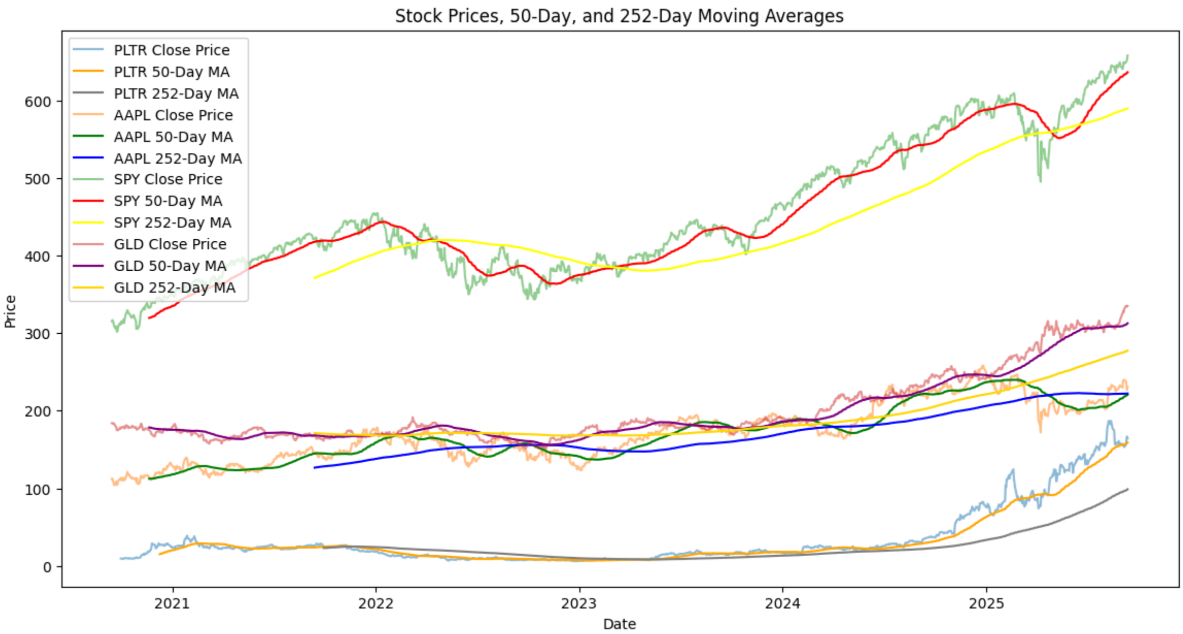
Price	Close	High	Low	Open	Volume
Ticker	AAPL	AAPL	AAPL	AAPL	AAPL
count	1255.000000	1255.000000	1255.000000	1255.000000	1.255000e+03
mean	170.555659	172.278192	168.661538	170.394216	7.444379e+07
std	36.392068	36.573578	36.120976	36.329834	3.338938e+07
min	103.925148	107.183774	100.287201	101.687917	2.323470e+07
25%	142.509613	144.002196	140.684603	142.024008	5.063945e+07
50%	168.092880	169.509652	166.802185	167.919308	6.692180e+07
75%	194.509666	196.100709	192.897685	194.172192	8.987460e+07
max	258.103729	259.179926	256.718662	257.276679	3.186799e+08

Price	Close	High	Low	Open	Volume
Ticker	SPY	SPY	SPY	SPY	SPY
count	1255.000000	1255.000000	1255.000000	1255.000000	1.255000e+03
mean	451.282639	453.734847	448.406472	451.167743	7.557356e+07
std	86.465747	86.480977	86.279666	86.437669	2.944854e+07
min	301.618500	305.507495	298.963576	300.291069	2.604870e+07
25%	387.335037	389.904762	384.474534	387.224433	5.600695e+07
50%	424.701813	426.633910	422.465776	424.104385	7.059130e+07
75%	521.619415	523.876260	518.098360	521.420841	8.943210e+07
max	657.630005	658.330017	653.590027	654.179993	2.566114e+08

Price	Close	High	Low	Open	Volume
Ticker	GLD	GLD	GLD	GLD	GLD
count	1255.000000	1255.000000	1255.000000	1255.000000	1.255000e+03
mean	198.858040	199.675307	197.939633	198.835801	8.157826e+06
std	44.330169	44.464110	44.022839	44.263558	4.089338e+06
min	151.229996	151.960007	150.570007	150.699997	1.436500e+06
25%	169.269997	169.894997	168.525002	169.210007	5.518950e+06
50%	179.240005	179.919998	178.369995	179.330002	7.214300e+06
75%	218.125000	219.044998	216.430000	217.885002	9.553900e+06
max	335.260010	338.309998	333.850006	337.029999	4.734770e+07

3.3 Feature Construction

To determine both short-term and long-term trends, stock prices were plotted against 50-day and 252-day moving averages. PLTR saw protracted downtrends dominated by sellers, as seen by prolonged spells below its MA50. AAPL and SPY, on the other hand, showed greater upward momentum as they frequently traded above their MA50. Prices frequently bounced off moving averages, which also served as dynamic levels of support and resistance. Notable Death Cross and Golden Cross occurrences were noted, indicating shifts in market sentiment from bullish to pessimistic. The moving averages' slope further emphasized momentum; sideways markets were indicated by flatter slopes, whereas steep rising trends indicated significant momentum.



Trend Direction (Price vs. MA)

- PLTR: Price stayed below the 252-day MA through 2021–2023, confirming a bearish phase, before shifting bullish in 2024–2025.
- AAPL: Consistently above both MAs, showing a strong long-term uptrend.
- SPY: Rebounded from a 2022 dip, returning above both MAs in 2023.
- GLD: Sideways in 2022–2023, then turned bullish from late 2023.

Support & Resistance

- PLTR: MA50 as resistance (2021–2023); MA252 as support post-2024.
- AAPL: MA50 provided reliable dynamic support; MA252 rarely tested.
- SPY: MA252 held during 2022 correction; recovery confirmed by MA50 reclaim in 2023.
- GLD: MA50 alternated as support/resistance until 2023, after which both acted as support.

Crossovers

- PLTR: Several Death Crosses (2021–2023), Golden Cross in 2024.
- AAPL: No major Death Crosses; bullish throughout.
- SPY: Death Cross in 2022, reversed by Golden Cross in 2023.
- GLD: Death Cross in 2022, Golden Cross in 2023.

Momentum (MA Slopes)

- PLTR: Negative until 2023, strong positive from 2024.
- AAPL: Upward-sloping MAs, sustained bullish momentum.
- SPY: Slowed in 2022, turned positive again in 2023.
- GLD: Flat in 2022, modestly positive after 2023.

The comparison study reveals unique features among assets, as indicated by the chart. PLTR is extremely erratic and speculative; it has only now gone from being bearish to positive. AAPL is positioned as a steady growth stock due to its persistent strength and endurance. With brief declines but a robust structural advance, SPY is a good indicator of the overall market. As a stabilizing asset, GLD provides consistent growth with less volatility. These results highlight the need of diversification in maximizing portfolio performance by striking a balance between defensive, steady assets and speculative growth.

3.4 Risk and Return Estimation

All assets that were selected due to their symmetric and time-additive characteristics had their log returns calculated. The normality assumption was validated by analyzing log return distributions, which made it possible to compute mean daily growth rates and volatility. The results indicated that PLTR had the greatest potential for growth, but it also fluctuated the most. Extreme price decrease probabilities, such as the chance that AAPL will fall more than a specific percentage in a day or a year, were calculated using the probability density function. After calculating Value at Risk (VaR) at 95% and 50% confidence levels, it was determined that GLD offered the lowest downside risk and PLTR the most.

PLTR

```
The probability that the stock price of PLTR will drop over 5% in a day is
0.1415
The probability that the stock price of PLTR will drop over 40% in 220 days
is 0.5633
The probability that the stock price of PLTR will drop over 20% in 220 days
is 0.6782
The 1-day VaR at 95% confidence level is -0.0754
The 1-day VaR at 50% confidence level is -0.0023
The 25% quantile of the daily log return is -0.0323
```

The 75% quantile of the daily log return is 0.0277

AAPL

The probability that the stock price of AAPL will drop over 5% in a day is 0.0031
The probability that the stock price of AAPL will drop over 40% in 220 days is 0.1535
The probability that the stock price of AAPL will drop over 20% in 220 days is 0.3912
The 1-day VaR at 95% confidence level for AAPL is -0.0303
The 1-day VaR at 50% confidence level for AAPL is -0.0006
The 25% quantile of the daily log return for AAPL is -0.0128
The 75% quantile of the daily log return for AAPL is 0.0116

SPY

The probability that the stock price of SPY will drop over 5% in a day is 0.0000
The probability that the stock price of SPY will drop over 40% in 220 days is 0.0472
The probability that the stock price of SPY will drop over 20% in 220 days is 0.3307
The 1-day VaR at 95% confidence level for SPY is -0.0185
The 1-day VaR at 50% confidence level for SPY is -0.0006
The 25% quantile of the daily log return for SPY is -0.0080
The 75% quantile of the daily log return for SPY is 0.0068

GLD

The probability that the stock price of GLD will drop over 5% in a day is 0.0000
The probability that the stock price of GLD will drop over 40% in 220 days is 0.0182
The probability that the stock price of GLD will drop over 20% in 220 days is 0.2505
The 1-day VaR at 95% confidence level for GLD is -0.0161
The 1-day VaR at 50% confidence level for AAPL is -0.0005
The 25% quantile of the daily log return for GLD is -0.0069
The 75% quantile of the daily log return for GLD is 0.0059

To illustrate the relationship between each stock class, covariance and correlation have also been computed using log return. According to the chart, AAPL and SPY are the most related, while PLTR and GLD have the smallest values and a dispersed pattern, indicating that technology stocks are unrelated to other asset classes like gold (GLD).

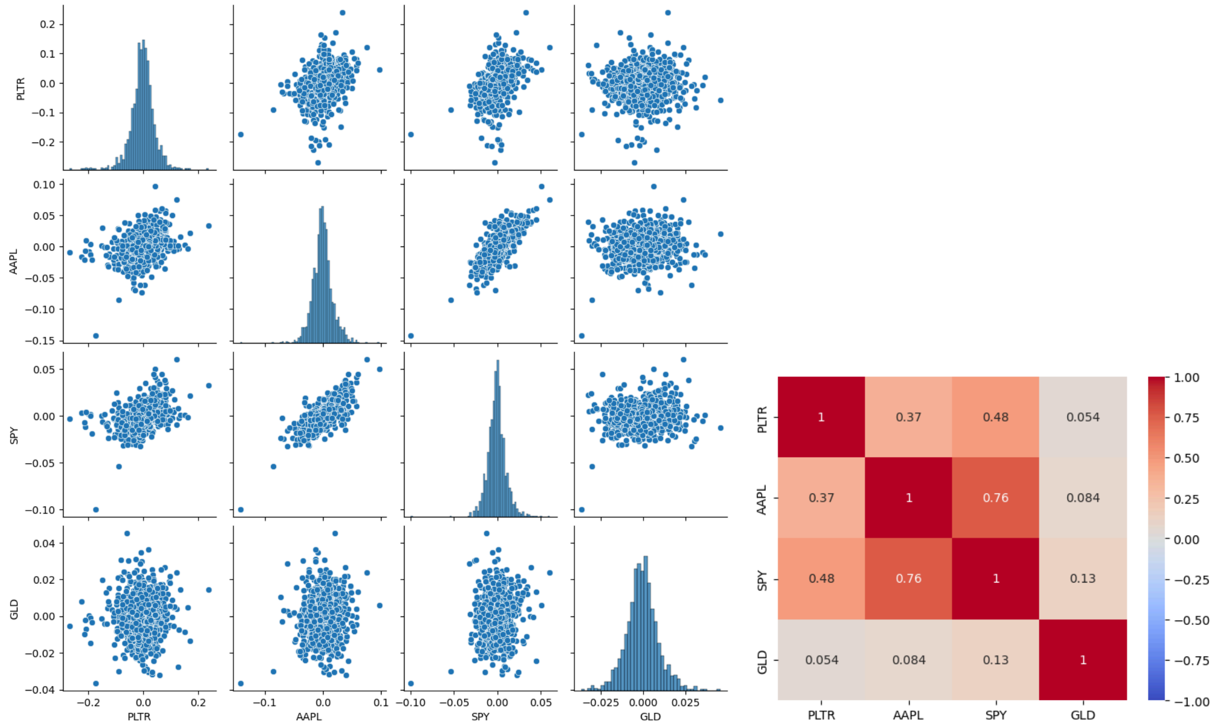


Figure of Covariance

3.5 Portfolio Construction

Three portfolios were constructed: (i) equal weights (25% each), (ii) equity-dominant (PLTR 30%, AAPL 30%, SPY 20%, GLD 20%), and (iii) PLTR-heavy (40%, 30%, 20%, 10%). For each portfolio, mean log return, volatility, and Value at Risk (VaR) at 95% and 50% confidence levels were calculated and visualized.

```
Equal Weights (25% each)
Portfolio Mean Log Return: -0.0010
Portfolio Standard Deviation of Log Return: 0.0157
The 252-day VaR at 95% confidence level for the portfolio is -0.6612
The 252-day VaR at 90% confidence level for the portfolio is -0.5706
The 252-day VaR at 50% confidence level for the portfolio is -0.2508
The 25% quantile of the daily log return for the portfolio is -0.4191
The 75% quantile of the daily log return for the portfolio is -0.0824

Equity-Dominant (PLTR 30%, AAPL 30%, SPY 20%, GLD 20%)
Portfolio Mean Log Return: -0.0011
Portfolio Standard Deviation of Log Return: 0.0179
The 252-day VaR at 95% confidence level for the portfolio is -0.7394
The 252-day VaR at 90% confidence level for the portfolio is -0.6363
The 252-day VaR at 50% confidence level for the portfolio is -0.2729
The 25% quantile of the daily log return for the portfolio is -0.4642
The 75% quantile of the daily log return for the portfolio is -0.0817

PLTR-heavy (40%, 30%, 20%, 10%)
```

```
Portfolio Mean Log Return: -0.0013
Portfolio Standard Deviation of Log Return: 0.0219
The 252-day VaR at 95% confidence level for the portfolio is -0.8894
The 252-day VaR at 90% confidence level for the portfolio is -0.7632
The 252-day VaR at 50% confidence level for the portfolio is -0.3179
The 25% quantile of the daily log return for the portfolio is -0.5522
The 75% quantile of the daily log return for the portfolio is -0.0835
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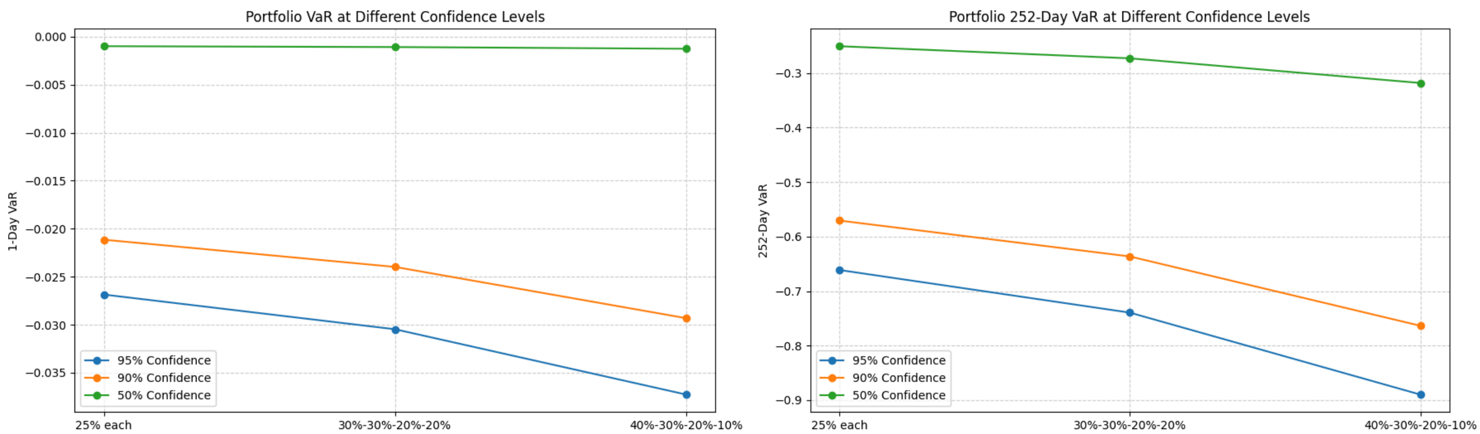

Figure of VaR 50 days and 252 Days for Portfolio Risk Management

According to the results, equal weighting captures balanced returns while substantially lowering risk as compared to holding PLTR separately. better PLTR allocations in a portfolio indicate better expected returns, but they also carry a significantly higher risk of volatility and downside. Value at Risk is decreased by diversification with SPY and particularly GLD, demonstrating unmistakable risk mitigation.

3.6 Regression Analysis and Prediction

Using PLTR returns as the dependent variable and AAPL, SPY, and GLD returns as explanatory variables, a regression model was used. The findings indicate that PLTR can be significantly explained by AAPL and SPY, but not by GLD. Despite capturing general co-movement patterns, the regression leaves a significant residual error margin, which is indicative of the strong idiosyncratic volatility of PLTR.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               PLTR_ret   R-squared:                       0.224
Model:                            OLS   Adj. R-squared:                  0.220
Method:                 Least Squares   F-statistic:                     59.21
Date:                Thu, 11 Sep 2025   Prob (F-statistic):           1.56e-64
Time:                        15:55:28   Log-Likelihood:                 2233.1
No. Observations:                1240   AIC:                            -4452.
Df Residuals:                    1233   BIC:                            -4416.
Df Model:                           6
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.0021      0.001      1.853      0.064      -0.000       0.004
AAPL_ret          0.0386      0.097      0.397      0.691      -0.152       0.229
SPY_ret           1.9055      0.161     11.808      0.000       1.589       2.222
GLD_ret          -0.0379      0.121     -0.313      0.754      -0.275       0.199
AAPL_ret_lag1    -0.0372      0.098     -0.382      0.703      -0.229       0.154
SPY_ret_lag1      0.2080      0.161      1.288      0.198      -0.109       0.525
GLD_ret_lag1     -0.2699      0.121     -2.236      0.026      -0.507      -0.033
==============================================================================
Omnibus:                      485.496   Durbin-Watson:                   1.911
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4777.730
Skew:                           1.530   Prob(JB):                         0.00
...
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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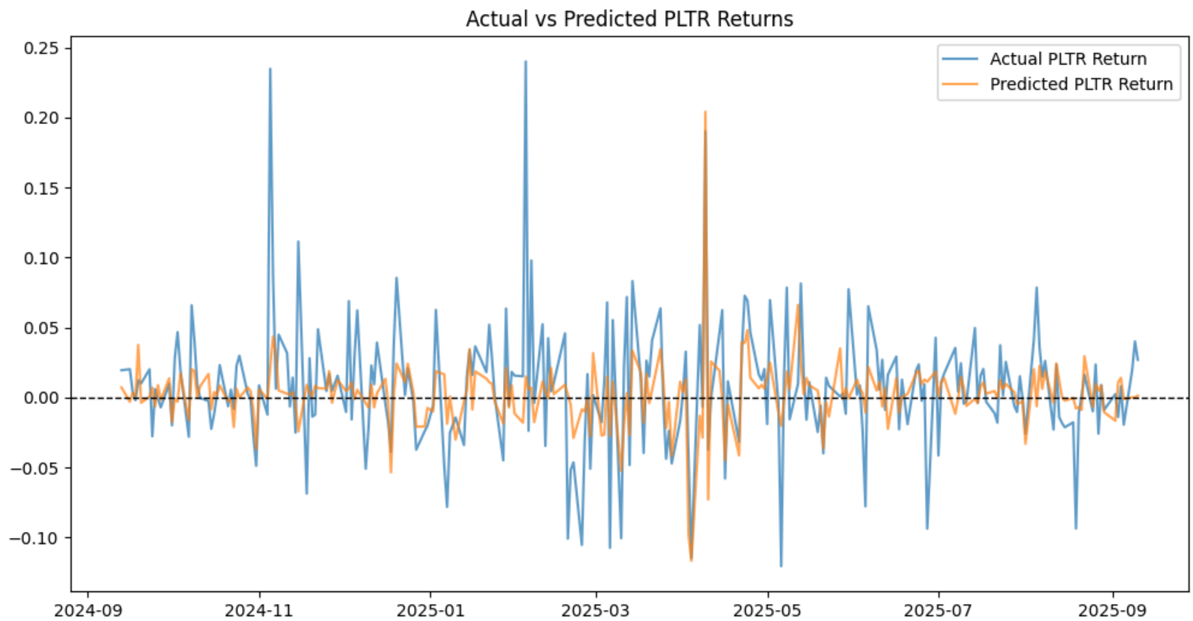
Regression-based predictive study indicates that although market-wide factors contribute to PLTR's movements, it is still challenging to accurately predict its returns. This demonstrates the advantages and disadvantages of using quantitative modeling in growth equities with significant volatility.

Test RMSE: 0.03800885093323578

Test R^2: 0.2845287691994587

Date	Actual	Predicted	Signal	Correct
2025-08-27	-0.025797	0.004720	📈 Up	False
2025-08-28	0.008933	0.008633	📈 Up	True
2025-08-29	-0.008917	-0.010492	📉 Down	True
2025-09-02	0.002425	-0.016528	📉 Down	False
2025-09-03	-0.013941	0.010803	📈 Up	False
2025-09-04	0.008005	0.014020	📈 Up	True
2025-09-05	-0.019406	-0.001124	📉 Down	True
2025-09-08	0.019528	0.000118	📈 Up	True
2025-09-09	0.040102	0.000144	📈 Up	True
2025-09-10	0.026977	0.001291	📈 Up	True



Directional Accuracy: 67.74%

Predicted PLTR return for tomorrow: 0.001291322788097485

📈 Model suggests PLTR will go UP tomorrow

Chapter 4: Analysis

4.1 Interpretation of Price Trends and Moving Averages

The combined chart of PLTR, AAPL, SPY, and GLD, along with their 50-day and 252-day moving averages, reveals important insights into asset behavior over the

2021–2025 period. Palantir Technologies' (PLTR) pattern is extremely volatile, with extended periods of poor performance interspersed with strong rallies. The price continuously remained below the 50-day and 252-day moving averages from 2021 until the beginning of 2023, indicating a protracted bearish trend. The stock continued to fall when a death cross in 2022 indicated additional downside danger. Only in the middle of 2024 did PLTR make a significant comeback, displaying a golden cross when the 50-day MA surpassed the 252-day MA. The steep slope of both upward and downward moves emphasizes that PLTR's price fluctuations are speculative in character, even though this points to a resumed bullish phase. Before profiting from unexpected rallies, investors would have to endure protracted declines.

Apple, or AAPL, has a far more consistent long-term upward trend. With only brief corrections in 2022 that brought the price closer to the long-term average, the price regularly remained above the 252-day MA. The bullish feeling was reinforced by several golden crosses. Crucially, the 50-day MA frequently served as support, halting more significant drops. This suggests a robust company model and high investor confidence. AAPL's drawdowns were shorter and recovered more quickly than PLTR's, indicating a more consistent return history.

The S&P 500 ETF, or SPY, is a reflection of larger market cycles. A death cross appeared in early 2022 as the price of stocks dropped below both moving averages due to pressure from inflation and rate hikes. The price continued to rise into 2024 and 2025 after a golden cross in 2023 restored bullish alignment. The market recovery was confirmed when the 252-day MA gradually moved upward once more. Although SPY's changes were not as sharp as PLTR's, they nonetheless closely followed macroeconomic developments.

Compared to stocks, GLD (Gold ETF) has distinct behavior. GLD's price confirmed its defensive tendency by finding support close to the 252-day MA during 2022's equities slump. But it wasn't until late 2023 that GLD displayed strong golden cross signs, in contrast to SPY or AAPL. With both moving averages sloping upward, gold prices then started a consistent upward trend. This implies that during erratic macroeconomic times, investors looked to gold as a hedge. It worked well as a portfolio stabilizer since its price movements were less erratic and more fluid than those of stocks.

4.2 Risk and Return Analysis

The risk and return characteristics of PLTR, AAPL, SPY, and GLD reveal a clear trade-off between growth potential and downside exposure. The company with the biggest negative risk is Palantir Technologies, or PLTR. Compared to the other assets, the likelihood of a daily loss of more than 5% is significantly higher at 14.15 percent. Severe long-term risk exposure is indicated by the 56.33% possibility of losing more than 40% and the 67.82% chance of losing more than 20% over a 220-day horizon. An investor could anticipate losing at least this much on one out of every twenty days, according to the 1-day 95% VaR of -7.54%. The broad interquartile range (–3.23% to +2.77%) indicates a high degree of volatility and the possibility of significant fluctuations. These findings support PLTR's status as a speculative growth asset with a high potential return but remarkably erratic behavior.

Apple's (AAPL) risk-return profile is more balanced. With a 15.35% possibility of losing more than 40% over 220 days, the long-term risk is lower than PLTR, and the probability of a daily loss of more than 5% is only 0.31%. The interquartile range (-1.28% to +1.16%) is significantly smaller, indicating stability, and the 1-day 95% VaR is –3.03%, which is less severe than PLTR. This implies that AAPL is a comparatively safer equity than PLTR since it provides steady returns with a moderate downside risk.

The S&P 500 ETF, or SPY, offers a steady risk-return balance and represents overall market performance. While the possibility of a 40% loss over 220 days is only 4.72%, much below PLTR or AAPL, the probability of a daily decrease exceeding 5% is practically zero. Its interquartile range (-0.80% to +0.68%) is narrow, demonstrating predictable behavior, and its 1-day 95% VaR is -1.85%, suggesting decreased daily volatility. As a result, SPY is a stable benchmark with lower drawdown risks that is strongly correlated with macroeconomic conditions.

The most secure profile is provided by GLD (Gold ETF). There is no chance of a daily decline of more than 5%, and there is only a 1.82% chance of losing more than 40% over 220 days. Out of the four assets, the 1-day 95% VaR is the lowest at -1.61%. Its low volatility is highlighted by the fact that the interquartile range is the narrowest, ranging from -0.69% to +0.59%. The stability of GLD demonstrates its value as a safe-haven investment that effectively lowers total portfolio risk, particularly during stock market downturns.

Based on the probability and Value at Risk (VaR) analysis, PLTR clearly carries the highest downside risk among the four assets. PLTR has a 14.15% chance of a daily decline of more than 5%, while AAPL has a 0.31% chance and SPY and GLD have virtually no chance. PLTR also exhibits the highest probability of significant losses over a longer time frame of 220 days, with a 56.33% chance of losing more than 40% and a 67.82% chance of falling more than 20%. GLD, on the other hand, has the most defensive behavior, with comparatively narrow quantile ranges and a little 1.82% chance of declining more than 40% during the same time frame.

This conclusion is supported by the VaR measures: PLTR's one-day 95% VaR is -7.54%, which is significantly higher than that of AAPL (-3.33%), SPY (-1.85%), or GLD (-1.61%). This implies that, in comparison to the other assets, an investor owning PLTR needs to be ready for far higher possible daily losses. While AAPL, SPY, and GLD show more stable, narrower distributions, PLTR's greater spread between the 25% and 75% quantiles suggests a higher potential return. Overall, the findings show a definite risk-return trade-off: GLD gives stability and serves as a hedge against market risk, whereas PLTR offers the potential for larger returns but far more volatility.

4.3 Portfolio Implications

The portfolio-level Value at Risk (VaR) results under different allocation strategies highlight the trade-off between diversification benefits and concentration risk. Three allocation scenarios were tested: equal weighting, equity-dominant weighting, and PLTR-heavy weighting.

4.3.1. Equal Weights (25% each)

The equal-weight portfolio delivers the most balanced risk profile. At a 95% confidence level, the 252-day VaR is -0.6612, which is less than allocations that are heavily weighted toward equity. The mean log return is -0.0010, and the volatility is moderate at 0.0157. This illustrates how diversification lowers downside risk by providing equal exposure to growth (PLTR, AAPL), market (SPY), and defensive (GLD) assets. In comparison to other portfolios, the 25% and 75% quantiles (-0.4191, -0.0824) continue to be less extreme.

4.3.2. Equity-Dominant (PLTR 30%, AAPL 30%, SPY 20%, GLD 20%)

Shifting the allocation toward equities increases both risk and potential return variability. The 252-day VaR with 95% confidence widens to -0.7394, and the standard deviation increases to 0.0179. Compared to the equal-weight scenario, the left-tail quantile at -0.4642 suggests a greater degree of downside risk. The overweighting of PLTR and AAPL creates greater volatility and drawdown potential, especially in unfavorable stock market conditions, even though GLD still has some hedging effect.

PLTR-Heavy (40%, 30%, 20%, 10%)

The highest concentration of risk is present in this portfolio. The 252-day VaR at 95% confidence level drops to -0.8894, indicating significant downside exposure, while the volatility spikes up to 0.0219. The high volatility profile of PLTR is shown in the left-tail quantile of -0.5522, which emphasizes the susceptibility to severe losses. The total fragility of the portfolio is increased when GLD is reduced to 10%, which reduces the benefits of hedging.

Comparative Implications

These conclusions are supported by the 1-day and 252-day VaR graphical results, which show that VaR values become increasingly negative and indicate higher risk as equity allocation rises, particularly PLTR weight. The best diversification impact is achieved with equal weighting, which keeps exposure to both gold and stocks while limiting downside risk. Portfolios that are PLTR-heavy and equity-dominant may have greater upside potential, but they come at a disproportionately higher risk, which makes them less appropriate for investors who are risk averse. In general, portfolio construction demonstrates a distinct trade-off between risk and return:

- Equal Weighting → Balanced diversification, controlled risk.
- Equity-Dominant → Higher equity exposure, increased volatility.
- PLTR-Heavy → Speculative, high volatility, most vulnerable to drawdowns.

4.4 Regression and Predictive Insights

4.4.1 Regression Models Insights

Using AAPL, SPY, and GLD returns and their lagged values as explanatory variables, an OLS regression model was built to evaluate the predictive association between Palantir Technologies' (PLTR) returns and the returns of other assets. With an R-squared of 0.223, the model indicates that the selected factors account for around 22.3% of the variation in PLTR returns. Even while this suggests that outside market factors have a significant impact on PLTR's performance, idiosyncratic factors continue to account for the majority of variation, which further supports PLTR's high risk profile.

SPY returns exhibit a robust and statistically significant positive coefficient (1.9057, $p < 0.01$) among the explanatory variables, suggesting that PLTR is extremely susceptible to changes in the overall market. Its increased beta in relation to the market is highlighted by the fact that a 1% increase in SPY returns is linked to about a 1.9% increase in PLTR returns. Lagged GLD returns, on the other hand, are adversely significant (-0.2706, $p < 0.05$), suggesting that changes in the price of gold have an inverse and delayed impact on PLTR. This points to a possible short-term hedging link in which gold's historical performance may indicate a slowdown in PLTR momentum.

The lack of statistical significance for other variables, such AAPL returns and their lagged terms, suggests that Apple's performance has no direct predictive value for PLTR in this model. Similarly, even while SPY lagged returns are positive, they are not statistically significant, indicating that PLTR responds more to immediate than to delayed market changes.

With a lagged inverse effect, gold plays a secondary but significant role in PLTR, which is mostly driven by current market conditions, especially broad equities movements (SPY), according to the regression results. This result supports PLTR's classification as a high-beta stock, which makes it an aggressive investment in portfolios. Investors can anticipate disproportionate gains in bull markets as well as heightened losses in down markets.

4.4.2. Predictive Insights based on Signals

The regression model shows a moderate ability to track PLTR’s daily returns. The predicted series generally aligns with the direction of actual returns, capturing broad trends while underestimating extreme volatility. This limitation is consistent with the modest explanatory power ($R^2 \approx 0.28$), reflecting that a large portion of PLTR’s price dynamics are driven by firm-specific or non-linear factors not captured in the model.

Performance metrics reinforce this conclusion: the model achieves a Test RMSE of 0.0380, indicating relatively small average prediction errors, and a Directional Accuracy of 67.74%, meaning it correctly predicts the up/down direction of returns in two out of three cases. While not perfect, this provides valuable guidance for short-term positioning.

Importantly, the model projects a PLTR return of +0.0013 for tomorrow, indicating a modest upward trend. The signal shows that the model can provide helpful short-term forecasting insights in addition to more comprehensive risk metrics like VaR, but it should be interpreted cautiously because of volatility underestimate.

4.5 Practical Implications for Investors

The examination of PLTR's stock returns offers investors with different risk tolerances useful information. Given its directional predictability and potential daily gains as indicated by the model, high-risk investors who are ready to endure volatility in exchange for possibly higher returns should think about utilizing short-term trading strategies or devoting a larger portion of their portfolio to PLTR. In order to reduce potential losses and yet profit from sporadic increases in the stock, investors who are looking for a moderate trade-off between risk and return could take a hybrid strategy, mixing PLTR with more reliable assets.

Low-risk investors that prioritize capital preservation may utilize the model's results for cautious involvement, such as small-scale position sizing or short-term hedging, rather than aggressive trading, to minimize exposure to abrupt price movements of more than 5%, which are not inconsequential. All things considered, the model's predictive insights assist investors in making well-informed decisions based on their unique risk tolerance and coordinating their trading tactics with their financial objectives.

4.6 Limitations and Future Research

It is important to recognize a number of limitations even if this study offers valuable prognostic insights for PLTR stock. First, the model may not adequately account for the effects of unforeseen news, market events, or macroeconomic factors because it mainly uses past price data and technical indicators like moving averages and log returns. Second, the model's predictive potential is limited and shouldn't be the only factor used to make investment decisions, as indicated by the relatively low test R2 (0.285), which implies that a significant amount of price fluctuation is still unexplained. Third, the study only looks at one stock, which limits how broadly the results can be applied to other stocks or asset classes.

Predictive accuracy may be increased for future studies by extending the model to incorporate more assets, different data sources (such as sentiment analysis, trading volumes, and macroeconomic indicators), and sophisticated machine learning methods. Deeper insights for investors with differing risk appetites would also be obtained by testing the model in various market scenarios and adding risk-adjusted performance metrics. The model's suitability for short-term investment strategies may also be improved by investigating intraday data or high-frequency trading signals.

Chapter 5: Conclusion

This study aimed to evaluate the performance of Palantir Technologies (PLTR) and investigate how portfolio diversification with Apple (AAPL), the S&P 500 index (SPY), and Gold (GLD) can optimize returns while mitigating investment risks. Diversification successfully strikes a balance between exposure to volatility and possible returns, as shown by the examination of correlations, individual risk assessments, and portfolio building. In the area of computational finance, regression-based modeling demonstrated PLTR's potential as a tool for well-informed investment decision-making by offering predicted insights into its price movements.

According to the findings, investors with different risk tolerances can customize their approaches: low-risk investors can take conservative positions to safeguard capital, balanced investors can combine PLTR with other assets for moderated risk-return trade-offs, and high-risk investors can seek short-term gains from the asset. Although the study demonstrates practical applicability, its limitations—such as its moderate predictive power and reliance on historical data—indicate that interpretation should be done with caution. Predictive accuracy and portfolio optimization tactics can be further improved by future research that incorporates broader asset classes, sophisticated modeling methodologies, and alternate data sources. All things considered, this work advances knowledge of how regression-based models can guide portfolio diversification and investing strategies, providing helpful advice for investors attempting to strike a balance between risk and return in volatile financial markets.

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