Summary Analysis Report

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This report explores how Nvidia has performed relative to the broader market and technology sector over the past six years. It also explores the effectiveness of various technical indicators and predictive models in understanding and forecasting Nvidia's price behavior.

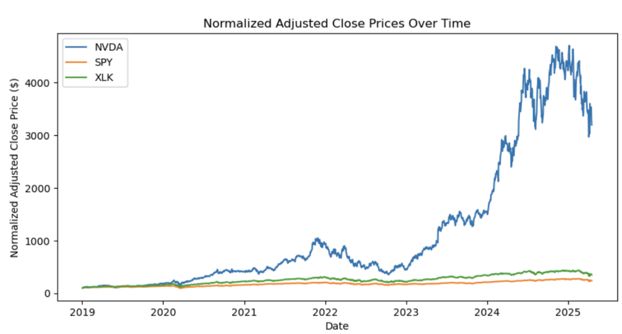
Dataset Description and Source

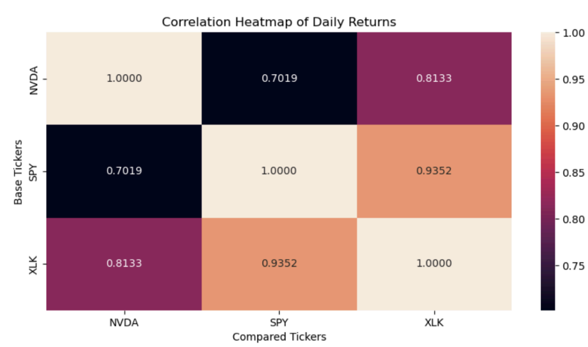
Daily historical stock data (Open, High, Low, Close, Volume) for Nvidia Corporation (NVDA) was retrieved from Yahoo Finance using the yfinance Python package. The dataset spans from January 1, 2019 to April 20, 2025, capturing both pre-pandemic conditions and Nvidia's recent AI-driven growth surge. For benchmarking and comparison, data for the S&P 500 (SPY) and Technology Select Sector ETF (XLK) were also collected from the same source.

Analysis Method Overview

Daily percent returns and log daily percent returns were calculated to observe profitability and standardize comparison of prices over time. This was particularly necessary as Nvidia showed significant growth over the selected period. Rolling mean and relative strength index were calculated over windows of 20 days to show. Rolling volatility was also calculated over a window of 20 days to show changes in stock riskiness.

For comparison of Nvidia stock prices to those of the broader market and the technology sector, stock adjusted close prices over the time period were plotted against each other. Afterwards stock prices were normalized to standardize returns over time and display true trends in growth. Correlation between daily percent returns of all three stocks were mapped to explore connections in growth.





Afterwards correlation between Nvidia technical indicators were explored to compare connections between them. These indicators included daily returns, log daily returns, rolling mean, relative strength index, and rolling volatility. Autocorrelation of stock prices, daily returns, and rolling volatility were also plotted to observe how past performance affected future indicators.

Market regime patterns were explored by calculating percent returns over time. Volatility patterns were also explored by comparing risk over time. To simulate future stock movement, geometric brownian motion was used. A principal component analysis was also run to identify key features affecting stock price data. Future stock modeling/forecasting was done with Logistic, LASSO, and ARIMA models. Volatility was predicted using a simple GARCH Model.

Reflection

Throughout the analysis period from 2019 to 2025, Nvidia's percent change in returns and log returns were relatively stable, fluctuating around 0% and generally remaining within a ±20% range. The simple moving average of its price showed remarkable growth, rising from under $10 to over $120, while the relative strength index hovered around a midpoint of 50, indicating balanced momentum over time. Rolling volatility typically remained below 4–5%, but there was a significant spike near 9% during early 2020, likely corresponding with COVID-19 market turbulence.

When comparing adjusted close prices with SPY (S&P 500) and XLK (Technology Sector ETF), all three tracked similar broad market trends. However, once normalized, Nvidia's performance clearly outpaced both indices, highlighting its accelerated growth. Correlation analysis showed strong relationships between the stocks, with coefficients above 70%, while correlations among Nvidia's internal technical indicators—such as daily returns, log returns, SMA, RSI, and volatility—were weak, implying these features were largely independent.

Autocorrelation plots revealed strong persistence in stock price levels, expected due to the cumulative nature of price data. In contrast, autocorrelation of daily returns was near zero, and autocorrelation of rolling volatility declined steadily with increasing lags, illustrating mean-reverting behavior. Bull and bear market segmentation showed Nvidia was predominantly in a bull phase, though it experienced bear periods during 2022–2023 and in recent months, possibly due to broader macroeconomic uncertainty. Volatility clustering further confirmed these transitions, with high-volatility periods overlapping those same timeframes.

A geometric Brownian motion simulation showed that under high volatility assumptions, some trajectories resulted in sharply rising prices due to compounding effects. Principal Component Analysis (PCA), used to reduce dimensionality and explain price variation, performed poorly—its predictions had a much higher mean squared error (MSE ≈ 72) than the baseline model without PCA (MSE ≈ 17), indicating Nvidia's price behavior could not be explained by a small number of components. Logistic regression, intended to classify future price direction based on lagged returns and volume, achieved accuracy only slightly better than random chance (~52%), while LASSO regression, which emphasizes feature selection, also failed to provide accurate price estimates (MSE ≈ 44).

In contrast, ARIMA was the most effective model for forecasting Nvidia's stock price. It achieved a relatively low root mean squared error (RMSE ≈ 4.16) and mean absolute error (MAE ≈ 3.03), while providing strong fit diagnostics (AIC ≈ 6574, BIC ≈ 6590). The GARCH model, used for volatility forecasting, successfully captured volatility clustering and indicated that periods of elevated risk often corresponded to either extreme gains or losses in return, reinforcing known stylized facts about financial markets.

In summary, Nvidia has significantly outperformed the broader market and technology sector over the past several years. Among all models tested, ARIMA proved most effective for forecasting future price trends, and GARCH was most reliable for modeling volatility. Meanwhile, PCA, LASSO, and logistic regression were less informative, emphasizing the limitations of simplified or feature-reduction approaches in capturing the complex dynamics of Nvidia's stock price behavior.