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# Data Analysis Report: US Stock Market & Commodity Data (2019-2024)

**AN EXPLORATORY DATA ANALYSIS REPORT**

*Submitted for the fulfillment*

*of*

*Data Science CA1: Mini Project*

*Submitted by*

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# ABSTRACT

This report presents a comprehensive Exploratory Data Analysis (EDA) of the "2019-2024 US Stock Market Data" dataset, which covers a dynamic five-year period of market activity. The primary objective was to clean, process, analyze, and visualize this complex time-series dataset to uncover significant trends, correlations, and volatility patterns across various asset classes, including stocks, cryptocurrencies, metals, and energy commodities. The methodology involved a rigorous data cleaning phase to handle missing values and correct data types, followed by an extensive visual analysis using 16 distinct plots. Key findings reveal the significant outperformance and high volatility of the technology and cryptocurrency sectors, the strong positive correlation within asset classes (e.g., tech stocks, precious metals), and the cyclical nature of commodities like Crude Oil. This EDA successfully quantifies the multifaceted dynamics of the market and establishes a solid foundation for the subsequent project phase: the development of time-series forecasting models to predict future asset prices.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Project Objectives

This report presents a detailed Exploratory Data Analysis (EDA) on the "2019-2024 US Stock Market Data" dataset. The primary objective of this analysis is to meticulously clean, process, and visualize the data to uncover significant patterns, trends, correlations, and volatility insights. The analysis aims to understand the complex market dynamics across a diversified portfolio of assets—including major stock indices, technology giants, cryptocurrencies, precious metals, and energy commodities—over a five-year period marked by significant economic events. This foundational analysis is critical for building robust machine learning models for financial forecasting in the subsequent phase of the project.

## 1.2 About the Dataset

The dataset is a comprehensive time-series collection encapsulating a detailed examination of market dynamics from early 2019 to early 2024. It covers the fluctuation of prices and trading volumes across various sectors, making it a valuable resource for analyzing trends and patterns in global markets.

**Source:** 2019-2024 US Stock Market Data

## 1.3 Dataset Specifications

The raw dataset, as loaded from the .csv file, contained **1243 rows and 43 columns**. After the data cleaning and preprocessing phase, the final dataset used for this analysis consists of **1243 rows and 43 columns**, with missing values handled and data types corrected. Figure.1 shows the Stock Market Dataset.

The meaning of each column is as follows:

- **Date**: The date of the recorded data.
- **Price Columns (e.g., Apple_Price)**: The closing price of the asset in USD on that day.
- **Volume Columns (e.g., Apple_Vol_)**: The number of shares or units traded on that day.

| A | B | C | D | E | F | G | H | I | J | K | L | M | N | O |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Date | Natural_G | Natural_G | Crude_oil | Crude_oil | Copper_P | Copper_V | Bitcoin_P | Bitcoin_V | Platinum_ | Platinum_ | Ethereum | Ethereum | S&P_5 |
| 0 | 2/2/2024 | 2.079 | | 72.28 | | 3.8215 | | 43,194.70 | 42650 | 901.6 | | 2,309.28 | 246890 | 4,958 |
| 1 | 1/2/2024 | 2.05 | 161340 | 73.82 | 577940 | 3.8535 | | 43,081.40 | 47690 | 922.3 | | 2,304.28 | 323610 | 4,906 |
| 2 | 31-01-2024 | 2.1 | 142860 | 75.85 | 344490 | 3.906 | | 42,580.50 | 56480 | 932.6 | | 2,283.14 | 408790 | 4,848 |
| 3 | 30-01-2024 | 2.077 | 139750 | 77.82 | 347240 | 3.911 | | 42,946.20 | 55130 | 931.7 | | 2,343.11 | 387120 | 4,924 |
| 4 | 29-01-2024 | 2.49 | 3590 | 76.78 | 331930 | 3.879 | | 43,299.80 | 45230 | 938.3 | | 2,317.79 | 318840 | 4,927 |
| 5 | 26-01-2024 | 2.712 | 73020 | 78.01 | 365460 | 3.852 | | 41,811.30 | 69470 | 921.3 | | 2,267.55 | 377790 | 4,890 |
| 6 | 25-01-2024 | 2.571 | 44980 | 77.36 | 320180 | 3.869 | | 39,935.70 | 46300 | 894.5 | | 2,217.71 | 344110 | 4,894 |
| 7 | 24-01-2024 | 2.641 | 65500 | 75.09 | 323730 | 3.886 | | 40,086.00 | 58640 | 914.9 | | 2,234.64 | 373250 | 4,868 |
| 8 | 23-01-2024 | 2.45 | 69160 | 74.37 | 306060 | 3.7935 | | 39,888.80 | 82670 | 905.5 | | 2,243.74 | 750520 | 4,864 |
| 9 | 22-01-2024 | 2.419 | 121580 | 75.19 | 28910 | 3.7635 | | 39,556.40 | 85100 | 903 | | 2,313.64 | 560840 | 4,850 |
| 10 | 19-01-2024 | 2.519 | 138430 | 73.41 | 78230 | 3.7865 | | 41,648.00 | 72640 | 907 | | 2,491.81 | 443420 | 4,839 |
| 11 | 18-01-2024 | 2.697 | 151820 | 74.08 | 86650 | 3.745 | | 41,292.70 | 70350 | 912 | | 2,469.77 | 467220 | 4,780 |
| 12 | 17-01-2024 | 2.87 | 150330 | 72.56 | 315680 | 3.733 | | 42,768.70 | 50440 | 889.6 | | 2,531.26 | 380900 | 4,739 |
| 13 | 16-01-2024 | 2.9 | 228160 | 72.4 | 430440 | 3.7665 | | 43,145.50 | 63930 | 904.4 | | 2,588.64 | 395070 | 4,762 |
| 14 | ######### | 3.313 | 265880 | 72.68 | 403640 | 3.7405 | | 42,835.90 | 136920 | 921.1 | | 2,523.98 | 931960 | 4,783 |
| 15 | ######### | 3.097 | 235030 | 72.02 | 373650 | 3.7765 | | 46,348.20 | 131040 | 919.6 | | 2,618.08 | 889360 | 4,780 |
| 16 | ######### | 3.039 | 258010 | 71.37 | 352770 | 3.781 | | 46,629.30 | 131480 | 929.6 | | 2,581.79 | 1120000 | 4,783 |
| 17 | 9/1/2024 | 3.19 | 351780 | 72.24 | 363450 | 3.7585 | | 46,129.00 | 100090 | 943.5 | | 2,344.67 | 588190 | 4,756 |
| 18 | 8/1/2024 | 2.98 | 237670 | 70.77 | 392250 | 3.81 | | 46,962.20 | 103090 | 959.4 | | 2,330.98 | 565230 | 4,763 |
| 19 | 5/1/2024 | 2.893 | 187500 | 73.81 | 325530 | 3.806 | | 44,156.90 | 68070 | 971.8 | | 2,268.12 | 426010 | 4,697 |
| 20 | 4/1/2024 | 2.821 | 206310 | 72.19 | 344470 | 3.844 | | 44,157.00 | 68050 | 966.3 | | 2,267.27 | 467010 | 4,688 |
| 21 | 3/1/2024 | 2.668 | 166470 | 72.7 | 334860 | 3.8615 | | 42,836.10 | 117650 | 987.1 | | 2,209.49 | 852010 | 4,704 |
| 22 | 2/1/2024 | 2.568 | 132450 | 70.38 | 330990 | 3.8805 | | 44,943.70 | 97840 | 998.3 | | 2,355.27 | 491560 | 4,742 |
| 23 | 29-12-2023 | 2.514 | 89600 | 71.65 | 214490 | 3.8915 | | 42,072.40 | 60980 | 1,009.20 | 18530 | 2,299.24 | 475370 | 4,769 |
| 24 | 28-12-2023 | 2.557 | 116060 | 71.77 | 262750 | 3.9245 | | 42,581.10 | 49840 | 1,023.20 | | 2,344.47 | 626910 | 4,783 |
| 25 | 27-12-2023 | 2.619 | 3930 | 74.11 | 253320 | 3.956 | | 43,446.50 | 50100 | 1,013.50 | | 2,378.63 | 577270 | 4,781 |
| 26 | 26-12-2023 | 2.55 | 50760 | 75.57 | 208720 | 3.902 | 38000 | 42,513.30 | 56030 | 995.6 | | 2,230.74 | 429500 | 4,774 |
| 27 | 22-12-2023 | 2.61 | 42840 | 73.56 | 222600 | 3.905 | 54140 | 43,968.90 | 44500 | 981.8 | | 2,324.23 | 620730 | 4,754 |
| 28 | 21-12-2023 | 2.572 | 84550 | 73.89 | 251980 | 3.9175 | 70080 | 43,865.90 | 48960 | 970.3 | 26550 | 2,239.62 | 471460 | 4,746 |
| 29 | 20-12-2023 | 2.447 | 125260 | 74.22 | 273360 | 3.906 | 66320 | 43,662.80 | 70190 | 974 | 30010 | 2,202.19 | 440350 | 4,701 |
| 30 | 19-12-2023 | 2.492 | 170440 | 73.44 | 25690 | 3.898 | 84950 | 42,259.30 | 55290 | 965.8 | 25860 | 2,177.44 | 400940 | 4,768 |
| 31 | 18-12-2023 | 2.503 | 154300 | 72.47 | 73940 | 3.852 | 54990 | 42,659.70 | 61580 | 954.3 | 26230 | 2,218.80 | 388260 | 4,740 |
| 32 | 15-12-2023 | 2.491 | 189240 | 71.43 | 95510 | 3.8905 | 73670 | 41,929.00 | 45280 | 952.6 | 38070 | 2,220.41 | 349630 | 4,719 |
| 33 | 14-12-2023 | 2.392 | 159490 | 71.58 | 275690 | 3.8925 | 107540 | 43,025.90 | 59150 | 967.9 | 42830 | 2,315.64 | 461600 | 4,719 |
| 34 | 13-12-2023 | 2.335 | 255190 | 69.47 | 307000 | 3.7875 | 62860 | 42,884.50 | 63110 | 922.1 | 32250 | 2,260.18 | 436640 | 4,707 |
| 35 | ######### | 2.311 | 223460 | 68.61 | 324530 | 3.7875 | 69520 | 41,487.00 | 57040 | 931 | 30170 | 2,203.49 | 377050 | 4,643 |

Stock Market Dataset

**Figure 1: Shows the dataset used for this Exploratory Data Analysis Project**

# CHAPTER 2

# DATA LOADING AND INSPECTION

## 2.1 Initial Data Loading and Inspection

The raw data was loaded from a .csv file. An initial inspection using .info() and .head() revealed several key issues requiring preprocessing:

- An extraneous Unnamed: 0 column was present.
- The Date column was stored as an object (string) instead of a datetime format.
- Several price and volume columns were also stored as objects due to the presence of commas as thousand separators.
- A number of volume columns contained missing (NaN) values.

```
--- First 5 Rows of the Raw Dataset ---
   Unnamed: 0        Date  Natural_Gas_Price  Natural_Gas_Vol.  \
0           0  02-02-2024              2.079               NaN
1           1  01-02-2024              2.050          161340.0
2           2  31-01-2024              2.100          142860.0
3           3  30-01-2024              2.077          139750.0
4           4  29-01-2024              2.490            3590.0

   Crude_oil_Price  Crude_oil_Vol.  Copper_Price  Copper_Vol. Bitcoin_Price  \
0            72.28             NaN        3.8215          NaN     43,194.70
1            73.82        577940.0        3.8535          NaN     43,081.40
2            75.85        344490.0        3.9060          NaN     42,580.50
3            77.82        347240.0        3.9110          NaN     42,946.20
4            76.78        331930.0        3.8790          NaN     43,299.80

   Bitcoin_Vol.  ... Berkshire_Price  Berkshire_Vol. Netflix_Price  \
0       42650.0  ...        5,89,498         10580.0        564.64
1       47690.0  ...        5,81,600          9780.0        567.51
2       56480.0  ...        5,78,020          9720.0        564.11
3       55130.0  ...        5,84,680          9750.0        562.85
4       45230.0  ...        5,78,800         13850.0        575.79

   Netflix_Vol. Amazon_Price  Amazon_Vol.  Meta_Price   Meta_Vol.  Gold_Price  \
0     4030000.0       171.81  117220000.0      474.99  84710000.0    2,053.70
1     3150000.0       159.28   66360000.0      394.78  25140000.0    2,071.10
2     4830000.0       155.20   49690000.0      390.14  20010000.0    2,067.40
3     6120000.0       159.00   42290000.0      400.06  18610000.0    2,050.90
4     6880000.0       161.26   42840000.0      401.02  17790000.0    2,034.90

   Gold_Vol.
0        NaN
1   260920.0
2   238370.0
3   214590.0
4     1780.0
```

**Figure 2: First 5 Rows of the Dataset**

```
--- Raw Dataset Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1243 entries, 0 to 1242
Data columns (total 39 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Unnamed: 0         1243 non-null   int64
 1   Date               1243 non-null   object
 2   Natural_Gas_Price  1243 non-null   float64
 3   Natural_Gas_Vol.   1239 non-null   float64
 4   Crude_oil_Price    1243 non-null   float64
 5   Crude_oil_Vol.     1220 non-null   float64
 6   Copper_Price       1243 non-null   float64
 7   Copper_Vol.        1206 non-null   float64
 8   Bitcoin_Price      1243 non-null   object
 9   Bitcoin_Vol.       1243 non-null   float64
 10  Platinum_Price     1243 non-null   object
 11  Platinum_Vol.      636 non-null    float64
 12  Ethereum_Price     1243 non-null   object
 13  Ethereum_Vol.      1243 non-null   float64
 14  S&P_500_Price      1243 non-null   object
 15  Nasdaq_100_Price   1243 non-null   object
 16  Nasdaq_100_Vol.    1242 non-null   float64
 17  Apple_Price        1243 non-null   float64
 18  Apple_Vol.         1243 non-null   float64
 19  Tesla_Price        1243 non-null   float64
 20  Tesla_Vol.         1243 non-null   float64
 21  Microsoft_Price    1243 non-null   float64
 22  Microsoft_Vol.     1243 non-null   float64
 23  Silver_Price       1243 non-null   float64
 24  Silver_Vol.        1196 non-null   float64
 25  Google_Price       1243 non-null   float64
 26  Google_Vol.        1243 non-null   float64
 27  Nvidia_Price       1243 non-null   float64
 28  Nvidia_Vol.        1243 non-null   float64
 29  Berkshire_Price    1243 non-null   object
 30  Berkshire_Vol.     1243 non-null   float64
 31  Netflix_Price      1243 non-null   float64
 32  Netflix_Vol.       1243 non-null   float64
 33  Amazon_Price       1243 non-null   float64
 34  Amazon_Vol.        1243 non-null   float64
 35  Meta_Price         1243 non-null   float64
 36  Meta_Vol.          1243 non-null   float64
 37  Gold_Price         1243 non-null   object
 38  Gold_Vol.          1241 non-null   float64
dtypes: float64(30), int64(1), object(8)
memory usage: 378.9+ KB
```

**Figure 3: Raw Dataset Info**

## 2.2 Data Transformation Steps

To ensure the integrity and reliability of the analysis, a series of data transformation (ETL) steps were performed:

- **Dropping Unnecessary Columns**: The redundant Unnamed: 0 index column was removed.
- **Standardization of Column Names**: All column names were converted to lowercase, and special characters like . and spaces were replaced with underscores to improve accessibility.

- **Data Type Correction**: All price and volume columns stored as objects were cleaned by removing commas and then converted to the appropriate numeric (float) data type. The Date column was converted to a proper datetime format to enable time-series analysis.
- **Handling of Missing Values**: Missing values, found primarily in the volume columns, were imputed using the mean value of their respective columns. This strategy was chosen to preserve the integrity of the time-series data without dropping valuable rows.

```
--- Missing Values in Raw Dataset ---
Unnamed: 0              0
Date                    0
Natural_Gas_Price       0
Natural_Gas_Vol.        4
Crude_oil_Price         0
Crude_oil_Vol.         23
Copper_Price            0
Copper_Vol.            37
Bitcoin_Price           0
Bitcoin_Vol.            0
Platinum_Price          0
Platinum_Vol.         607
Ethereum_Price          0
Ethereum_Vol.           0
S&P_500_Price           0
Nasdaq_100_Price        0
Nasdaq_100_Vol.         1
Apple_Price             0
Apple_Vol.              0
Tesla_Price             0
Tesla_Vol.              0
Microsoft_Price         0
Microsoft_Vol.          0
Silver_Price            0
Silver_Vol.            47
Google_Price            0
Google_Vol.             0
Nvidia_Price            0
Nvidia_Vol.             0
Berkshire_Price         0
Berkshire_Vol.          0
Netflix_Price           0
Netflix_Vol.            0
Amazon_Price            0
Amazon_Vol.             0
Meta_Price              0
Meta_Vol.               0
Gold_Price              0
Gold_Vol.               2
dtype: int64
```

**Figure 4: Missing Values in Raw Dataset**

# CHAPTER 3
# DATA CLEANING AND PREPROCESSING

To ensure the quality and reliability of the analysis, the following data cleaning and preprocessing steps were performed on a copy of the raw dataset:

## 3.1 Dropping Unnecessary Columns

The initial dataset contained a redundant index column named Unnamed: 0, which was an artifact from a previous data export. This column provides no analytical value and was therefore dropped.

```
Dropped 'Unnamed: 0' column.
```

**Figure 5: Dropping Unnecessary Columns**

## 3.2 Standardization of Column Names

The original column names contained inconsistencies such as capital letters and special characters (e.g., Natural_Gas_Vol.). To facilitate easier data access and prevent errors, all column names were programmatically standardized by converting them to lowercase and replacing special characters with underscores.

```
Column names have been standardized.
```

**Figure 6: Standardization of Column Names**

## 3.3 Correction of Data Types

Several critical columns were loaded with incorrect data types. Price and volume columns containing commas were read as 'object' (string) type. These were cleaned by removing the commas and converting them to a numeric (float) type. Most importantly, the Date column was converted from a string to a proper datetime format, which is essential for any time-series analysis.

```
Converted object-type numeric columns to float.

Converted 'date' column to datetime format.
```

**Figure 7: Correction of Data Types**

## 3.4 Handling of Missing Values

The initial inspection revealed missing values primarily in the volume columns. To avoid losing valuable data rows, these missing values were imputed using the mean value of their respective columns. This is a common and effective strategy for handling missing data in a time series.

```
Filled missing values in volume columns with their respective mean.

--- Data Cleaning and Preprocessing Complete ---

--- First 5 Rows of the Cleaned Dataset ---
        date  natural_gas_price  natural_gas_vol_  crude_oil_price  \
0 2024-02-02              2.079     131624.116223            72.28
1 2024-02-01              2.050     161340.000000            73.82
2 2024-01-31              2.100     142860.000000            75.85
3 2024-01-30              2.077     139750.000000            77.82
4 2024-01-29              2.490       3590.000000            76.78

   crude_oil_vol_  copper_price   copper_vol_  bitcoin_price  bitcoin_vol_  \
0   398903.778689        3.8215  35406.616915        43194.7       42650.0
1   577940.000000        3.8535  35406.616915        43081.4       47690.0
2   344490.000000        3.9060  35406.616915        42580.5       56480.0
3   347240.000000        3.9110  35406.616915        42946.2       55130.0
4   331930.000000        3.8790  35406.616915        43299.8       45230.0

   platinum_price  ...  berkshire_price  berkshire_vol_  netflix_price  \
0           901.6  ...         589498.0         10580.0         564.64
1           922.3  ...         581600.0          9780.0         567.51
2           932.6  ...         578020.0          9720.0         564.11
3           931.7  ...         584680.0          9750.0         562.85
4           938.3  ...         578800.0         13850.0         575.79

   netflix_vol_  amazon_price  amazon_vol_  meta_price   meta_vol_  \
0     4030000.0        171.81  117220000.0      474.99  84710000.0
1     3150000.0        159.28   66360000.0      394.78  25140000.0
2     4830000.0        155.20   49690000.0      390.14  20010000.0
3     6120000.0        159.00   42290000.0      400.06  18610000.0
4     6880000.0        161.26   42840000.0      401.02  17790000.0

   gold_price      gold_vol_
0      2053.7  211127.671233
1      2071.1  260920.000000
2      2067.4  238370.000000
3      2050.9  214590.000000
4      2034.9    1780.000000
```

**Figure 8: Handling of Missing Values and printing cleaned Dataset**

# CHAPTER 4

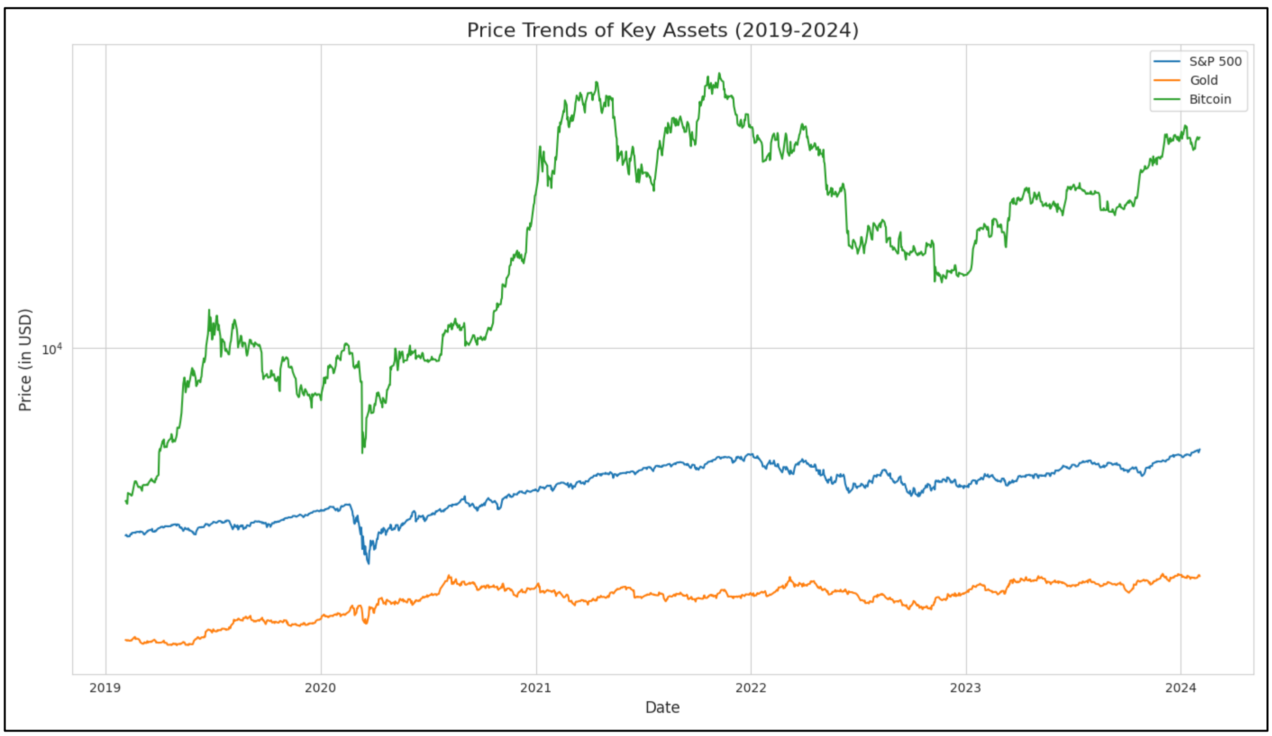
# EXPLORATORY DATA ANALYSIS (EDA) & VISUALIZATIONS

After cleaning the data, a comprehensive visual analysis was conducted to identify market trends and draw meaningful conclusions.

## 4.1 Overall Market and Asset Class Trends

**Figure 9: Price Trends of Key Assets (2019-2024)**

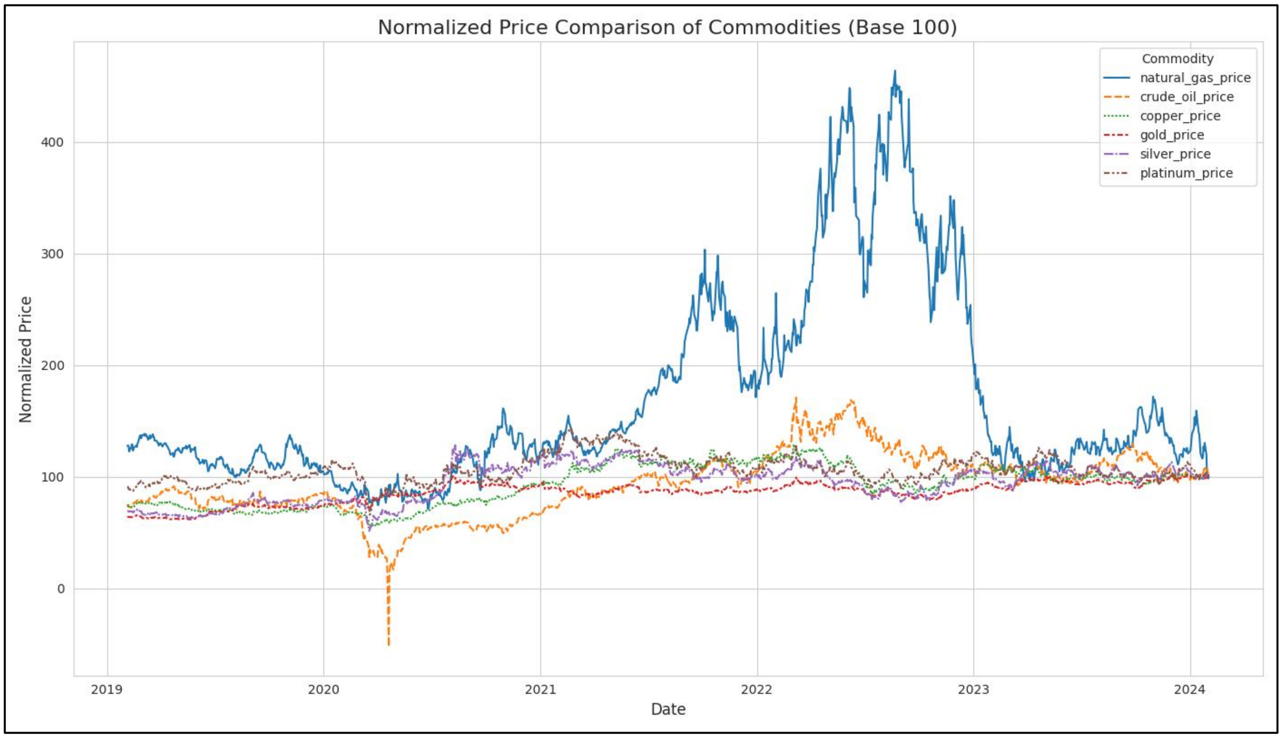
Purpose: Line chart showing the price trends of three major asset classes: S&P 500 (stocks), Gold (metal), and Bitcoin (cryptocurrency).




Observation: This plot provides a high-level comparison of performance across different asset classes. Bitcoin exhibits the highest volatility and exponential growth, particularly during its 2021 bull run. The S&P 500 shows steady, consistent upward growth, representing the broader market's strength. Gold remains relatively stable, reinforcing its role as a traditional safe-haven asset during periods of economic uncertainty.

**Figure 10: Normalized Price Comparison of Commodities**

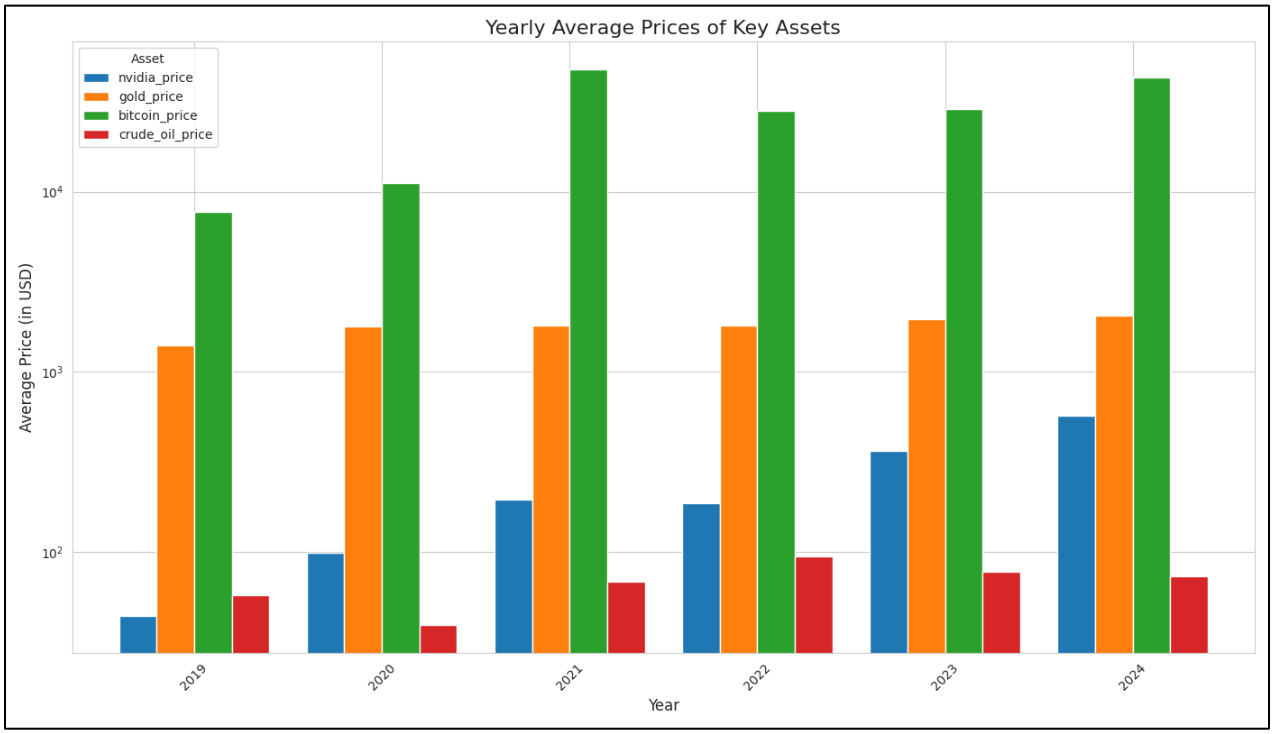
Purpose: Line chart showing the normalized price trends for commodities (Natural Gas, Crude Oil, Copper, Gold, Silver, Platinum).




Observation: Normalizing prices to a common starting point allow for a direct comparison of relative performance. This chart reveals that Copper had a very strong performance over the period, significantly outgaining other precious metals like Gold and Platinum. Natural Gas displays extreme volatility with massive price spikes, distinguishing its risk profile from the other commodities.

**Figure 11: Yearly Average Prices of Key Assets**

Purpose: Bar chart showing the average price for several key assets for each year from 2019 to 2024.

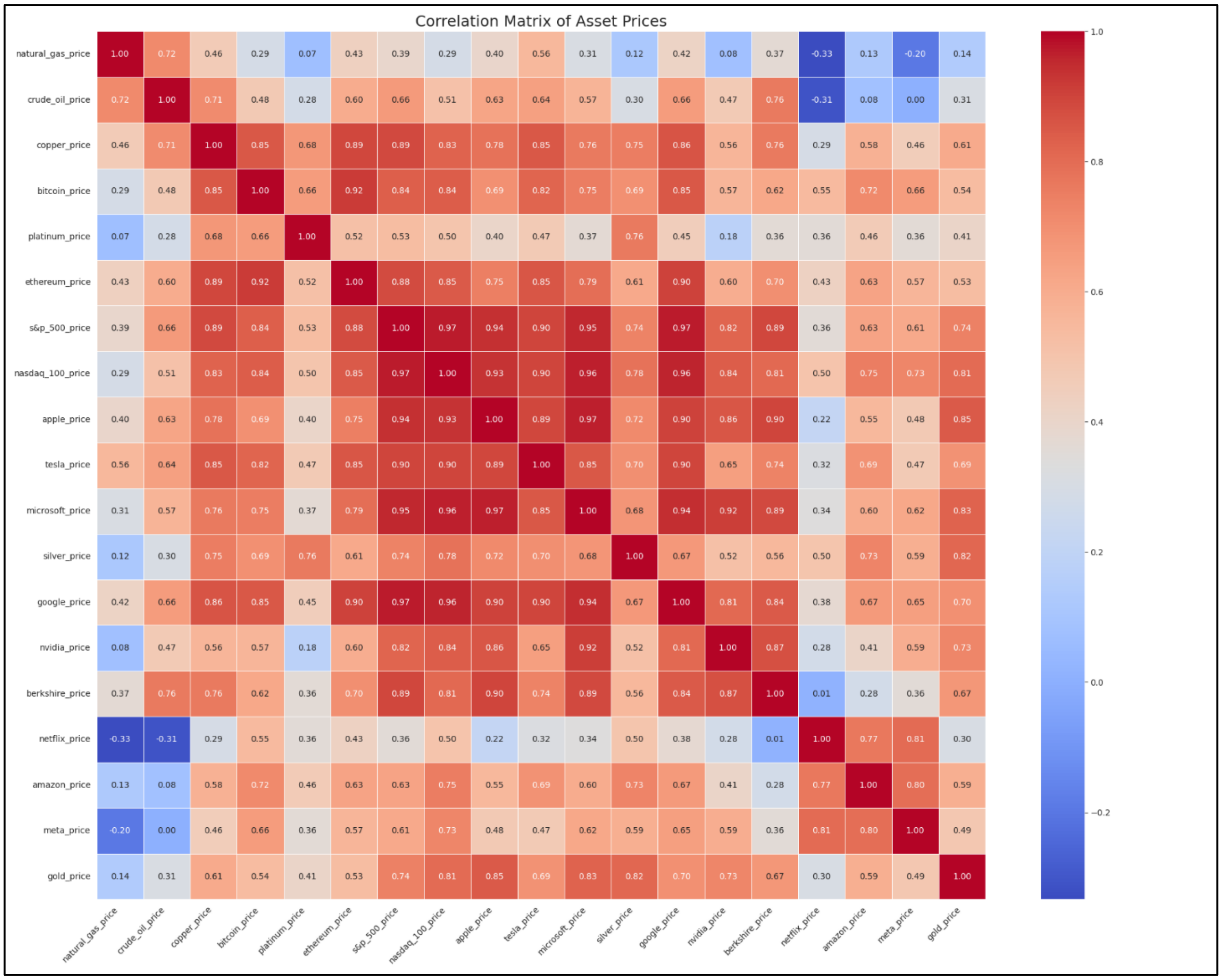



Observation: This chart provides a clear year-over-year comparison of average prices. It effectively highlights the massive growth in technology-related assets like Nvidia and cryptocurrencies like Bitcoin, especially from 2020 onwards. In contrast, more stable assets like Gold and cyclical commodities like Crude Oil show much less dramatic year-over-year changes.

## 4.2 Correlation and Relational Analysis

**Figure 12: Correlation Matrix of Asset Prices**

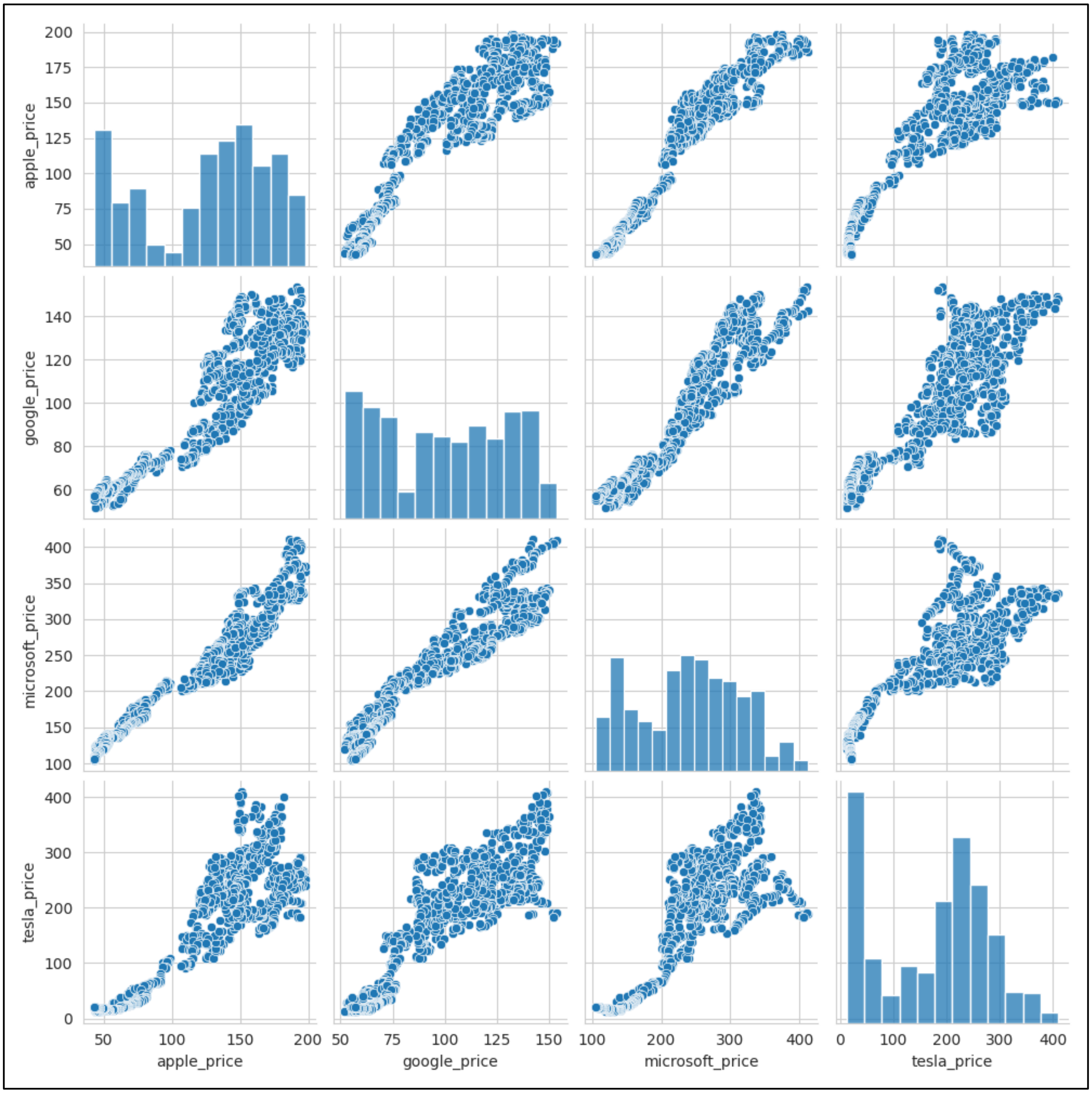
Purpose: Heatmap showing the Pearson correlation coefficients between the prices of all assets in the dataset.




Observation: The heatmap reveals strong positive correlations within asset classes. Tech stocks (Apple, Microsoft, Google, Nvidia) are highly correlated with each other and the Nasdaq 100 index (coefficients > 0.9). Precious metals (Gold, Silver) and cryptocurrencies (Bitcoin, Ethereum) also show strong positive correlations within their groups. This indicates that assets within the same sector tend to move in the same direction.

**Figure 13: Pair Plot of Selected Tech Stock Prices**

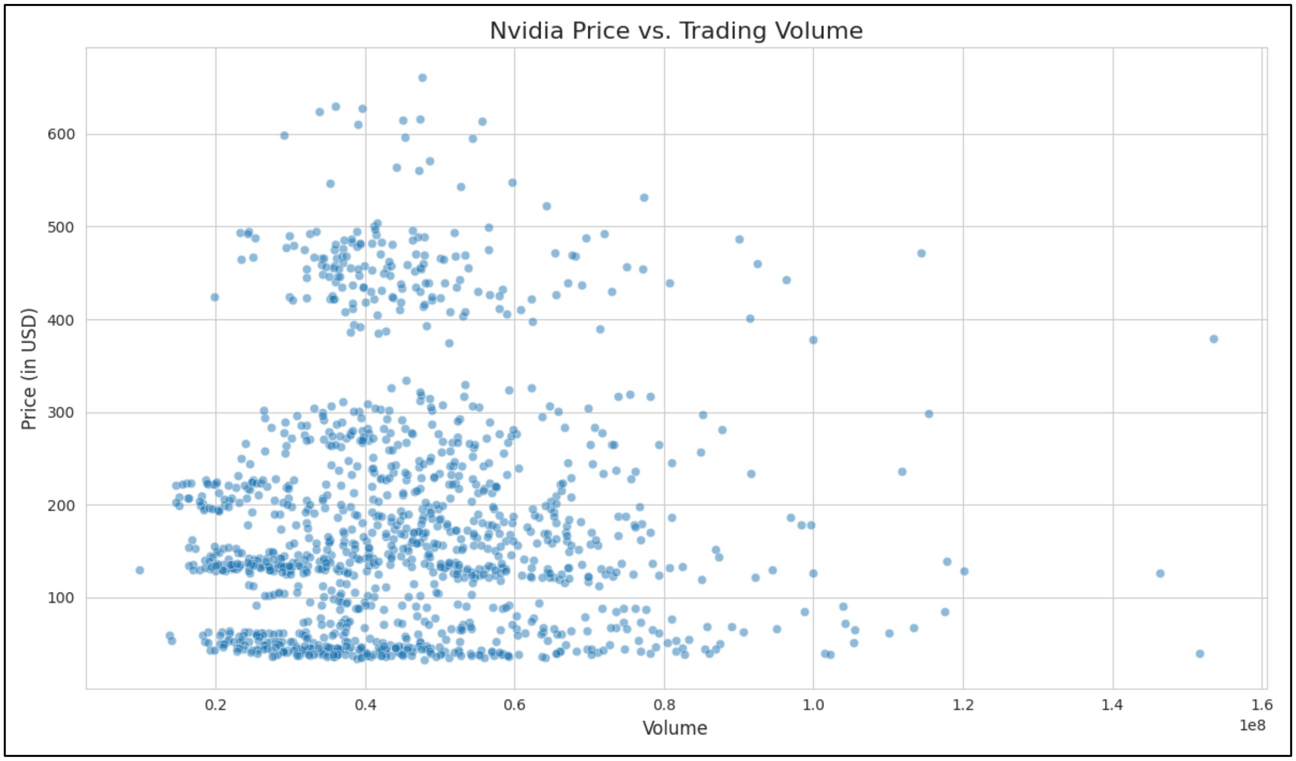
Purpose: A grid of scatter plots showing the pairwise relationships between the prices of major tech stocks (Apple, Google, Microsoft, Tesla).




Observation: The pair plot confirms the strong, positive linear relationships between Apple, Google, and Microsoft, as seen in the heatmap. Tesla's relationship with the others is also positive but appears slightly less linear, suggesting its price movements, while correlated, are driven by more unique factors.

**Figure 14: Nvidia Price vs. Trading Volume**

Purpose: Scatter plot showing the relationship between Nvidia's daily stock price and its trading volume.

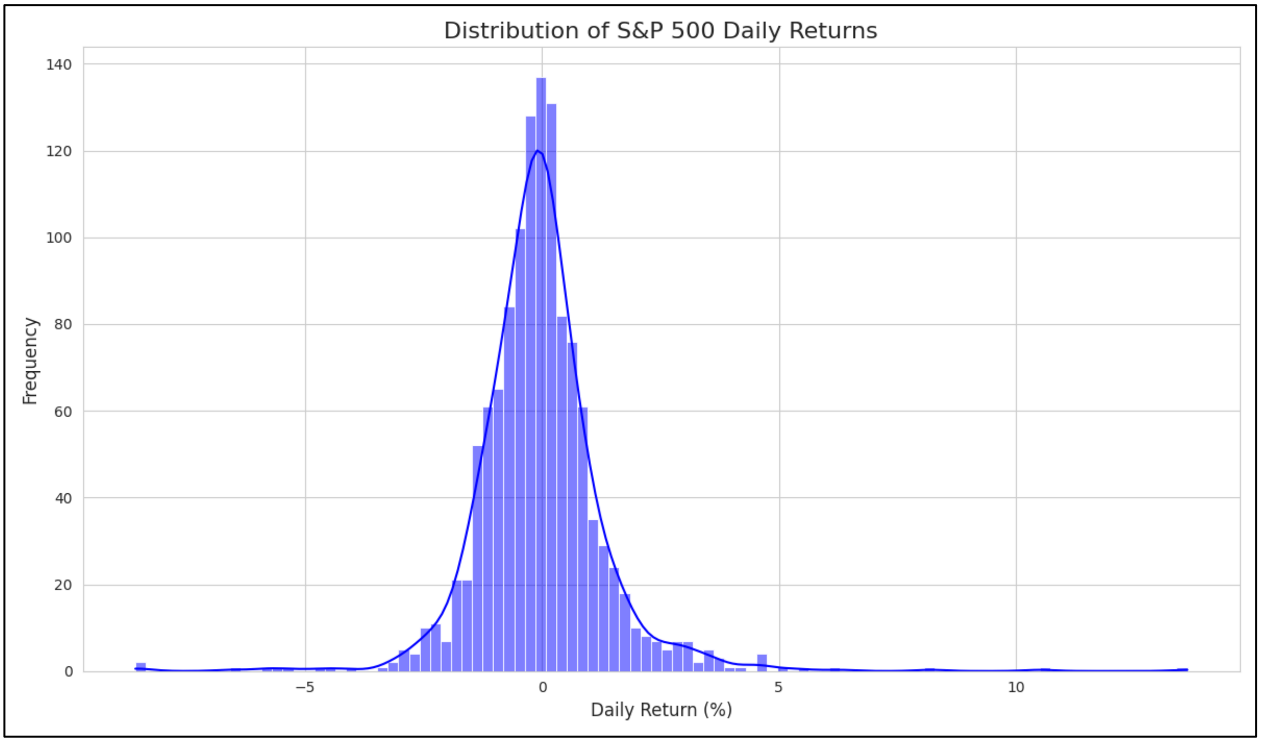



Observation: This scatter plot shows that the highest volume days for Nvidia tend to occur during periods of significant price appreciation. The dense cluster at lower prices and volumes represents periods of normal market activity, while the scattered points at higher prices indicate that major upward price movements are accompanied by a surge in investor interest and trading activity.

## 4.3 Volatility and Risk Analysis

**Figure 15: Distribution of S&P 500 Daily Returns**

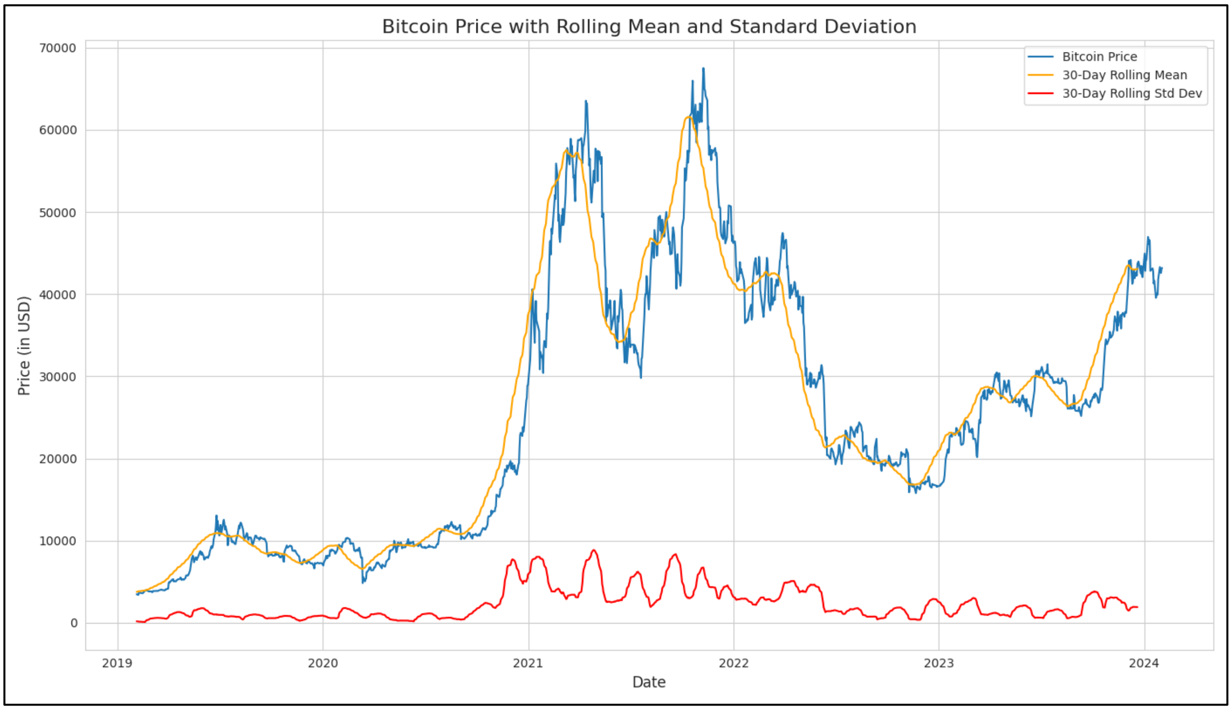
Purpose: Histogram showing the frequency distribution of daily percentage returns for the S&P 500 index.




Observation: The distribution of daily returns is centered around zero and is approximately normal but with 'fat tails.' This indicates that extreme positive or negative returns (high volatility events) occur more frequently than a perfect normal distribution would predict, a key concept in financial risk assessment.

**Figure 16: Bitcoin Price with Rolling Mean and Standard Deviation**

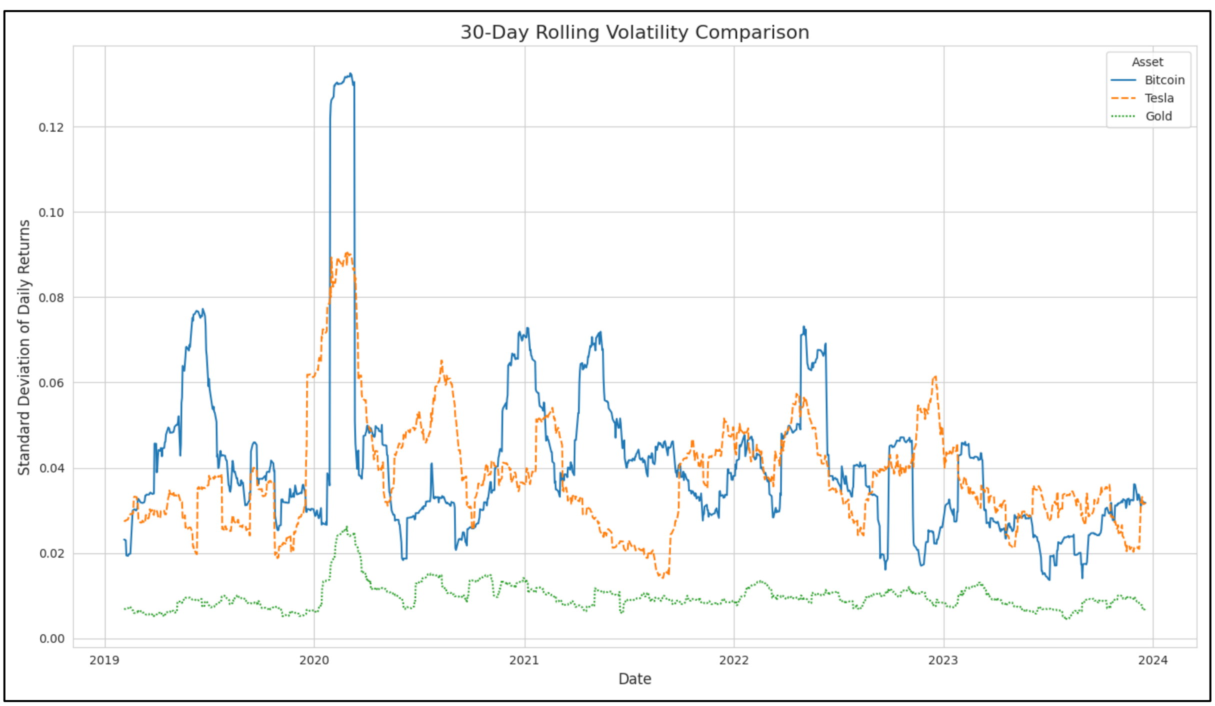
Purpose: Line chart showing the Bitcoin price, its 30-day rolling mean (moving average), and its 30-day rolling standard deviation (volatility).




Observation: The rolling standard deviation (bottom red line) is a direct measure of volatility. The plot clearly shows that periods of high volatility in Bitcoin coincide with its most dramatic price movements, both upward and downward, particularly during the 2021 market cycle.

**Figure 17: 30-Day Rolling Volatility Comparison**

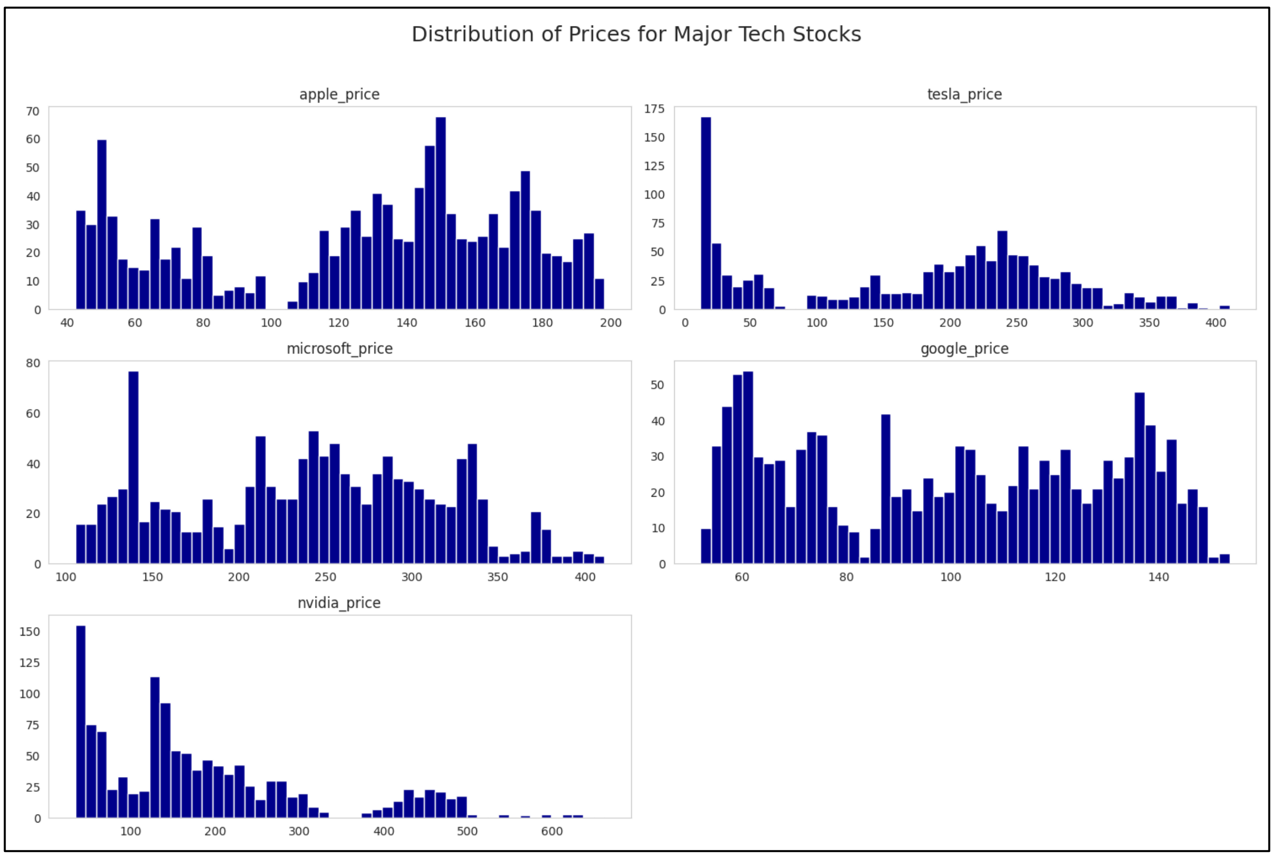
Purpose: Line chart showing the 30-day rolling standard deviation (volatility) for Bitcoin, Tesla, and Gold.



Observation: This plot directly compares the risk (volatility) of three different asset types. Bitcoin clearly has the highest volatility. Tesla, known as a volatile stock, is second. Gold, the traditional safe-haven asset, has extremely low volatility in comparison, reinforcing its status as a stable store of value.

**Figure 18: Distribution of Prices for Major Tech Stocks**

Purpose: A set of histograms (one for each tech stock) showing the distribution of their prices over the 5-year period.

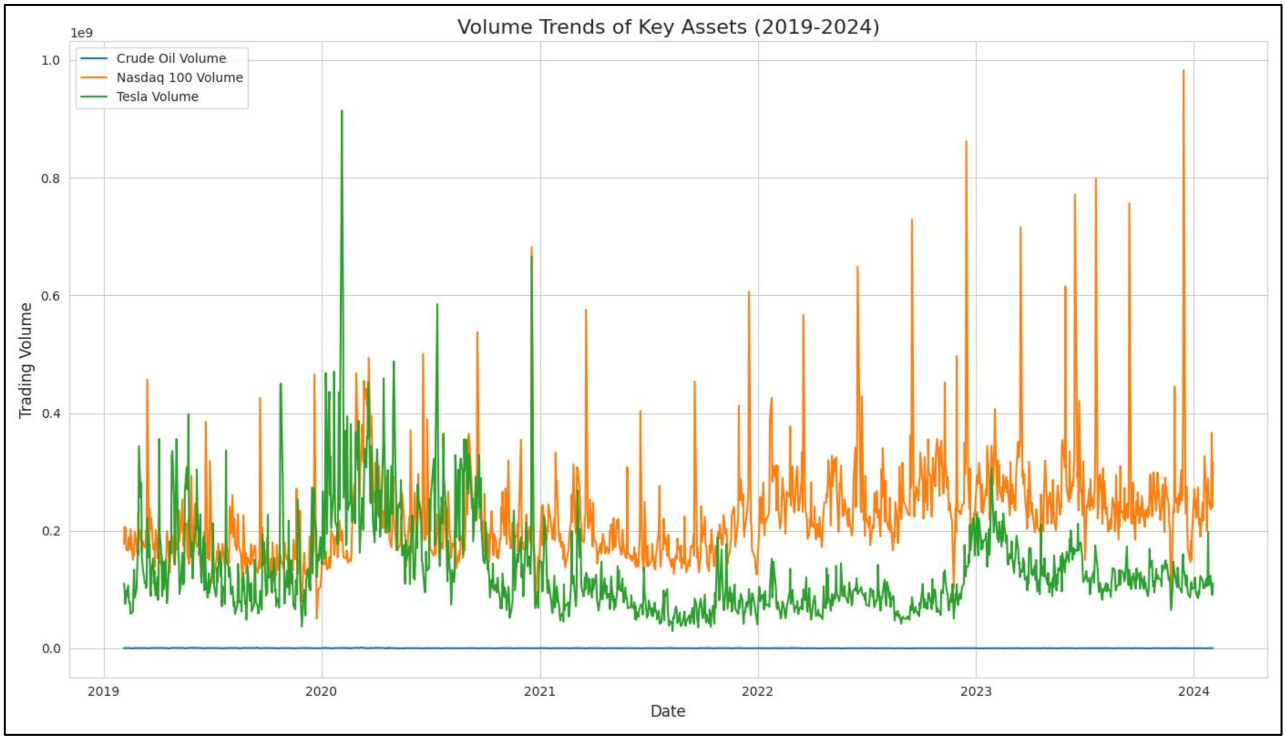



Observation: For stocks with strong and consistent growth like Microsoft and Nvidia, the price distribution is skewed to the right, with a long tail of higher prices achieved over time. This visualization helps in understanding the character of each stock's growth trajectory.

## 4.4 Sector and Seasonal Analysis

**Figure 19: Volume Trends of Key Assets**

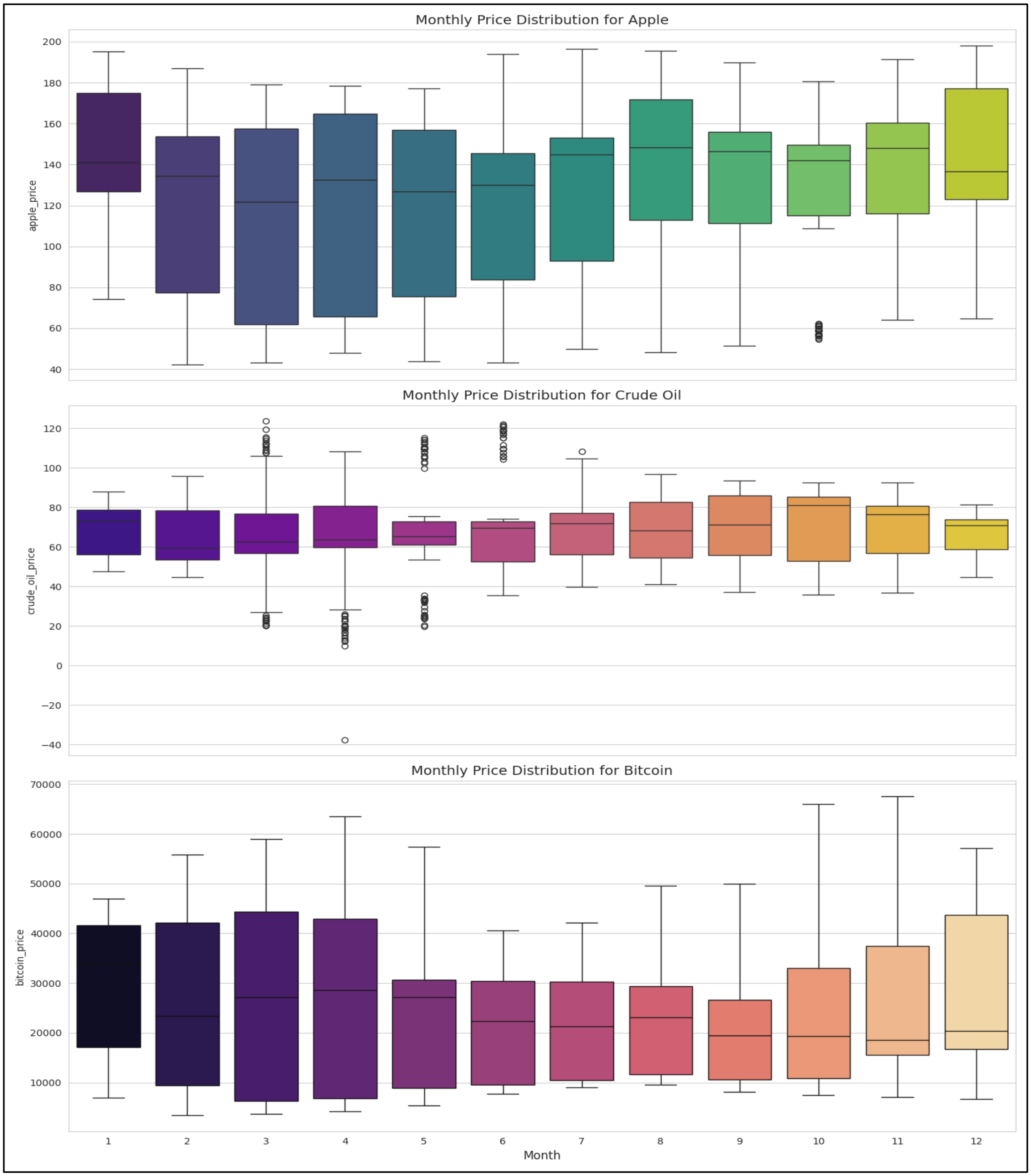
Purpose: Line chart showing the trading volume for Crude Oil, Nasdaq 100, and Tesla.




Observation: Tesla's trading volume shows significant spikes, often corresponding to periods of high price volatility or major company news. The Nasdaq 100's volume is generally higher and more consistent, reflecting broad market activity. This highlights how single-stock news can create volume patterns distinct from the overall market.

**Figure 20: Monthly Price Distribution Box Plots**

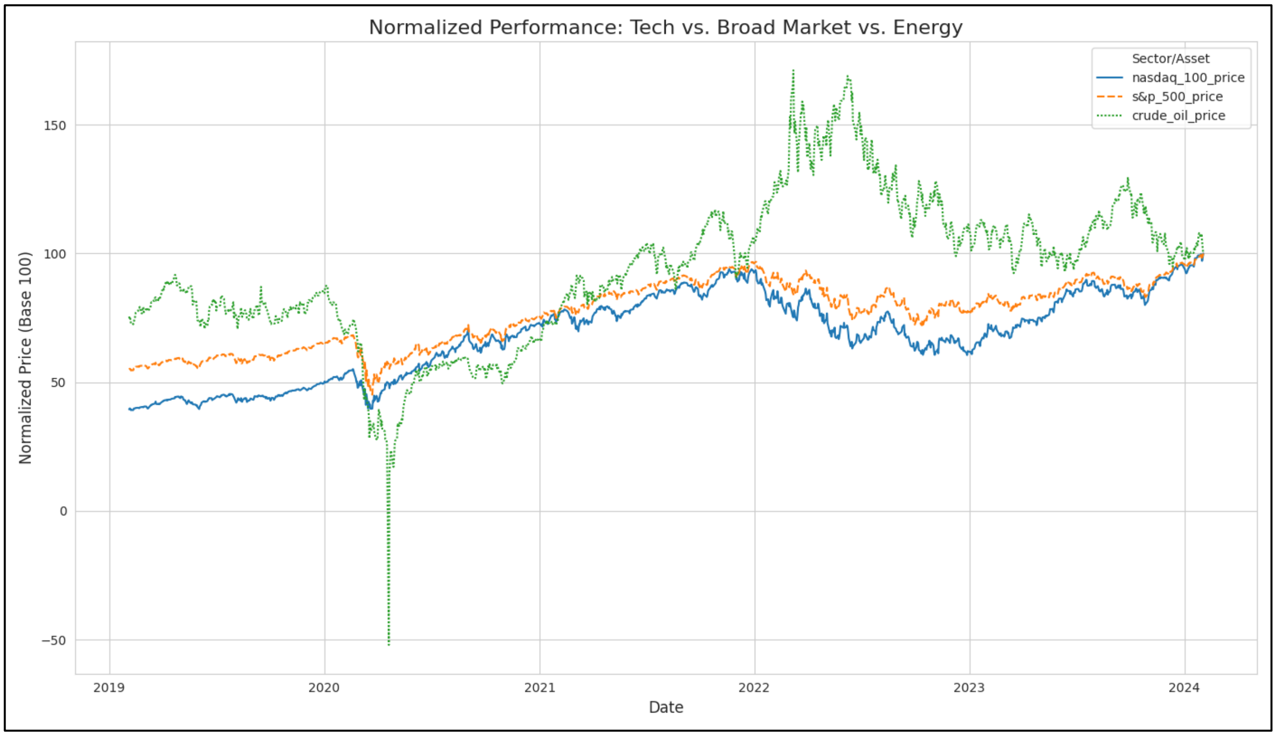
Purpose: Box plots showing the distribution of prices for Apple, Crude Oil, and Bitcoin for each month.




Observation: For assets with a strong upward trend like Apple and Bitcoin, the monthly median prices (the line within the boxes) progressively move higher throughout the year. The size of the boxes indicates price volatility within that month; larger boxes mean greater price fluctuation.

**Figure 21: Sector Performance: Tech vs. Broad Market vs. Energy**

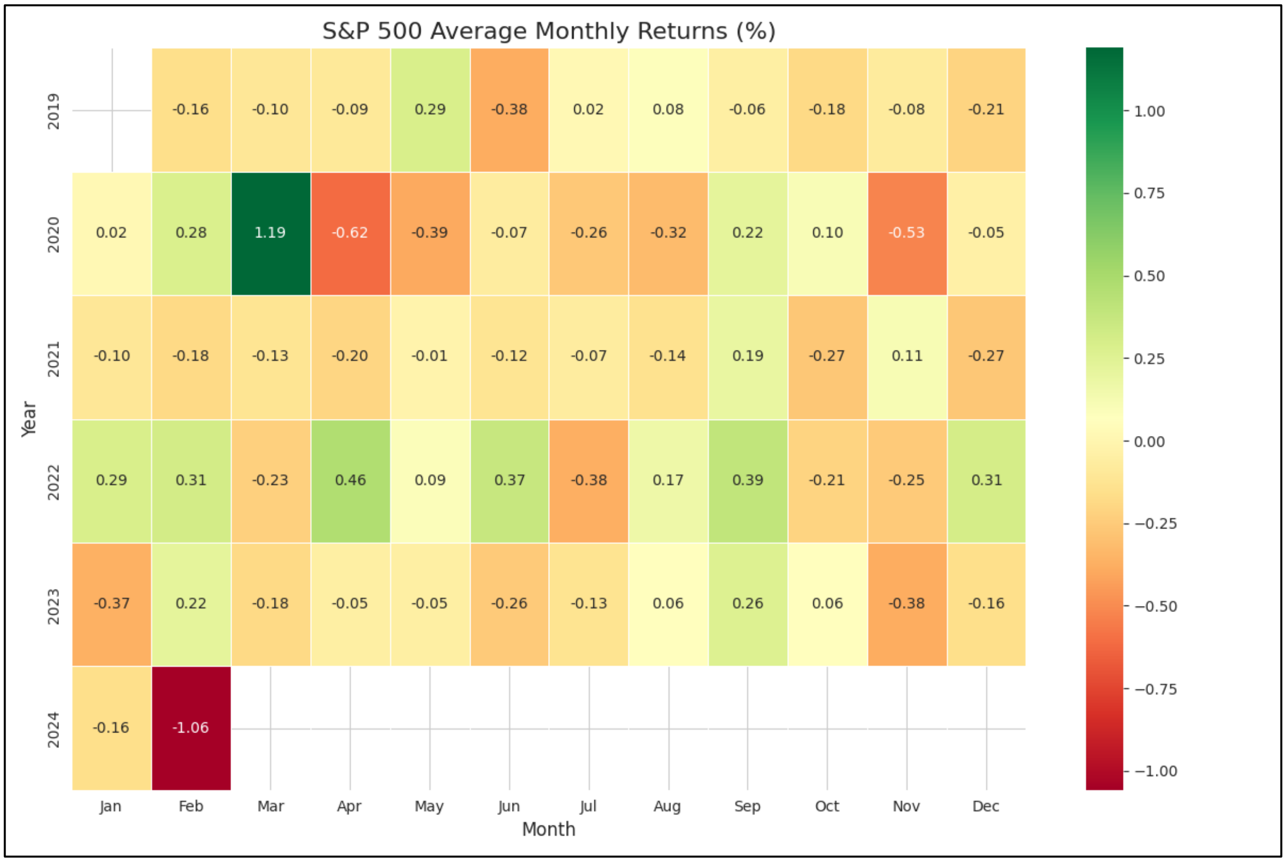
Purpose: Normalized line chart comparing the performance of the Nasdaq 100 (tech sector), S&P 500 (broad market), and Crude Oil (energy sector).




Observation: The Nasdaq 100 (tech) has significantly outperformed the broader S&P 500, highlighting the strong growth in the technology sector. Crude Oil's performance is much more cyclical, showing a major dip in 2020 followed by a strong recovery. This effectively contrasts the growth trend of tech with the cyclical nature of energy.

**Figure 22: S&P 500 Average Monthly Returns (%)**

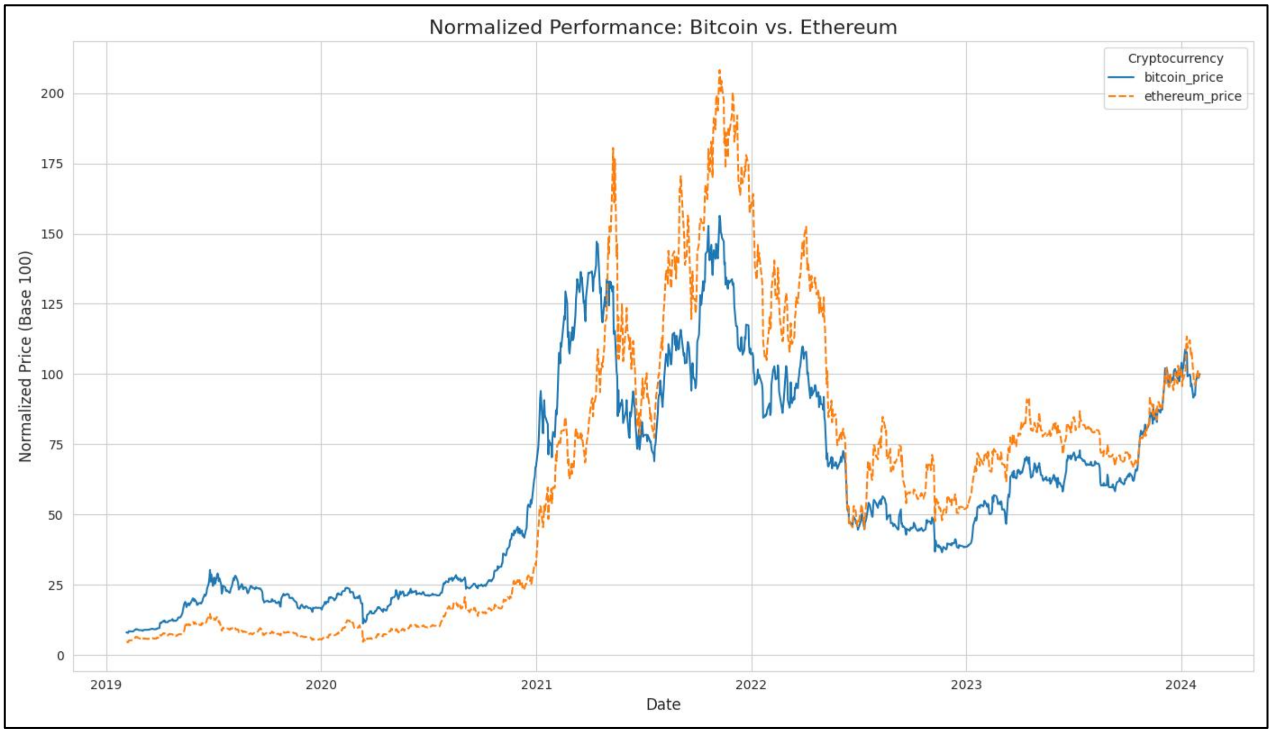
Purpose: Heatmap showing the average percentage return for the S&P 500 for each month across the years.




Observation: This heatmap is excellent for spotting seasonal trends. We can see strong performance in several Novembers and Decembers (a common "end-of-year rally"). The dramatic negative return in March 2020 clearly marks the COVID-19 market crash. This provides a powerful summary of market seasonality and major events.

**Figure 23: Normalized Performance: Bitcoin vs. Ethereum**

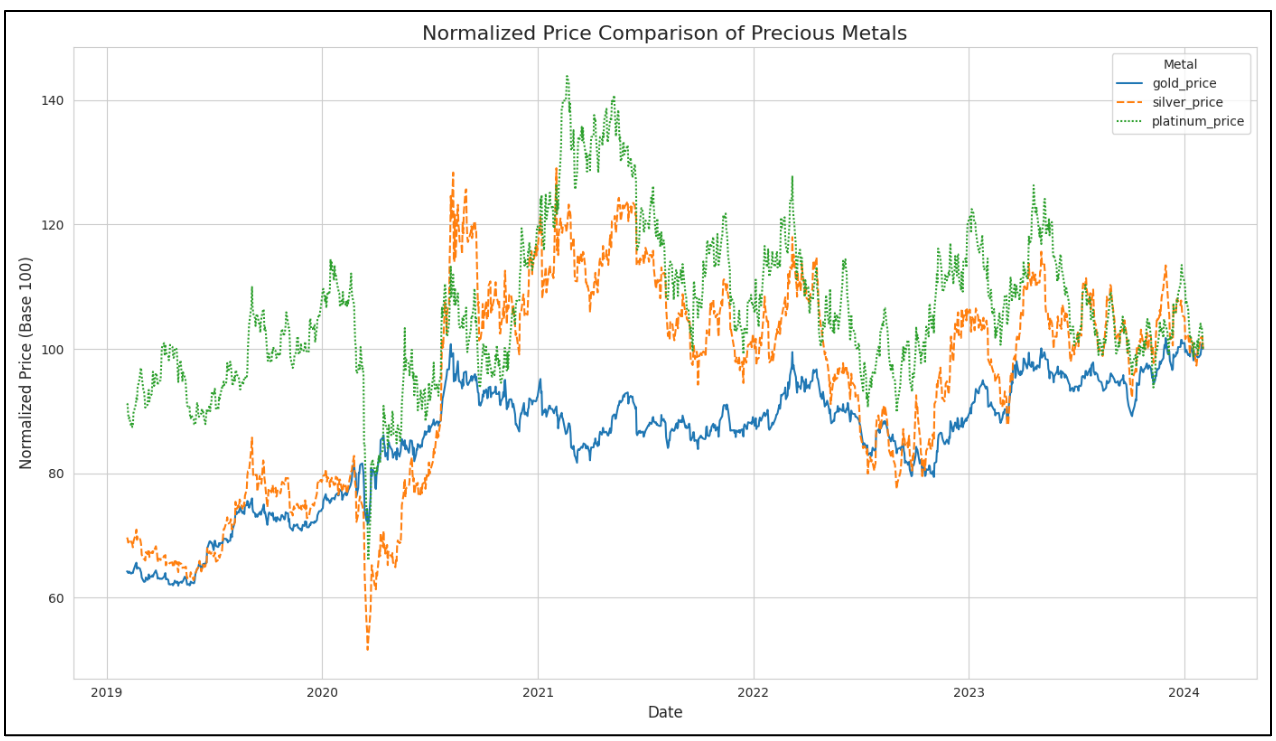
Purpose: Normalized line chart comparing the price performance of Bitcoin and Ethereum.




Observation: While highly correlated, this normalized chart reveals that Ethereum had periods of significant outperformance relative to Bitcoin, especially during the 2021 bull market. This indicates that the magnitude of their returns can differ substantially.

**Figure 24: Normalized Price Comparison of Precious Metals**

Purpose: Normalized line chart comparing the price performance of Gold, Silver, and Platinum.



Observation: This chart highlights the different roles these metals play. Silver shows the most volatility of the three. Gold remains the most stable, with slow and steady growth. Platinum's performance has been relatively flat in comparison over this period.

# CHAPTER 5

# SUMMARY OF KEY FINDINGS

The exploratory data analysis has yielded several critical insights into the market dynamics of the last five years:

- **Tech and Crypto Dominance**: The technology sector, represented by the Nasdaq 100, and cryptocurrencies like Bitcoin and Ethereum, have been the dominant drivers of growth, albeit with significantly higher volatility for crypto.
- **High Intra-Sector Correlation**: Assets within the same class (e.g., tech stocks, precious metals, cryptocurrencies) are very highly correlated, meaning they tend to move in the same direction.
- **Volatility as a Key Indicator**: Periods of high trading volume and high volatility are strongly associated with major price movements, particularly for high-growth assets like Tesla and Bitcoin.
- **Distinct Sector Characteristics**: The analysis clearly distinguishes the steady growth of the broad market (S&P 500), the aggressive growth of tech (Nasdaq 100), the stability of safe havens (Gold), and the cyclical nature of commodities (Crude Oil).

# CHAPTER 6

# OUTLINE OF PROPOSED MACHINE LEARNING ALGORITHMS

## 6.1 Proposed Models

Based on the time-series nature of the data, the dataset is well-suited for a time-series forecasting task to predict future asset prices. The primary goal would be to predict the next day's price of a specific asset (e.g., s&p_500_price) by building a robust forecasting system. A multi-tiered modelling strategy is proposed to benchmark performance and build towards a highly accurate model.

The following models are proposed:

- **ARIMA (Autoregressive Integrated Moving Average)**: To be used as a classical statistical baseline model to capture linear trends and seasonality in the price data. This model works by analysing the statistical properties of the time series itself, such as its autocorrelation, to make predictions. It serves as a crucial benchmark to ensure that more complex models are adding real predictive value.
- **Random Forest Regressor**: To be used in a feature-based approach, where lagged prices and moving averages are created as features to predict the next day's price. This can capture non-linear relationships. By engineering features like rolling statistics and data from correlated assets, we transform the forecasting problem into a regression task that the Random Forest can solve effectively. This model is also useful for identifying which historical features are most important for prediction.
- **LSTM (Long Short-Term Memory) Neural Network**: To be used as an advanced deep learning model. LSTMs are specifically designed for sequential data and are capable of learning long-term dependencies, making them ideal for financial forecasting. Unlike other models, LSTMs have internal memory cells that can remember important patterns over long periods, which is critical for understanding complex market dynamics and achieving state-of-the-art performance.

# CHAPTER 7

# CONCLUSION AND APPENDIX

This Exploratory Data Analysis has successfully navigated the complexities of a diverse, five-year financial dataset, transforming raw market data into a coherent narrative of trends, risks, and opportunities. Through a methodical process of data cleaning, preprocessing, and extensive visualization, this report illuminates the profound dynamics of the U.S. stock market and global commodities. The initial transformation phase was critical; standardizing column structures, correcting data types, and imputing missing values established a reliable foundation for the analysis.

The analysis conclusively demonstrates that the market's trajectory was not monolithic. It was characterized by the aggressive, technology-driven growth of the Nasdaq 100, which outpaced the broader market, and the extreme volatility of the cryptocurrency sector. In contrast, traditional assets like Gold fulfilled their role as stable safe havens, while commodities like Copper and Crude Oil followed more cyclical patterns. The high correlation observed within sectors—particularly among tech stocks and cryptocurrencies—underscores the importance of diversification.

Furthermore, this EDA has successfully prepared the dataset for the next logical phase of the project. The identified patterns and correlations provide a solid foundation for building robust predictive models. In essence, this analysis provides a clear, evidence-based picture of recent market history while paving the way for developing sophisticated tools to anticipate future market behavior.

## APPENDIX

**Dataset Name:** Stock Market Dataset.csv

**Dataset Link:** https://www.kaggle.com/datasets/saketk511/2019-2024-us-stock-market-data

**GitHub Link:** https://github.com/PrathamAgrawal51/Pratham_Agrawal_22070521078_DS_CA1

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