Exploring Trading Strategies Based on Semiconductor Stocks and Bitcoin Correlation

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Abstract

This paper investigates the correlation between Bitcoin and the semiconductor industry during the period from 2014 to 2024. The study discovers that Bitcoin, initially considered as a hedging instrument against market downturns, now exhibits a strong positive correlation with major market indices such as the S&P 500 and NASDAQ, with this transformation becoming particularly evident since 2019. Detailed empirical analysis reveals that from 2022 to 2024, the correlation coefficients between Bitcoin and both the S&P 500 and NASDAQ indices exceeded 0.7, leading to the conclusion that Bitcoin no longer serves as a reliable hedge against downtrends in the U.S. stock market. Furthermore, the research identifies a very strong positive correlation between Bitcoin and the semiconductor industry. Through meticulous analysis using Bollinger Bands and the Average True Range (ATR) as primary technical indicators, this study examines their effectiveness in generating reliable trading signals based on the dynamic changes in Bitcoin's price movements. The research introduces two main trading strategies: a momentum-based strategy and a mean reversion strategy. The momentum-based strategy, utilizing Bollinger Bands and ATR, demonstrates strong performance during periods of market downturns by aligning trading signals with periods of high volatility and directional momentum, suggesting its utility in bearish stock market conditions. Conversely, the mean reversion strategy faces challenges due to shifts in market dynamics, the inherent complexity of predicting mean reversion points in volatile markets like cryptocurrencies and semiconductors, and the recent trends in the semiconductor industry, resulting in its underperformance.

Keywords: Bitcoin, Semiconductor Stocks, Bitcoin Halving, Market Index, Correlation, Cross-correlation, Bollinger Bands, Average True Range, Trading Signals, Trading Strategies

1 Introduction

Since its inception in 2009 by the enigmatic creator Satoshi Nakamoto, Bitcoin has risen to dominate the cryptocurrency market by capitalization. As of April 2024, Bitcoin's market valuation has surged to an impressive $1.206 trillion, marking a significant milestone that underscores its burgeoning role in the global financial landscape. Distinct from traditional fiat currencies, Bitcoin operates exclusively in a digital format without any physical tokens. It utilizes a blockchain platform, ensuring that all transactions are immutable and transparent. This not only prevents any single entity from altering the historical record but also positions Bitcoin as a decentralized, global financial exchange medium.

Bitcoin's infrastructure is fundamentally different from traditional financial systems. It relies on a decentralized network of computers, known as nodes, which stark contrast to the centralized systems of banks and governmental financial institutions. This architecture promotes not only decentralization but also enhances security and reduces dependence on established financial infrastructures, challenging the conventional mechanisms of financial governance.

One of Bitcoin's critical economic mechanisms is its 'halving' process, which occurs every four years and reduces the mining reward by fifty percent. This event is designed to limit the inflow of new bitcoins, thereby instilling a deflationary characteristic similar to that of precious metals. The halving events, which are scheduled to continue until approximately 2140, have historically led to significant increases in Bitcoin's price. For instance, in the 30 days leading up to the July 2016 halving, Bitcoin's price rose by 13% from $574.63 to $650.96. Similarly, before the May 2020 halving, the price surged by 25% from $6,859.08 to $8,601.80. The next halving, scheduled for April 20th, 2024, is expected to attract significant attention from both the academic and investment communities due to the historical price surges following past halvings. These patterns of substantial price increases post-halving suggest a predictable speculative interest that has fueled both market anticipation and investor speculation.

Bitcoin mining is an integral component of its ecosystem, heavily relying on the semiconductor industry for the necessary hardware like Graphics Processing Units (GPUs) and Application-Specific Integrated Circuits (ASICs). The demand for these components is highly sensitive to Bitcoin's price fluctuations, which can lead to significant impacts on the semiconductor industry. When Bitcoin prices are high, mining profitability increases, boosting the demand for GPUs and ASICs. Conversely, a decline in Bitcoin prices can drastically reduce the demand for these components, leading to potential instability in semiconductor manufacturing cycles.

Recent research by Bouri (2023) highlights Bitcoin's significant predictive power on U.S. stock market volatility, suggesting an inverse relationship between Bitcoin prices and stock sector volatility. This implies that rising Bitcoin prices might act as a buffer against stock market fluctuations, potentially serving as a novel hedging strategy. Furthermore, Bouri (2024) notes that the persistence in cross-correlation is more pronounced with cryptocurrencies during market uptrends and with the Nasdaq during downtrends, indicating nuanced investment dynamics across different market conditions.

Additional studies have corroborated and expanded upon these findings, showing Bitcoin's broader economic impact and its interaction with various financial assets. For instance, Wang, Liu, and Wu (2022) utilized the ADCC-GARCH model to examine the correlation between Bitcoin and major financial assets, finding a positive linkage with risk assets and a negative correlation with safe havens such as the U.S. dollar during times of market stress, suggesting Bitcoin's role as a diversifier in investment portfolios. Moreover, Kristjanpoller, Nekhili, and Bouri (2024) explored the multifractal and asymmetric cross-correlations between blockchain ETFs, cryptocurrencies, and the Nasdaq, revealing enhanced predictability of asset prices in downward trending markets, which could offer substantial hedging opportunities.

This study seeks to build on these insights by examining the relationship between stocks in the semiconductor sector—highly correlated with Bitcoin—and Bitcoin's price movements. Additionally, it aims to assess the current extent of Bitcoin's correlation with major market indexes. By exploring these relationships, this research intends to identify potential trading signals and develop trading strategies that capitalize on the unique economic and financial dynamics presented by Bitcoin.

2 Data and empirical methodology

2.1 Correlation Analysis: Bitcoin and Major Market Indices

Initially, our investigation seeks to elucidate the correlation between Bitcoin and major stock market indices. This analysis is predicated on the prevalent assumption among investors that Bitcoin may function as a hedging asset. Historically, numerous stakeholders have posited that Bitcoin could serve as a counterbalance to downward risks in the U.S. stock markets, reflecting its potential role in diversifying investment portfolios during times of economic uncertainty.

Recent academic studies provide a nuanced view of Bitcoin's role as a hedging asset against stock market downturns, especially concerning the U.S. stock markets. The findings suggest that Bitcoin's relationship with traditional financial markets, including its hedging ability, varies depending on market conditions and over time. For instance, Bouri et al. (2020) indicate that Bitcoin has shown potential as a hedging tool against U.S. stock market downturns, particularly in periods of market stress. However, the effectiveness of Bitcoin as a hedge is not consistent across all conditions. Under normal market conditions, Bitcoin may act more as a diversifier than a stable hedge, as its correlation with traditional markets can vary significantly (Bouri et al., 2020).

Another study conducted during the COVID-19 pandemic further illustrated that Bitcoin could serve as a hedge in certain situations, yet its role as a safe haven was sensitive to the type of asset market and the specific time horizon considered. The study employed a smooth transition regression approach to demonstrate how Bitcoin's hedging and safe-haven properties might change from pre-pandemic to during the pandemic (Abdelmalek & Benlagha, 2023).

These insights are important for investors considering Bitcoin as part of a hedging strategy. They suggest that while Bitcoin has potential hedging capabilities, especially in volatile or crisis periods, it does not consistently function as a safe haven. Therefore, the inclusion of Bitcoin in investment portfolios should be carefully considered, weighing its performance across different market conditions to optimize risk management strategies. For more detailed analysis and data, accessing studies such as those published in the Journal of Risk Finance might provide deeper insights (Abdelmalek & Benlagha, 2023).

In our investigation into the correlation between Bitcoin and the semiconductor industry, we meticulously curated a dataset tailored specifically to meet the research objectives, focusing on variables that influence market dynamics and technological advancements. The dataset included only stocks that are directly involved in the production of semiconductor chips and related technologies, encompassing sectors such as electronic components, and networking and wireless technologies.

To maintain a standard of reliability and to mitigate the impact of market anomalies, the dataset was refined with specific financial thresholds. Stocks considered for the analysis were required to have a minimum share price of $5, thereby excluding penny stocks which are typically prone to higher volatility and may distort analytical outcomes. Additionally, to ensure the liquidity and representativeness of the data, only stocks with a three-month average daily trading volume exceeding 200,000 shares were included. This criterion was crucial for minimizing liquidity-related biases and for enhancing the robustness of our statistical analyses.

The temporal scope of our dataset spanned from September 17, 2014, to April 17, 2024. This period was chosen based on the availability of complete and consistent data from Yahoo Finance. Although the span does not cover the entirety of Bitcoin's issuance since 2009, it captures significant market trends and technological evolutions pertinent to both the semiconductor and cryptocurrency markets.

Figure 1: Annual change in correlation between BTC and other assets from 2014 to 2024

However, our analysis of correlation has different observation. As Figure 1 shown, it presents the change in annual correlation between selected semiconductor sector stocks plus SPY and QQQ, as representatives of the S&P500 and Nasdaq indexes respectively, and Bitcoin from 2014 to 2024.

In the empirical analysis depicted in the last row of the graphical illustrations, a noteworthy transition in the correlation between Bitcoin and major market indices such as the S&P 500 ETF (SPY) and the NASDAQ-100 ETF (QQQ) is observed. Initially, in 2014, the correlation between Bitcoin and these indices was negative, indicating an inverse relationship. Over time, this correlation shifted towards a more positive alignment. Specifically, by 2018, the correlation between Bitcoin and SPY approached neutrality (near zero), while the correlation with QQQ was approximately -0.2.

From 2019 through 2024, there was a marked increase in the positive correlation between BTC and these market indices, with the exception of 2021. Notably, from 2022 to 2024, the correlation values consistently exceeded 0.7. These findings suggest a significant departure from Bitcoin's earlier characterization as a hedge against U.S. stock market downturns. Instead, the data indicate that Bitcoin has evolved to exhibit a strong positive correlation with the market, underscoring its integration and alignment with broader market dynamics rather than serving as a countercyclical asset. This evolution challenges the notion of Bitcoin as a reliable safe haven during market downturns and suggests a reevaluation of its role in investment portfolios, given its current high correlation with market movements. Similarly, we further observe the correlation changes between other semiconductor stocks and Bitcoin, and there are similar patterns.

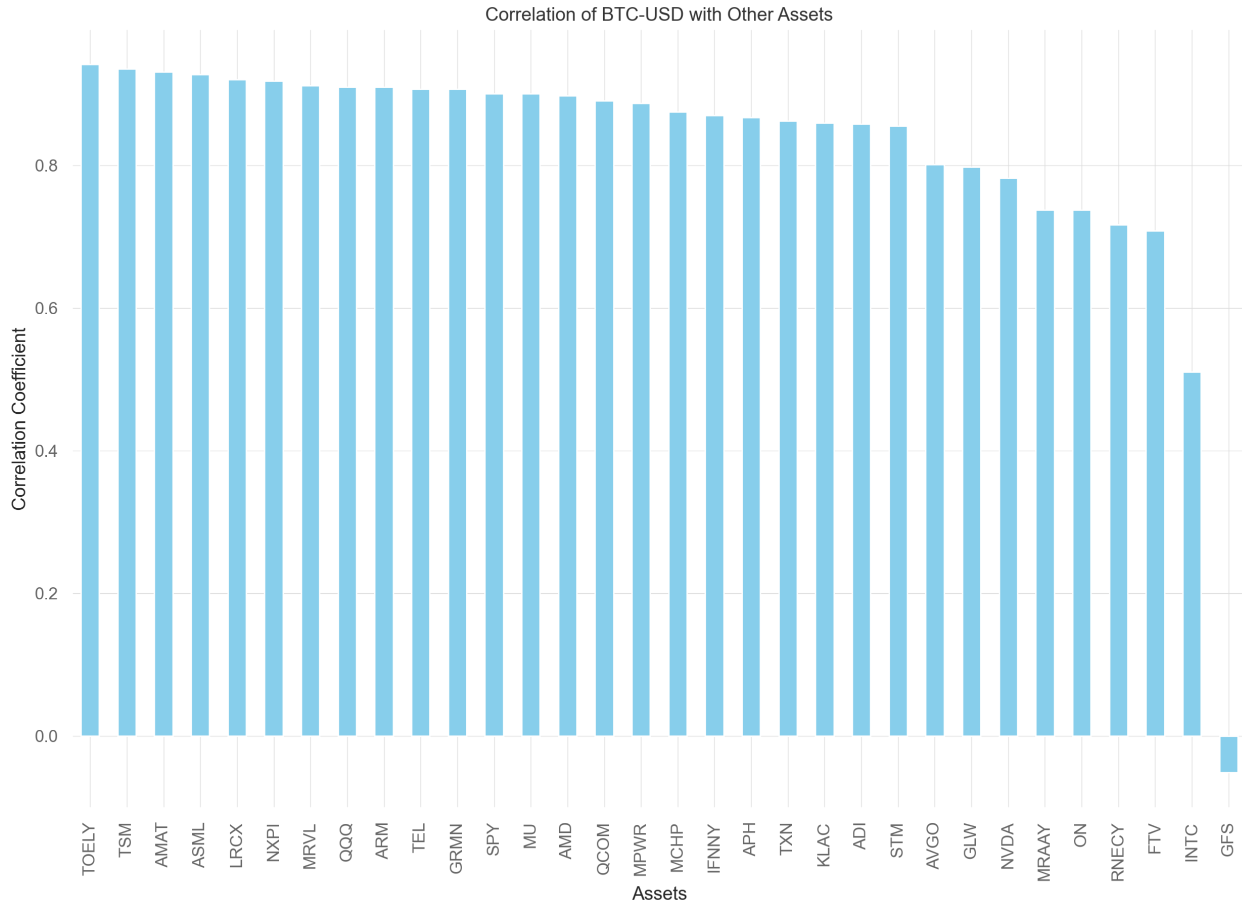

Figure 2: Correlation of Bitcoin with other assets

Upon examining the empirical evidence, it is observed that there is a notably strong positive correlation between the semiconductor sector stocks and Bitcoin, as depicted in Figure 2. This correlation holds true across the board with the exception of GlobalFoundries (GFS), which exhibits a divergent pattern from the broader trend. The substantial alignment in market movements between the semiconductor sector and Bitcoin suggests potential avenues for deriving trading signals. This correlation might be leveraged to develop strategies that capitalize on synchronized price movements, thus offering opportunities for tactical asset allocation and portfolio optimization.

2.2 Cross-Correlation Analysis

In light of the observed high correlation between semiconductor stocks and Bitcoin, our research endeavors to explore the unique trading hour differentials between Bitcoin and U.S. equities. It is well-documented that U.S. stock markets operate from Monday to Friday, 9:30 a.m. to 4:30 p.m. Eastern Time, whereas the cryptocurrency markets, including Bitcoin, are characterized by their round-the-clock trading schedule. This temporal disparity raises intriguing questions about the intermarket dynamics, particularly whether the weekend price movements in Bitcoin yield observable impacts on semiconductor stocks when the equity markets reopen.

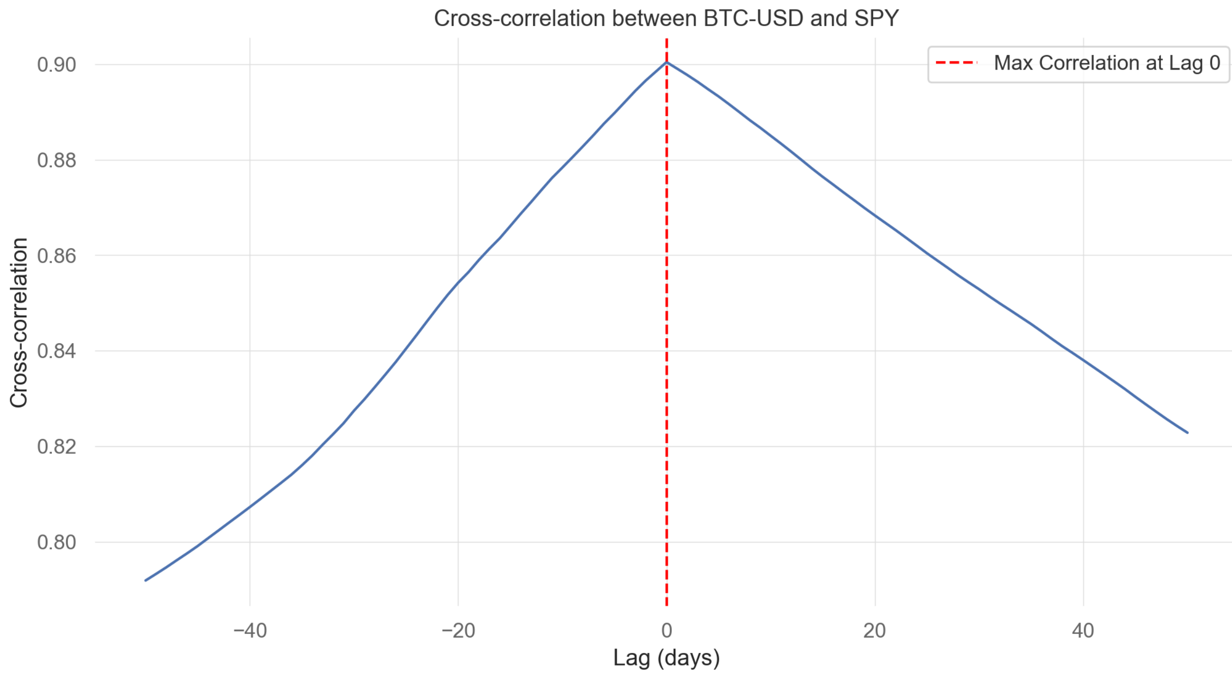

Figure 3: Cross correlation between BTC and SPY

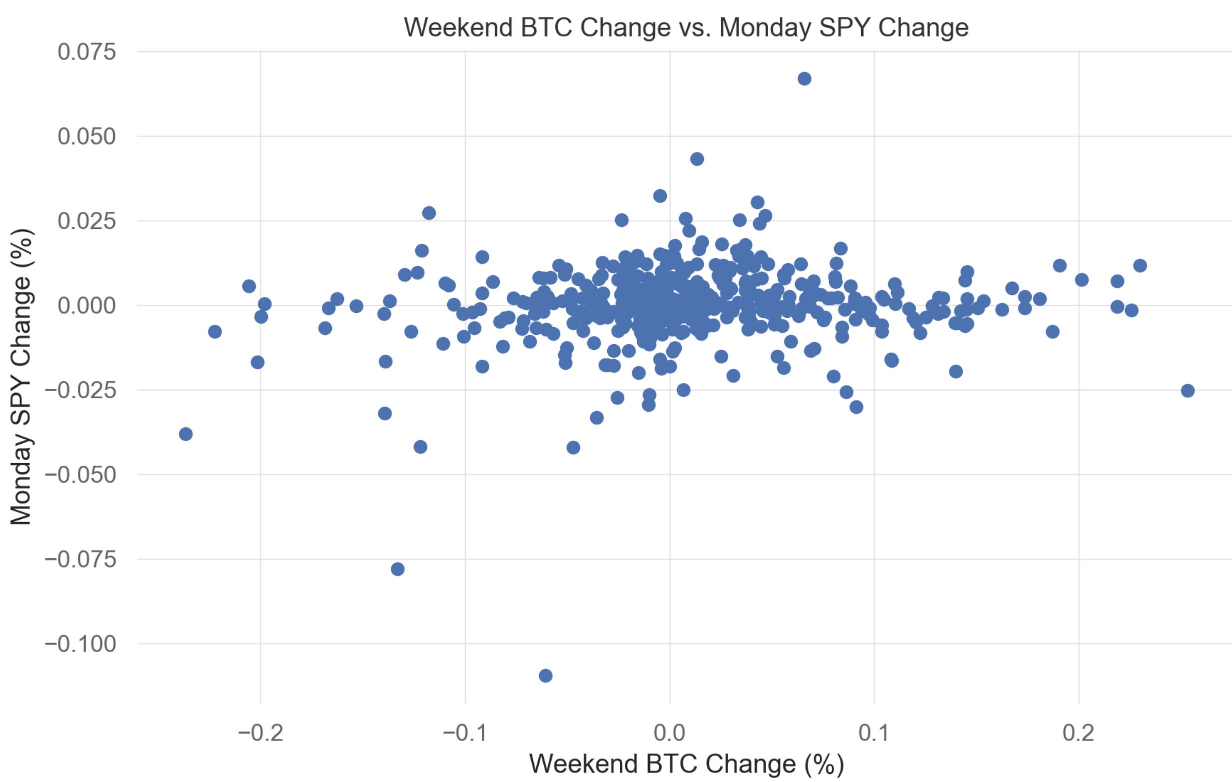

Figure 4: Weekend BTC Change vs. Monday SPY Change

The empirical evidence as illustrated in the two figures reveals a multifaceted relationship between the price movements of Bitcoin and traditional equity markets, notably the semiconductor sector and broader indices such as the S&P 500. Figure 3 delineates a pronounced peak in cross-correlation at Lag 0, suggesting a contemporaneous relationship between Bitcoin and the S&P 500 ETF (SPY), indicative of synchronous price movements during the period under review. This relationship is further substantiated by Figure 4, which presents a discernible positive correlation coefficient of 0.12 with a p-value of 0.005, pointing to a statistically significant association between weekend Bitcoin price changes and the subsequent Monday price adjustments in the SPY.

The Pearson correlation coefficient is a measure of the linear correlation between two variables X and Y. It is defined as the covariance of the two variables divided by the product of their standard deviations:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{1}$$

Where:

- $cov(X,Y)$ is the covariance between variables X and Y.
- σ_X and σ_Y are the standard deviations of X and Y respectively.
- E is the expectation operator.
- μ_X and μ_Y are the means of X and Y respectively.

The established positive correlation, particularly during standard trading hours, invites an in-depth examination of the interplay between these two asset classes. Given the cryptocurrency market's uninterrupted trading cycle, in contrast to the U.S. equity market's more traditional hours, the observable changes in Bitcoin's price over the weekend appear to provide early indicators of market sentiment. This could, in turn, exert influence on the trading behaviors in semiconductor stocks as the equity markets reopen for the week.

2.3 Trading Signals: Bollinger Bands and Average True Range

These findings compel us to consider the ramifications for investment strategies and portfolio management. The significant correlation and the potential for Bitcoin to act as an early signal for market movements underscore the need for investors to remain vigilant of cryptocurrency trends even during non-trading periods for traditional equities. Moreover, this evidence challenges the traditional view of Bitcoin as merely a hedge against market downturns and highlights its evolving role as a correlated asset in the financial ecosystem. Consequently, our research suggests a recalibration of risk assessments and asset allocation models to account for the heightened correlation between Bitcoin and stock market indices, particularly within the semiconductor sector, which could inform both short-term trading and long-term investment decisions.

The Bollinger Bands are defined as:

$$\text{Middle Band (MB)} = \text{SMA}(N) = \frac{1}{N}\sum_{i=1}^{N} P_i$$

$$\text{Upper Band (UB)} = \text{MB} + k \times \sigma(P, N)$$

$$\text{Lower Band (LB)} = \text{MB} - k \times \sigma(P, N)$$

Where:

- N is the number of periods used for the SMA.
- P_i is the price of the asset at time i.
- k is the number of standard deviations away from the SMA (typically set to 2).
- $\sigma(P, N)$ is the standard deviation of the prices over N periods.

The True Range (TR) and Average True Range (ATR) are measures of market volatility and are defined as follows:

$$TR = \max\left(H - L, |H - C_{\text{prev}}|, |L - C_{\text{prev}}|\right)$$

$$ATR = \frac{1}{N}\sum_{i=1}^{N} TR_i$$

$$ATR_t = \frac{1}{N} TR_t + \left(1 - \frac{1}{N}\right) ATR_{t-1}$$

Where:

- H is the current high price.
- L is the current low price.
- C_{prev} is the previous closing price.
- N is the number of periods over which the ATR is calculated.

Transitioning to the topic of Bitcoin's volatility, it's important to note that such market behavior presents both challenges and opportunities. The trajectory of Bitcoin's price, as captured by the cumulative returns presented in Figure 5, elucidates an asset that has undergone significant appreciation over the examined period. The graph indicates an exponential growth trajectory, particularly noticeable post-2020, highlighting periods of vigorous market participation and investor interest. This marked ascension in cumulative returns reflects not only the burgeoning investor confidence but also the increased acceptance of Bitcoin as a mainstream financial asset.

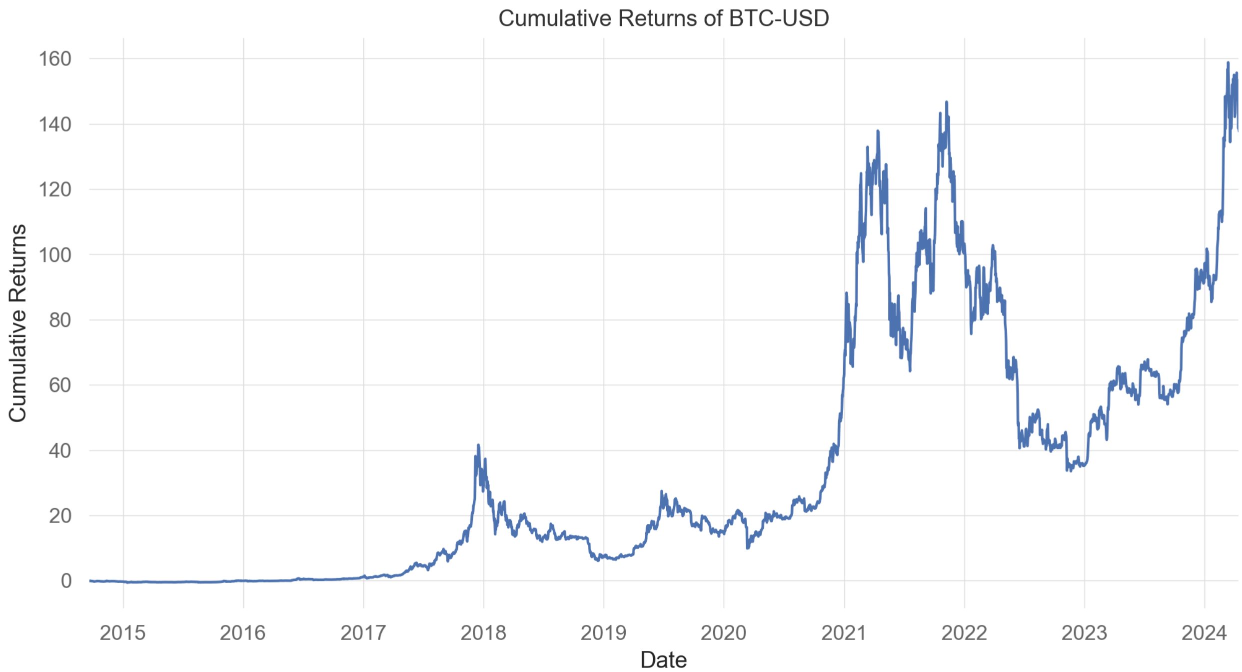

Figure 5: Cumulative Returns of BTC

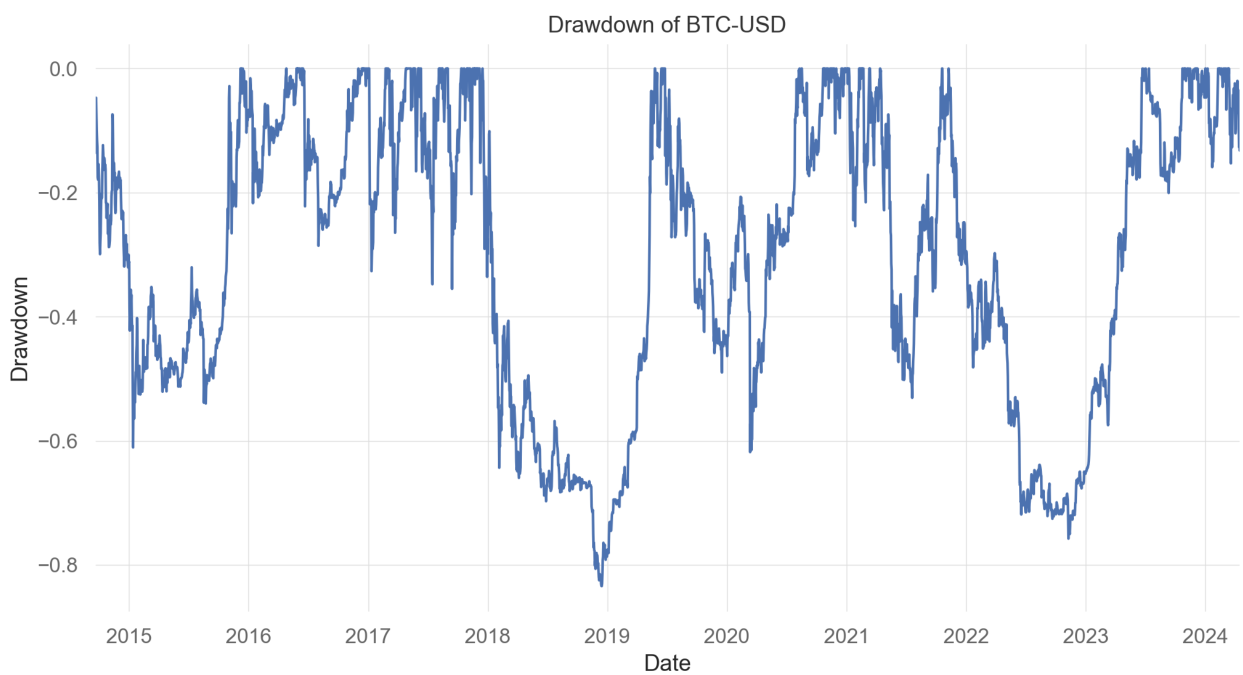

Figure 6: Drawdown of BTC

Simultaneously, the drawdown chart in Figure 6, which details the declines from previous highs, illustrates the inherent volatility and the risk profile associated with Bitcoin. The pronounced drawdowns witnessed periodically throughout the timeline underscore the asset's susceptibility to sharp value retractions after substantial run-ups in price. The stark juxtaposition between the potential for high returns and significant drawdowns is indicative of the high-risk, high-reward nature intrinsic to Bitcoin's market behavior.

This pronounced volatility, inherently captured in both figures, provides a segue to the application of Bollinger Bands and the Average True Range (ATR) in trading signal generation. Given Bitcoin's marked price fluctuations, these technical analysis tools are particularly apposite for discerning periods of potential market entry and exit. Bollinger Bands can be calibrated to identify overbought or oversold conditions within this volatile landscape, while the ATR may serve as a gauge for the magnitude of Bitcoin's trading volatility, informing position sizing and risk management.

In deploying these tools, investors and analysts can refine their strategies to account for the heightened volatility and the evolving correlation patterns between Bitcoin and traditional equity markets. Such measures are instrumental in crafting a data-driven, probabilistic framework for trading decision-making, particularly within sectors that exhibit strong correlation with Bitcoin, such as the semiconductor industry. The incorporation of Bollinger Bands and the ATR into our analytical framework is intended to harness the volatility and correlation attributes of Bitcoin, leveraging these dynamics to generate actionable trading signals that are predicated upon statistical rigor and market acumen.

2.4 Trading Strategies

Strategy 1: Momentum-Based Trade on Correlation

The cornerstone of this strategy is predicated on the concept of market momentum and its correlation with Bitcoin's price dynamics. Empirical research has demonstrated that Bitcoin's market movements exhibit a leader-follower relationship with certain equity sectors, most notably semiconductors. This strategy aims to exploit this relationship by identifying buy and sell signals based on the convergence of two technical indicators: the Bollinger Bands and the Average True Range.

Buy Signal: The initiation of a buy signal occurs when Bitcoin's closing price exceeds the upper Bollinger Band, concomitant with an increase in the ATR. The upper Bollinger Band is defined as the two standard deviations above the 20-day simple moving average (SMA) of the price, serving as an indicator of overextension in the price movement. An increase in the ATR—a measure of volatility based on the true range of asset prices—suggests that the current trend has the momentum to continue. The convergence of these two factors indicates a robust uptrend, justifying the acquisition of semiconductor stocks, which are anticipated to benefit from the positive sentiment in the cryptocurrency market.

Sell Signal: Conversely, a sell signal is generated when Bitcoin's closing price descends below the lower Bollinger Band, simultaneously with a high or increasing ATR. This scenario typically indicates an overextension to the downside and increasing volatility, signaling a potential market correction or bearish phase. Given the demonstrated correlation, such conditions suggest a prudent divestiture of semiconductor equities to mitigate the risks of a market downturn.

This strategy, therefore, synthesizes technical analysis and market sentiment, supported by the quantitative indicators provided by Bollinger Bands and the ATR. The underlying thesis posits that Bitcoin's market behavior serves as a leading indicator for the semiconductor sector, with its price movements offering foresight into the future performance of these equities.

$$\text{Upper Bollinger Band (UB)} = \text{SMA}_{20} + 2\sigma_{20}$$
$$\text{Lower Bollinger Band (LB)} = \text{SMA}_{20} - 2\sigma_{20}$$
$$\text{Average True Range (ATR)} = \frac{1}{N}\sum_{t=1}^{N} \text{True Range (TR)}_t$$

Where:

- SMA_{20} is the 20-day simple moving average of the Bitcoin price.
- σ_{20} is the standard deviation of the Bitcoin price over the last 20 days.
- True Range (TR) is the maximum range achieved by comparing today's high and low, today's high and yesterday's close, and today's low and yesterday's close.
- N is the period over which the ATR is calculated (typically 14 days).

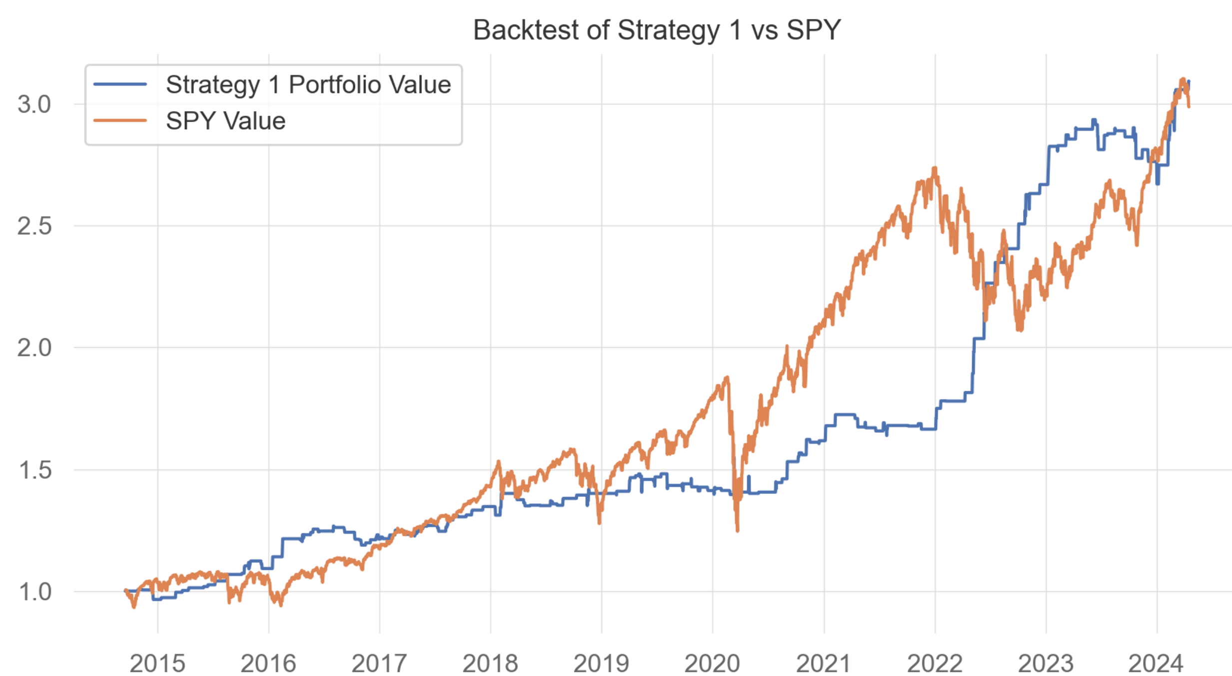

Figure 7: Backtest of Strategy 1 vs SPY

The backtest analysis, as depicted in the Figure 7, chronicles the performance of a momentum-based trading strategy predicated on Bitcoin's volatility and its correlative impact on semiconductor stocks, juxtaposed against the S&P 500 index from the year 2015 through 2024. The strategic premise hinges on the observation that Bitcoin's excursions beyond its Bollinger Bands, in conjunction with fluctuations in the Average True Range, herald commensurate movements in semiconductor equity prices.

The acquisition signal is operationalized when Bitcoin's closure exceeds the upper echelon of the Bollinger Bands, concomitant with an escalation in the ATR, signaling burgeoning market volatility alongside a pronounced bullish trend. The strategy demonstrates periods of outstripping the SPY, particularly emblematic during phases where Bitcoin's bullish signals ostensibly cascaded to an uplift in semiconductor stocks, substantiating the strategy's efficacy in capturing upward market momentum.

In contrast, the divestiture signal of the strategy is activated upon Bitcoin's descent beneath the lower threshold of the Bollinger Bands, aligned with an elevated or intensifying ATR. This is interpreted as an impending bearish trajectory. Notably, from 2020 to 2022, the strategy's relative underperformance to SPY is evident, which may stem from the strategy's predisposition to interpret heightened ATR, irrespective of Bitcoin's price position relative to its Bollinger Bands, as a harbinger of a market downturn. The heightened ATR, however, may merely signal an increase in market volatility, not necessarily presaging a decline in asset prices, thereby possibly eliciting premature sell signals.

The strategy excels in its drawdown control, especially manifest during significant market retractions early in 2020 and from 2022 to 2023. Despite broader market tumult, the strategy maintained commendable resilience, underscoring its robustness in adverse market conditions. The analytical focus, therefore, is the recalibration of the sell signal protocol, with an aim to more accurately discern true market downturns from mere volatility spikes. The current evidence suggests that while the strategy requires refinement in signal generation, particularly in decoding the nuanced signals of volatility indicators, it holds substantial promise in mitigating downside risk and preserving capital during market distress.

In conclusion, the strategy's historical performance elucidates its potential for attenuating downside exposure in tumultuous market periods. The imperative for the strategy moving forward is to refine its exit signals to better distinguish between genuine market downturns and transient volatility, thus optimizing its defensive posture in turbulent markets and enhancing its comparative performance against traditional market benchmarks like the SPY.

Strategy 2: Mean Reversion Using Bollinger Bands

Investment Thesis: This strategy capitalizes on the mean reversion principle applied to semiconductor stocks, hinging on the statistical Bollinger Bands method.

Buy Signal: When a semiconductor stock closes below its lower Bollinger Band, it is inferred to be oversold, implying a subsequent reversion towards its mean, represented by the middle Bollinger Band (20-day Simple Moving Average).

Sell Signal: Conversely, a stock closing above its upper Bollinger Band suggests an overbought condition, portending a pullback towards the mean.

Bollinger Bands Calculation: The Bollinger Bands consist of a middle band being a N-period simple moving average (SMA), an upper band at K times an N-period standard deviation above the middle band, and a lower band at K times an N-period standard deviation below the middle band.

$$\begin{aligned} \text{Middle Band} &= \text{SMA}(N) \\ \text{Upper Band} &= \text{SMA}(N) + K \times \sigma(N) \\ \text{Lower Band} &= \text{SMA}(N) - K \times \sigma(N) \end{aligned} \tag{2}$$

where:

- SMA(N) is the Simple Moving Average over N periods

- $\sigma(N)$ is the standard deviation of the stock price over N periods
- K is the number of standard deviations to offset the upper and lower bands (typically $K = 2$)

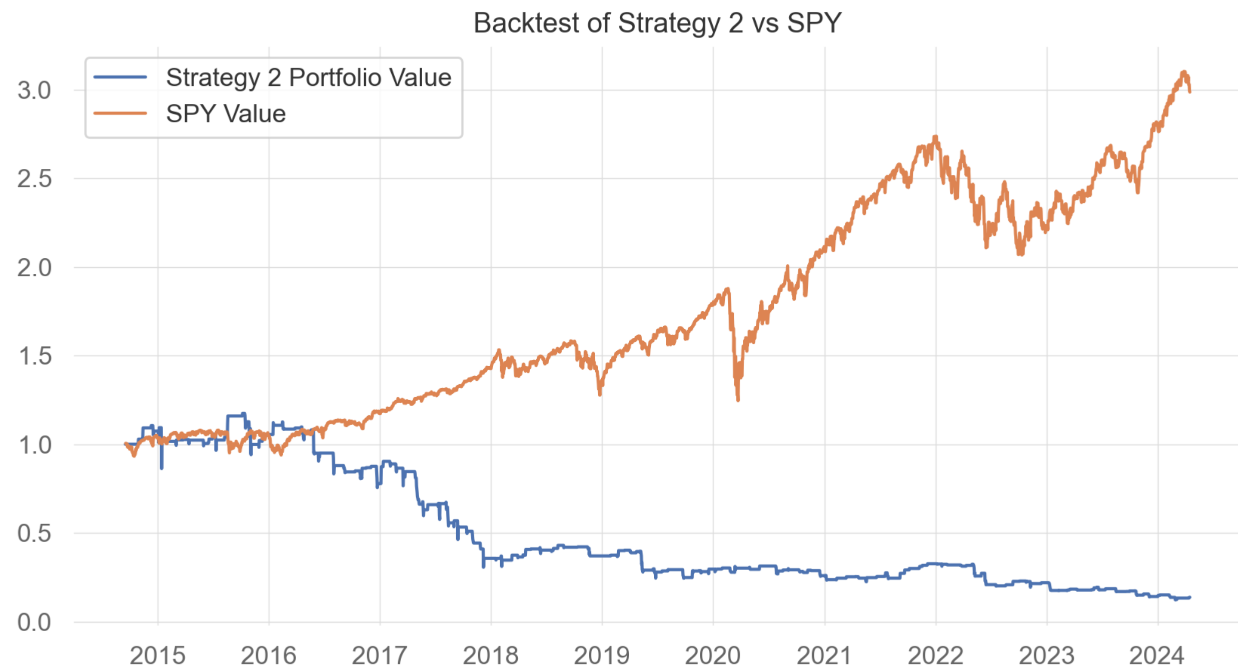

Figure 8: Backtest of Strategy 2 vs SPY

Strategy 2, which employs a mean reversion approach using Bollinger Bands, exhibits subpar performance in recent years, warranting a detailed examination of potential underlying factors contributing to its lackluster results.

One plausible explanation for the underperformance of Strategy 2 lies in shifts within the market environment. The strategy relies on the assumption that stock prices will revert to their mean following deviations beyond the Bollinger Bands. However, changes in market dynamics, such as alterations in investor sentiment, shifts in market structure, or variations in macroeconomic conditions, may have rendered this mean reversion principle less effective in recent years.

Moreover, there exists a possibility of overfitting during the strategy development process. While the strategy may have demonstrated favorable results during backtesting using historical data, it may lack robustness when exposed to unseen market conditions. Overfitting occurs when the strategy is excessively tailored to historical data patterns, leading to a lack of generalizability and poor performance in real-world scenarios.

Finally, the absence of robust risk management measures may exacerbate the poor performance of Strategy 2. Failure to implement adequate risk controls, such as stop-loss mechanisms, position sizing strategies, or portfolio diversification techniques, could expose the portfolio to excessive downside risk, resulting in significant drawdowns during adverse market conditions.

In conclusion, the suboptimal performance of Strategy 2 can be attributed to a confluence of factors, including shifts in market dynamics, concerns of overfitting, transaction costs and market frictions, data quality issues, and deficiencies in risk management practices. A comprehensive understanding of these factors is essential for refining the strategy and enhancing its robustness in varying market conditions.

3 Conclusion

This paper has thoroughly examined the evolving relationship between Bitcoin and the semiconductor sector, alongside its correlation with major stock market indices like the S&P 500 and NASDAQ, over a decade spanning 2014 to 2024. Our findings elucidate a significant transformation in Bitcoin's role in the financial markets—from an initial hedge against market downturns to a positively correlated asset with major market indices, with correlation coefficients notably exceeding 0.7 in the period from 2022 to 2024. This paradigm shift suggests that Bitcoin's behavior in the financial markets is more reflective of broader economic trends rather than acting as a countercyclical asset. The robust correlation with the semiconductor sector underscores the potential of Bitcoin to serve as a predictive tool for movements within this industry, influenced heavily by technological advancements and Bitcoin's own demand dynamics.

The study also explored the application of Bollinger Bands and Average True Range (ATR) as mechanisms to generate actionable trading signals, driven by the price volatility of Bitcoin. The momentum-based strategy utilizing these indicators proved effective during market downturns, capitalizing on the high volatility and directional momentum of Bitcoin to align with significant market movements. In contrast, the mean reversion strategy highlighted some of the challenges faced in volatile markets, such as cryptocurrencies and semiconductors, where predicting mean reversion points proved complex and was exacerbated by recent shifts in market dynamics.

The empirical analysis provided a nuanced understanding of the interplay between Bitcoin's price movements and stock market behavior, particularly within the semiconductor industry. The findings indicate that significant market movements in Bitcoin over weekends have a tangible impact on semiconductor stocks at market opening on Mondays, revealing a lagged yet pronounced correlation that could influence trading strategies and risk management practices. This suggests a need for investors and portfolio managers to remain vigilant to the cryptocurrency market movements even outside traditional stock market operating hours.

Looking forward, the research suggests several areas for further exploration and refinement. Firstly, improving the mean reversion strategy by incorporating more dynamic and adaptive threshold settings could potentially enhance its responsiveness to sudden market changes. Secondly, a deeper investigation into the causative factors behind Bitcoin's correlation with market indices could offer insights into underlying economic drivers or externalities affecting these relationships. Additionally, expanding the dataset to include a broader range of technology and financial assets may provide a more comprehensive understanding of the market dynamics at play. Lastly, integrating more sophisticated risk management tools and techniques could help mitigate potential losses during periods of high volatility and market downturns, ensuring more stable returns on investment.

In conclusion, this study not only advances our understanding of Bitcoin's integration into the financial ecosystem but also highlights the importance of adaptive strategies in an increasingly interconnected and digital financial landscape. As Bitcoin continues to mature and its market behavior becomes more intricately linked with traditional financial markets, the insights derived from such research will be crucial for developing robust investment strategies that can withstand the complexities of modern financial systems.

4 Appendix

```
import numpy as np
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
import pandas_datareader as pdr
import quantstats as qs
import scipy.optimize as sco
from scipy.optimize import minimize
from scipy import stats
from scipy.signal import correlate
from scipy.stats import pearsonr

%config InlineBackend.figure_format = 'retina'

tickers = [
"NVDA", "TSM", "AVGO", "ASML", "AMD", "QCOM", "AMAT", "INTC",
    "TXN", "MU",
"LRCX", "TOELY", "ARM", "ADI", "KLAC", "APH", "NXPI", "MRVL",
    "MCHP", "IFNNY",
"TEL", "STM", "MRAAY", "MPWR", "RNECY", "FTV", "ON", "GRMN",
   "GLW", "GFS", "SPY", "QQQ", "BTC-USD"
]


start_date = '2014-09-17'
end_date = '2024-04-17'
data = yf.download(tickers, start=start_date, end=end_date)['
   Adj Close']

data

correlation_matrix = data.corr()

plt.figure(figsize=(50, 50))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='
   coolwarm', cbar=True)
plt.title('Correlation Matrix of Assets')
plt.show()

cumulative_returns = (data.pct_change() + 1).cumprod()
```

```
cumulative_returns.plot(figsize=(10, 8))
plt.title('Cumulative Returns of Stocks from 2014 to 2024')
plt.xlabel('Date')
plt.ylabel('Cumulative Returns')
plt.legend(title='Ticker', bbox_to_anchor=(1.05, 1), loc='
   upper left')
plt.show()

daily_returns = data['BTC-USD'].pct_change()

cumulative_returns = (1 + daily_returns).cumprod() - 1

plt.figure(figsize=(12, 6))
cumulative_returns.plot()
plt.title('Cumulative Returns of BTC-USD')
plt.xlabel('Date')
plt.ylabel('Cumulative Returns')
plt.grid(True)
plt.show()

filtered_btc = pd.DataFrame(data)

filtered_btc['Rolling Max'] = filtered_btc['BTC-USD'].rolling
   (window=365, min_periods=1).max()

filtered_btc['Drawdown'] = (filtered_btc['BTC-USD'] -
   filtered_btc['Rolling Max']) / filtered_btc['Rolling Max']

bear_markets = []
in_bear_market = False
bear_start = None
post_bear_market_peak = None
lowest_point = None

for date, row in filtered_btc.iterrows():

if not in_bear_market:
if post_bear_market_peak is None or row['BTC-USD'] >=
   post_bear_market_peak:
post_bear_market_peak = row['BTC-USD']
elif row['BTC-USD'] < post_bear_market_peak * 0.8:
in_bear_market = True
bear_start = date
lowest_point = row['BTC-USD']
else:
```

```
if row['BTC-USD'] < lowest_point:
lowest_point = row['BTC-USD']

if row['BTC-USD'] >= lowest_point * 1.2:
bear_markets.append((bear_start, date))
in_bear_market = False
post_bear_market_peak = row['BTC-USD']

for start, end in bear_markets:
print(f"Bear market started on {start.strftime('%Y-%m-%d')} and ended on {end.strftime('%Y-%m-%d')}")

plt.figure(figsize=(12, 6))
filtered_btc['Drawdown'].plot()
plt.title('Drawdown of BTC-USD')
plt.xlabel('Date')
plt.ylabel('Drawdown')
plt.grid(True)
plt.show()

results = pd.DataFrame(columns=['Asset', 'Correlation', 'P-Value', 'N'])

for asset in tickers[:-1]:
btc_asset_data = data[['BTC-USD', asset]].dropna()
n = len(btc_asset_data)

if n > 2:
correlation = btc_asset_data['BTC-USD'].corr(btc_asset_data[asset])
t_stat = correlation * np.sqrt((n - 2) / (1 - correlation ** 2))
p_value = stats.t.sf(np.abs(t_stat), n-2) * 2

result_row = pd.DataFrame({
  'Asset': [asset],
  'Correlation': [correlation],
  'P-Value': [p_value],
  'N': [n]
})
results = pd.concat([results, result_row], ignore_index=True)
else:
print(f"Insufficient data for asset {asset}")

```

```python
results_sorted = results.sort_values(by='Correlation', ascending=False)
print(results_sorted)

plt.figure(figsize=(15, 10))

results_sorted.set_index('Asset')['Correlation'].plot(kind='bar', color='skyblue')
plt.title('Correlation of BTC-USD with Other Assets')
plt.ylabel('Correlation Coefficient')
plt.xlabel('Assets')
plt.grid(True)
plt.show()

data_copy = data.copy()

data_copy['year'] = data_copy.index.year


num_assets = len(tickers) - 1
num_columns = 3
num_rows = (num_assets + num_columns - 1) // num_columns


fig, axes = plt.subplots(nrows=num_rows, ncols=num_columns, figsize=(20, 5 * num_rows))
axes = axes.flatten()


for i, asset in enumerate(tickers[:-1]):
if asset != 'BTC-USD':
annual_correlation = data_copy.groupby('year').apply(lambda x : x['BTC-USD'].corr(x[asset]))

ax = axes[i]
annual_correlation.plot(kind='bar', ax=ax, title=f'Annual Correlation: BTC-USD vs {asset}')
ax.set_xlabel('Year')
ax.set_ylabel('Correlation Coefficient')
else:
axes[i].axis('off')

for j in range(i + 1, len(axes)):
axes[j].axis('off')

```

```
plt.tight_layout()
plt.show()

BTC_returns = data['BTC-USD'].pct_change().dropna()

returns = data.pct_change().dropna()

betas = pd.DataFrame(columns=['Asset', 'Beta'])

for asset in tickers:
if asset != 'BTC-USD':
combined_returns = pd.DataFrame({
  'BTC-USD': BTC_returns,
  asset: returns[asset]
}).dropna()

X = sm.add_constant(combined_returns['BTC-USD'])
y = combined_returns[asset]

model = sm.OLS(y, X).fit()
beta = model.params['BTC-USD']

new_row = pd.DataFrame({'Asset': [asset], 'Beta': [beta]})
betas = pd.concat([betas, new_row], ignore_index=True)

betas_sorted = betas.sort_values(by='Beta', ascending=False)

betas_sorted

btc_prices = data['BTC-USD'].dropna()
spy_prices = data['SPY'].dropna()

common_dates = btc_prices.index.intersection(spy_prices.index
   )
btc_prices = btc_prices.loc[common_dates]
spy_prices = spy_prices.loc[common_dates]


lags = np.arange(-50, 51)
corr = correlate(btc_prices - btc_prices.mean(), spy_prices -
    spy_prices.mean(), mode='full')
corr /= np.std(btc_prices) * np.std(spy_prices) * len(
   btc_prices)
```

```python
    center = len(corr) // 2
    corr = corr[center - 50 : center + 51]

    lag_max_corr = lags[np.argmax(np.abs(corr))]

    plt.figure(figsize=(12, 6))
    plt.plot(lags, corr)
    plt.title('Cross-correlation between BTC-USD and SPY')
    plt.xlabel('Lag (days)')
    plt.ylabel('Cross-correlation')
    plt.axvline(lag_max_corr, color='red', linestyle='--', label=
       f'Max Correlation at Lag {lag_max_corr}')
    plt.legend()
    plt.grid(True)
    plt.show()

    print(f"The maximum correlation is at lag {lag_max_corr} days
       .")

    btc_prices_weekday = btc_prices.index.to_series().dt.
       dayofweek
    spy_prices_weekday = spy_prices.index.to_series().dt.
       dayofweek

    btc_friday_close = btc_prices[btc_prices_weekday == 4]
    btc_sunday_close = btc_prices.shift(-2)[btc_prices_weekday ==
        4]
    btc_weekend_change = (btc_sunday_close - btc_friday_close) /
       btc_friday_close

    spy_monday_open = spy_prices.shift(-1)[spy_prices_weekday ==
       4]
    spy_friday_close = spy_prices[spy_prices_weekday == 4]
    spy_monday_change = (spy_monday_open - spy_friday_close) /
       spy_friday_close

    btc_weekend_change = btc_weekend_change.dropna()
    spy_monday_change = spy_monday_change.dropna()

    common_dates = btc_weekend_change.index.intersection(
       spy_monday_change.index)
    btc_weekend_change = btc_weekend_change.loc[common_dates]
    spy_monday_change = spy_monday_change.loc[common_dates]

```

```
correlation_coefficient, p_value = pearsonr(
   btc_weekend_change, spy_monday_change)

print(f'Pearson correlation coefficient: {
   correlation_coefficient}')
print(f'p-value: {p_value}')


plt.figure(figsize=(10, 6))
plt.scatter(btc_weekend_change, spy_monday_change)
plt.title('Weekend BTC Change vs. Monday SPY Change')
plt.xlabel('Weekend BTC Change (%)')
plt.ylabel('Monday SPY Change (%)')
plt.grid(True)
plt.show()

halving_dates = ["2016-07-09", "2020-05-11"]

periods = {
  '1m': pd.DateOffset(months=1),
  '3m': pd.DateOffset(months=3),
  '6m': pd.DateOffset(months=6),
  '1y': pd.DateOffset(years=1)
}

returns = pd.DataFrame(columns=['Date', 'Asset', 'Period', '
   Return'])

for date in halving_dates:
for ticker in tickers:
start_price = data.loc[date:].iloc[0].get(ticker, np.nan)
for period, offset in periods.items():
end_date = pd.Timestamp(date) + offset
end_price = data.loc[:end_date].iloc[-1].get(ticker, np.nan)
if pd.notna(start_price) and pd.notna(end_price):
log_return = np.log(end_price / start_price)
results_row = pd.DataFrame({
  'Date': [date],
  'Asset': [ticker],
  'Period': [period],
  'Return': [log_return]
})
returns = pd.concat([returns, results_row], ignore_index=True
   )

```

```
    returns

    tickers = [
    "NVDA", "TSM", "AVGO", "ASML", "AMD", "QCOM", "AMAT", "INTC",
        "TXN", "MU",
    "LRCX", "TOELY", "ARM", "ADI", "KLAC", "APH", "NXPI", "MRVL",
        "MCHP", "IFNNY",
    "TEL", "STM", "MRAAY", "MPWR", "RNECY", "FTV", "ON", "GRMN",
       "GLW", "GFS", "SPY", "QQQ", "BTC-USD"
    ]

    start_date = '2014-09-17'
    end_date = '2024-04-17'

    data = yf.download(tickers, start=start_date, end=end_date)

    for ticker in tickers:

    ticker_data = data.loc[:, (slice(None), ticker)].dropna()
    ticker_data.columns = ticker_data.columns.droplevel(1)

    ticker_data['Middle Band'] = ticker_data['Adj Close'].rolling
       (window=20).mean()
    ticker_data['Upper Band'] = ticker_data['Middle Band'] + 1.96
        * ticker_data['Adj Close'].rolling(window=20).std()
    ticker_data['Lower Band'] = ticker_data['Middle Band'] - 1.96
        * ticker_data['Adj Close'].rolling(window=20).std()

    ticker_data['HL'] = ticker_data['High'] - ticker_data['Low']
    ticker_data['absHC'] = abs(ticker_data['High'] - ticker_data[
       'Adj Close'].shift())
    ticker_data['absLC'] = abs(ticker_data['Low'] - ticker_data['
       Adj Close'].shift())
    ticker_data['TR'] = ticker_data[['HL', 'absHC', 'absLC']].max
       (axis=1)
    ticker_data['ATR'] = ticker_data['TR'].rolling(window=14).
       mean()

    plt.figure(figsize=(12, 5))
    plt.title(f'Bollinger Bands for {ticker}')
    plt.plot(ticker_data['Adj Close'], label='Close Price', color
       ='blue')
    plt.plot(ticker_data['Middle Band'], label='Middle Band',
       color='black')
```

```
    plt.plot(ticker_data['Upper Band'], label='Upper Band', color
       ='red', linestyle='--')
    plt.plot(ticker_data['Lower Band'], label='Lower Band', color
       ='green', linestyle='--')
    plt.xlabel('Date')
    plt.ylabel('Price')
    plt.legend()
    plt.show()

    plt.figure(figsize=(12, 5))
    plt.title(f'Average True Range for {ticker}')
    plt.plot(ticker_data['ATR'], label='ATR', color='orange')
    plt.xlabel('Date')
    plt.ylabel('ATR')
    plt.legend()
    plt.show()
```

5 References

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