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Bitcoin cyclicality and investment strategy

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Abstract

Purpose: To investigate Bitcoin's cyclic price behavior around scheduled halving events, develop a technical-analysis-based active investment strategy tailored to these cycles, and rigorously assess its performance relative to a passive buy-and-hold benchmark.
Design/Methodology/Approach: This research employs historical daily BTC /USD price series (June 2012–May 2025), applies a suite of technical indicators to define systematic, halving-anchored entry and exit rules, and then conducts rigorous statistical evaluations to test whether Bitcoin's protocol-driven supply cycles yield reproducible, actionable investment signals.
Findings: Over thirteen overlapping sample windows, the active strategy outperforms passive BTC holding in ten, with positive "alpha" coefficients that are statistically significant at the conventional 5% level in each of those windows (and, in most cases, with p-values below 2.5%). It captures outsized gains in post-halving bull runs (e.g. 2013, 2017, 2021) and meaningfully limits drawdowns in bear phases (e.g. 2014, 2018, 2022). Equity curve simulations demonstrate compounded account growth that markedly surpasses passive returns.
Practical Implications: Crypto asset managers and individual investors can implement the halving-centric strategy using readily available charting tools and API-accessible price feeds to automate buy/sell signals, thereby enhancing return potential and mitigating drawdowns without requiring deep on-chain analytics expertise. This framework also provides a transparent risk-management overlay—leveraging predefined exit rules—that can be calibrated to varying risk tolerances and seamlessly integrated into broader multi-asset portfolios.
Originality/Value: This study is among the first to integrate Bitcoin's protocol-driven halving schedule with a multi-indicator technical framework and to validate its efficacy through extensive statistical tests over four market cycles (including the 2024 halving). It offers practitioners a replicable, data-driven strategy for navigating crypto's unique cyclical dynamics.
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INTRODUCTION

Bitcoin (BTC) has become the benchmark asset of the cryptocurrency market and a focal point in discussions about digital money and alternative investments. Since its launch in 2009, BTC has exhibited pronounced price volatility and large boom–bust cycles, which many observers link to its fixed supply schedule and, in particular, to the protocol-defined "halving" events that reduce the rate of new coin issuance approximately every four years. The first halving occurred in November 2012, followed by July 2016, May 2020, and April 2024, and each has been associated with distinct phases of appreciation and subsequent correction in BTC's price (Freeman 2025).

A growing academic literature suggests that Bitcoin's return dynamics are not always consistent with weak-form market efficiency. Studies document return predictability and momentum effects in cryptocurrency markets, indicating that past price behavior can have explanatory power for future returns (Urquhart 2016; Grobys and Sapkota 2019; Jia et al. 2022). Event-study and time-series analyses further show that halving events tend to coincide with systematic multi-year accumulation and distribution phases, in which post-halving bull markets and follow-on bear markets display relatively regular timing patterns (Fabus et al. 2024). Parallel work on technical trading rules finds that moving-average- and breakout-based strategies can generate statistically and economically significant excess returns relative to simple buy-and-hold exposure in Bitcoin and related crypto-assets (Corbet et al. 2019; Gerritsen et al. 2020). Together, these strands of evidence motivate the idea that BTC's protocol-driven supply cycle and its price dynamics may be amenable to rule-based exploitation.

The present study builds on this literature by examining whether a trading strategy explicitly anchored to Bitcoin's halving cycle and implemented through a set of technical indicators can outperform a passive BTC benchmark (Kibar et al. 2023). The objective is twofold. First, the paper characterizes BTC's historical price behavior around halving events and the associated cycles. Second, it proposes and evaluates a transparent, rule-based strategy that combines halving timing with technical signals (such as moving averages and cycle-top indicators) to determine entry and exit points, and then assesses whether this strategy generates positive and statistically significant alpha relative to buy-and-hold.

Methodologically, the analysis employs daily BTC/USD price data over multiple cycles and applies standard financial econometric tools, including regression analysis and hypothesis testing, to quantify performance differentials between the active strategy and the passive benchmark across overlapping sample windows. The study also relates the empirical findings to broader macro-financial considerations—such as monetary conditions, investor risk appetite, and the role of BTC as a scarce digital asset—thereby situating the results within both the growing academic literature on cryptocurrency markets and the practical context of portfolio management and investment strategy design (Singal 2023).

METHODS

This paper employs different theoretical tools widely used in the financial world to support or reject the idea behind the investment strategy.

Jensen's Alpha

Jensen's alpha is based on systematic risk. Any given portfolio's systematic risk can be measured by estimating the market model, which is done by regressing the portfolio's daily return on the market's daily return. The coefficient on the market return is an estimate of the beta risk of the portfolio. To calculate the risk-adjusted return of the portfolio, it is necessary to use the beta of the portfolio and the CAPM. The difference between the actual portfolio return and the calculated risk-adjusted return is a measure of the portfolio's performance relative to the market portfolio and is called Jensen's alpha. By definition, α of the market is zero. Jensen's alpha is also the vertical distance from the Security Market Line (SML) measuring the excess return for the same risk as that of the market and is given by:

$$\alpha_p = R_p - \{R_f + \beta_p[E(R_m) - R_f]\} \tag{1}$$

Where:
R_p – realized return of the investment
R_f – risk-free rate of return for the time period
R_m – realized return of the market index
β_p – beta of the portfolio of investment with respect to the chosen market index

If the period is long, it may contain different risk-free rates, in which case R_f represents the average risk-free rate. Furthermore, the returns in the equation are all realized, actual returns. The sign of α_p indicates whether the portfolio has outperformed the market. If α_p is positive, then the portfolio has outperformed the market; if α_p is negative, the portfolio has underperformed the market. Jensen's alpha is commonly used for evaluating most institutional managers, pension funds, and mutual funds. Values of alpha can be used to rank different managers and the performance of their portfolios, as well as the magnitude of underperformance or overperformance.

In this work Jensen's Alpha is used slightly differently, given that the data analyzed is from the crypto market where a Rf doesn't exist. The alpha coefficient then becomes a sort of "raw alpha", indicating whether the strategy outperformed the market, or not.

Regression Analysis

Regression analysis, both the simple and multiple forms, are used by financial analysts and portfolio managers to examine whether a variable is useful for explaining another variable. It also allows for the use of hypotheses testing to examine the strength of the relationship between the variables. The variable whose variation is being explained is referred to as the dependent variable or explained variable, typically denoted by Y. Whereas, the variable used to explain the variation of the dependent variable is known as the independent variable, denoted by X (Drake 2023b). In the current paper the dependent variable Y is the investment strategy, and the independent variable X is the benchmark, BTC. Given that there is only one independent variable, the regression analysis used is a Simple Linear Regression (SLR) and it takes the following form:

$$Y = \alpha + \beta_0 X + \varepsilon \tag{2}$$

Where:
Y – dependent variable
X – independent variable
α – Intercept
β_0 – Slope coefficient
ε – residual error

In the context of SLR, there are some concepts that play an important role in understanding and interpreting the relationship between the independent and dependent variables. These concepts are the Mean, Variance and Standard deviation.

The mean is used to calculate the average return of a financial asset or investment over a specific period. It provides a measure of the central tendency of the data. Investors and analysts use the mean return to assess the historical performance of an investment or portfolio. It helps in understanding the average gain or loss over a given time frame.

In SLR, the mean is often used to calculate the average values of the variables involved. For instance, the mean of the independent variable X and the mean of the dependent variable Y are crucial in determining the coefficients of the regression equation.

$$Mean(\bar{X}) = \frac{\sum_{i=1}^{n} x}{n} \tag{3}$$

Where:
X – variable value
n – number of periods

Variance measures the dispersion or spread of a set of financial returns around the mean. In finance, variance is used to assess the volatility or risk associated with an investment. A higher variance indicates greater price volatility, which is often associated with riskier investments. Investors and portfolio managers use variance to understand the potential fluctuations in the value of an asset. In SLR, it helps assess how much individual data points deviate from the mean of the dependent variable.

$$Variance(X) = \frac{\sum_{i=1}^{n} (X_i - \bar{X})}{n-1} \tag{4}$$

Where:
$\bar{X}$ – variable mean
X_i – variable value
n – number of periods

Standard deviation is closely related to variance and is another measure of the risk or volatility of a financial asset. It is often preferred over variance because it is expressed in the same units as the original data. Investors and analysts use standard deviation to quantify the degree of uncertainty or risk associated with an investment. A higher standard deviation implies higher risk.

$$Standard\ Deviation\ (X) = \sqrt{Var(X)} \tag{5}$$

Where:
$Var(X)$ – variance

Hypothesis testing

In regression analysis, statistical hypothesis testing is often used to assess the significance of the regression coefficients, including the intercept $\alpha$and the slope β_0. The significance of these coefficients is tested using the t-statistic and the associated p-value. The null hypothesis H_0 typically states that the coefficient is equal to zero, implying no effect, while the alternative hypothesis H_a suggests that the coefficient is different from zero. The procedure for hypothesis testing is as follows.

The first step is defining the hypotheses.

The null hypothesis is the value assumed to be true and tested for validity. In this case, the assumption is that the strategy returns are similar to the benchmark, $H_0: \alpha = 0$. The alternative hypothesis is everything that is not the null; here, that the strategy returns are different from the benchmark's, $H_a: \alpha \neq 0$.

The second step is calculating the statistics for the test and the corresponding p-value. A generic test of whether a sample mean differs from a hypothesized population mean can be written as:

$$Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \tag{6}$$

Where:
$\bar{X}$ – sample mean
μ – population mean
σ – standard deviation
n – number of samples

The p-value associated with the t-statistic (or Z-statistic in large samples) is then used to assess the statistical significance of the coefficient. A low p-value, below the chosen significance level, indicates that the coefficient is statistically significant.

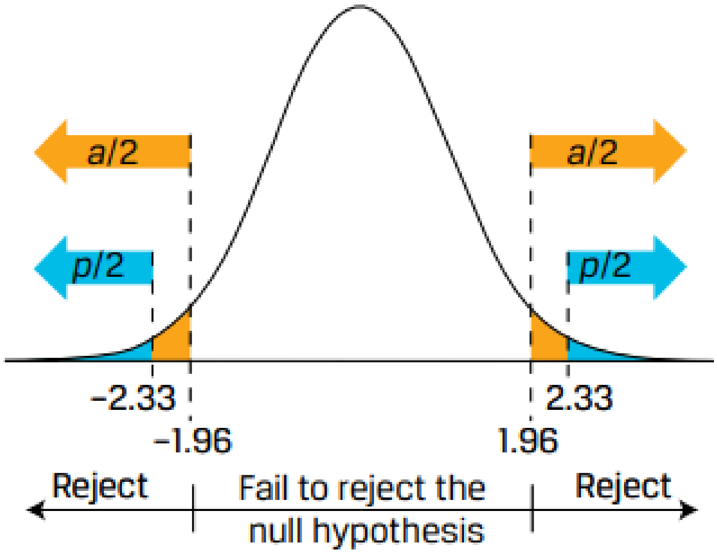
In this study, we adopt the conventional 5% significance level ($\alpha = 0.05$) for two-sided tests. Coefficients with p-values below 5% are therefore regarded as statistically significant. The 2.5% figure referred to in the analysis corresponds to the per-tail critical region ($\alpha/2$) of a two-tailed test at the 5% level, and reflects the fact that many of the estimated p-values are substantially smaller than 5%, indicating particularly strong evidence against the null hypothesis.

A similar logic applies when working with proportions, where a generic Z-test can be written as:

$$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}} \tag{7}$$

Where:
$\hat{p}$ – sample proportion
p_0 – assumed population proportion in the null hypothesis

The third step is establishing the critical values and rejection zones of H_0, taking into consideration Type I and Type II errors. Type I error is the incorrect rejection of a true H_0(false positive), and Type II error is the probability of incorrectly retaining $H_0$when it does not hold for the population (false negative). In the current case, the significance level α has been set at 5%, and since it is a two-tailed test, the critical region in each tail is $\alpha/2 = 2.5\%$.



Source: CFA 2023, Level 1, Volume 1 Quantitative methods
Figure 1. Null Hypothesis rejection

The fourth and final step is taking a decision based on the results. The critical value for rejecting H_0 will be all those observations of the intercept that are in excess of approximately two standard deviations from zero (i.e. $|t| > 1.96$ for large samples) (Drake 2023a). The p-value is used as an additional means of confirmation of this decision, but not as the sole criterion for the rejection of H_0.

Investment strategy

Active vs passive approach

There are basically two ways of approaching investments in risky assets, an active pursuit in which the investor seeks to be compensated by his exposure to risk by maximizing his return, called alpha. Under this strategy the investor will have an active role in choosing the entry and exit points of his investment, believing it is possible to outperform the benchmark. And there is a passive strategy in which the investor believes that the performance of the benchmark cannot be beaten and therefore the strategy is simple. Invest in the benchmark and do not try to generate an excess return by taking opportunities during the market cycle.

The strategy outlined hereafter seeks to take advantage of the key events that characterize the BTC market cycle and outperform the returns of a passive investment strategy.

The asset and platform

The chosen asset for this strategy is BTC paired against the US Dollar (BTC/USD). BTC is a decentralized digital currency and a pioneer in the world of cryptocurrencies. It was created in 2009 by an anonymous individual or group of individuals using the pseudonym Satoshi Nakamoto. BTC operates on a technology called blockchain, which is a distributed ledger that records all transactions across a network of computers.

BTC was created to address various shortcomings in traditional financial systems, including centralization, lack of transparency, and issues related to trust and security. It aimed to provide an open, decentralized, and secure means of transferring value and conducting transactions in a digital world. Its impact has extended beyond its initial goals, influencing not only the broader cryptocurrency and blockchain ecosystem but also financial institutions. Currently there are 25 BTC Spot ETFs worldwide, with 11 being in the US (Shen 2023).

The chosen platform was Bitstamp, for being one of the earliest and most well-established cryptocurrency exchanges in the world. But also, for having one of the most complete data sets for the BTC pair. Founded in 2011, Bitstamp has earned a reputation for reliability and security in the cryptocurrency industry. Overall, the platform has played a pivotal role in the development and maturation of the cryptocurrency market. Its commitment to security, compliance, and user experience has made it a trusted platform for buying, selling, and trading cryptocurrencies for both individual and institutional investors.

Indicators and concepts

Simple moving average (SMA)

Is a commonly used technical indicator in financial analysis that smooth price data over specific periods to identify trends. Its calculation is quite straight forward and can be calculated over different time frames. The formula is as follows:

$$SMA = \frac{\sum_{i=1}^{n} P}{n} \tag{8}$$

Where:
P – price value.
n – number of periods.

Exponential moving average (EMA)

Is another commonly used technical indicators in financial analysis, similar to the SMA. However, the key difference with the EMA, is that it gives more weight to recent price data, making it more responsive to recent price changes. The formula is as follows:

$$EMA = (P * \alpha) + (Previous\ EMA * (1 - \alpha)) \tag{9}$$

Where:
P – current price
α – smoothing factor = $\frac{2}{1+n}$
n – number of periods

Bull market support band (BMSB)

The bull market support band is an indicator that combines a 20 week SMA and a 21 week EMA. These two together create a band that has historically acted as support for the price during bull markets and as resistance during bear market (Senado 2023).

Source: Authors' data (https://www.tradingview.com/ platform)
Figure 2. BMSB

Pi cycle top indicator

This indicator has gained notoriety for indicating with days difference the highs of previous market cycles. It combines both a daily 111 SMA and a 350 SMA x2. When the 111 SMA approaches the 350 SMAx2 from below and crosses over, this signal indicates a market top (Swift 2019).

Source: Authors' data (https://www.tradingview.com/ platform)
Figure 3. Pi cycle indicator

RSI

The Relative Strength Index (RSI) is a popular technical indicator used alike in traditional assets and in cryptocurrencies. It is a momentum oscillator that measures the speed and change of price movements. The main feature of the RSI is that it can help investors identify overbought and oversold conditions in an asset, together with potential trend reversals. The formula is as follows:

$$RSI = 100 - \frac{100}{1 + RS} \tag{10}$$

Where:
RS - Relative Strength $= \frac{\text{Avg Gain}}{\text{Avg Loss}}$

Both Average Gain and Loss are calculated over a period of 14 consecutive days. Positive and negative results are summed separately and divided by 14 to obtain the RS.

The results are going to range between 0 and 100 and the way to interpret them is the following:

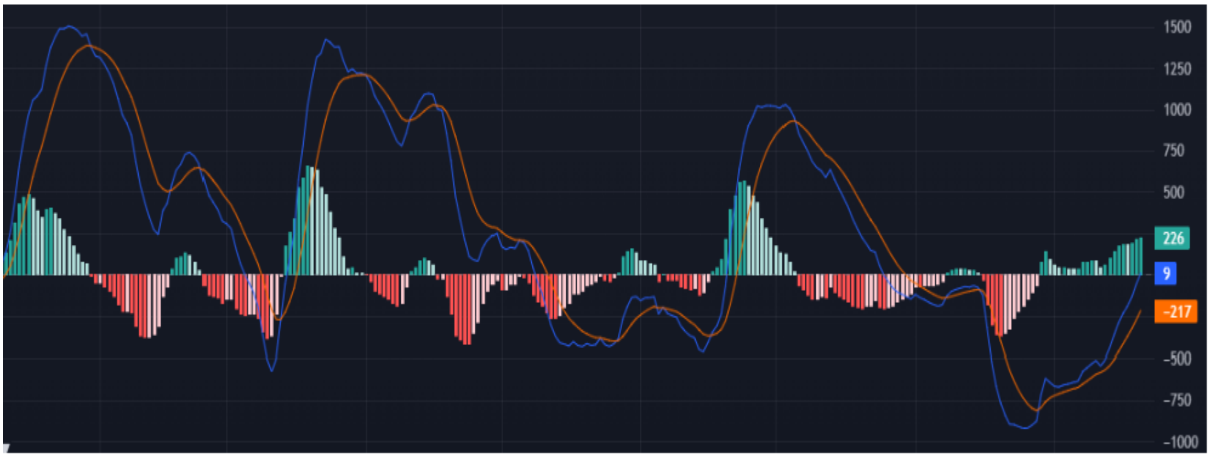
- Overbought: If the RSI is above 70 it is in the overbought region. This suggests that the asset might be overvalued and that a correction or reversal might be close.
- Oversold: If the RSI is below 30, it is in the oversold region. It suggests that the asset might be oversold and a reversal might be possible.
- Trend reversal: Besides the oversold or overbought regions, RSI can be used in conjunction with price. If divergences are forming between the price and the indicator, this might signal a bullish or bearish reversal.

Source: Authors' data (https://www.tradingview.com/ platform)
Figure 4. RSI Indicator

MACD

The Moving Average Convergence Divergence (MACD) is used in financial analysis, including stock, cryptocurrency, and other asset trading. The MACD is used to analyze the strength and direction of a price trend and to identify potential trend reversals. It consists of three main components:

- MACD Line (Blue Line): The MACD line is calculated by subtracting the 26-period EMA from the 12-period EMA. The result is plotted as a continuous line on a chart.
- Signal Line (Orange Line): The Signal line, also known as the 9-period EMA of the MACD line, is plotted on the same chart. It helps smooth out the MACD line and provides signals for potential buy or sell opportunities.
- Histogram (Bar Graph): The Histogram is the visual representation of the difference between the MACD line and the Signal line. It is plotted as vertical bars on a chart. The height of each bar represents the divergence between the two lines.



Source: Authors' data (https://www.tradingview.com/ platform)
Figure 5. MACD Indicator

The common ways to interpret the MACD are the following:

- Crossovers: When the MACD line crosses above the Signal line, it generates a bullish signal, suggesting it may be a good time to buy. Conversely, when the MACD line crosses below the Signal line, it generates a bearish signal, suggesting it may be a good time to sell.

- Histogram: The Histogram is used to visualize the momentum of a trend. When it moves above the zero line, it indicates increasing bullish momentum. When it moves below the zero line, it indicates increasing bearish momentum.
- Divergence: Traders also look for divergences between the MACD and the price. For example, if the price is making lower lows while the MACD is making higher lows, it may signal a potential bullish reversal, and vice versa.

Divergences

Divergences in the context of cryptocurrency trading refer to a situation where the price of a cryptocurrency and a technical indicator (RSI, MACD or other oscillators) move in opposite directions or show a disparity. These divergences can provide traders with important signals about potential trend reversals or shifts in market sentiment (CryptoJelleNL 2022). There are two main types of divergences in cryptocurrency trading: bullish and bearish divergences.

- Bullish Divergence: occurs when the price of an asset is making lower lows, but the technical indicator is making higher lows. This can be an early indication of a potential upward price reversal. It suggests that while the price is still in a downtrend, the momentum or strength of the downtrend is weakening, and a bullish reversal may be imminent. Bullish divergences are often seen as a buying signal.
- Bearish Divergence: occurs when the price of a cryptocurrency is making higher highs, but the technical indicator is making lower highs. This can be a warning sign of a potential downward price reversal. It suggests that although the price is still in an uptrend, the momentum or strength of the uptrend is waning, and a bearish reversal may be approaching. Bearish divergences are often seen as a selling signal.

BTC Halving event

This is not an indicator, as the previously described, but rather an event that is programmed into the BTC protocol and occurs approximately every 4 years. Every 210,000 blocks mined, the reward that miners receive is halved, making the asset scarcer. The first halving occurred in 2012 when the reward went from 50 to 25 BTCs per block. The second halving occurred in 2016, reducing the reward to 12.5 BTCs. The third halving occurred in 2020, bringing the reward down to 6.25 BTCs. The last BTC halving is due to occur around the year 2140.

This event is of importance because it is designed to mimic the scarcity of precious metals like gold. By reducing the rate at which new BTCs are created, the total supply is capped at 21 million, creating a deflationary model.

Source: Authors' data (https://www.tradingview.com/ platform)

Figure 6. Halvings

Strategy and objectives

The aim of the strategy outline here is to outperform the benchmark in the long term by utilizing a mix of signals from the indicators and concepts mentioned previously; and avoid the periods of drawdown that BTC has become famous for.

This strategy enters a long position – non-leveraged- and exits into cash according to the signals given by the indicators mentioned previously.

The Pi cycle top indicator, on a daily frequency, identifies with great accuracy the current market cycle top price, thus acting as a sell signal.

The BMSB, on a weekly frequency, acts as the trigger for entering or exiting a long position.

The market cycle bottom range is identified by a combination of signals from different indicators, that as a standalone, don't tell much. But used together give a strong signal, this is known as a confluence.

Long buy criteria

- Enter long position when price opens for two consecutive weekly candles on top of bull market support band.
- Exception to rule, open long position close to market cycle bottom given by the confluence of the following indicators:
    - Halving event must have occurred (1 every 4 years).
    - Post halving, price has closed below the BMSB (with a 2 weekly frequency)
    - Price must be below BMSB (Weekly frequency)
    - There must be over 105 weekly candles since the latest halving.
    - Divergence in MACD histogram and BTC price (Weekly frequency)
    - Weekly RSI must have bottomed out in the oversold region of 30 and higher low structure confirmed on RSI. When all previous signals are confirmed, higher low RSI executes Long Buy.

Sell Criteria

- When weekly candle price opens below BMSB.
- Pi cycle top signal has been confirmed after daily candle close.
- Back-up signal. In case the Pi cycle top signal is not triggered, the combination of the following indicators executes a sell order close to market cycle top. For this, the weekly 60 SMA and 90 EMA are used in combination with the MACD. Once the halving has occurred, the cross over of the 90 EMA on top of the 60 SMA, triggers a sell order when the MACD histogram has confirmed and closed red (or the blue line crossed beneath the orange). But this signal is only valid once per cycle. If the Pi cycle top indicator is activated, the sell order of the back-up signal is cancelled. And in case the back-up signal sell order is executed, it is retired for the remainder of the current cycle. It will only become active again after the next halving—and only if, following that halving, the 90 EMA crosses back above the 60 SMA.
- Exception to rule:
    - Long position has been opened closed to mkt cycle bottom, do not sell till Pi cycle top signal or the back-up signal.

RESULT AND DISCUSSION

From scratch to results

Although several platforms provide BTC/USD price histories, not all offer sufficiently long samples and there are discrepancies across exchanges. The first step was therefore to identify an exchange with a reliable and lengthy dataset—Bitstamp—and to write a Python script to fetch the BTC/USD OHLCV (Open, High, Low, Close, Volume) data. Days with missing OHLCV values or zero trading volume were dropped. No additional manual outlier filtering was applied: extreme returns were retained as part of the realized price history (see Annex, Figure 10, for the data-extraction script).

Once obtained the daily OHLCV for BTC data set in a .csv file, this was imported and formatted in an excel file. Within this excel file, in a new separate sheet were consolidated the date range, close and open prices, all related to the benchmark, BTC. An additional column was added to calculate the percentual gain or loss compared to the same day opening price. Immediately, next to these, three columns were added and are related to the strategy per se. The first column defines the condition "Long" vs "sold". Where value 1 represents taking a long position in the asset and 0 represents selling into cash. The second column is the result of multiplying the daily returns by either the long or sold condition; returning the exact same daily return percent as the benchmark, in the case of "Long" condition and 0 for "Sold". The last column provides the name of the key event triggering the Long or Sold. In brief, the two most important columns of this table are: the benchmark's daily returns and the strategy returns. The starting point in time for both the passive and active strategies is the 11th of June 2012 when the long signal is confirmed, and the last day of the dataset is 10th of May 2025.

Having obtained the returns for the benchmark and the strategy, the next step was performing the linear regression using the strategy daily returns as the dependent variable Y and the benchmark daily returns as the independent variable X. For this, in a separate excel sheet were added the results of the regression analysis. The first period examined was from 11th June 2012 up till 10th May 2025. After these results, subsequent regression results were added to the same excel sheet but moving the entry point to approximately 1 year after, taking the starting point as 1st of June. The second regressed period was 1st June 2013 up till dataset end. Next period was 1st June 2014 and repeating this process up till the last examined period of 1st June 2023 till 10th May 2025. The idea behind performing several regression analyses with different entry points in time, was to have an additional valuation measure as to if the results are statistical significant or not.

To obtain the accumulated results of the strategy in time - and to keep things structured - an additional sheet containing the same data as the second sheet, was created. In this sheet, the cumulative returns were calculated for both the passive approach and the active strategy. To obtain a better means of comparison the returns were calculated on a yearly basis.

Lastly, on a separate excel sheet, utilizing the open & close prices in conjunction with the key events triggering the long or sell signals, equity curves were created for the different long/sell signals. The equity curves simulate the growth of the trading account, assuming 1000 US$ were invested in each the passive and active strategy, with no other additional injection of capital. Thus, the passive strategy remains with a constant amount of BTC, determined at the moment the long is triggered; whereas the active strategy experiences a compounding effect with the different long and sell signals. In order to have a point of comparison with the active strategy, in terms of account value expressed in US$, the value of the passive account was also calculated at the date of long and sell signals.

Strategy Conclusions

The aim of this work was to explore and analyze with statistical tools if the proposed active strategy could beat the performance of the benchmark, BTC. The short answer is that the strategy is successful. Furthermore, these results align with empirical findings that Bitcoin exhibited periods of weak-form inefficiency in its earlier years, providing conditions under which rule-based active strategies can generate statistically significant excess returns (Urquhart 2016).

Regression Analysis Results

Based on the regression results, the null hypothesis stating that the average daily returns of the strategy are no different from the benchmark's is rejected in favor of the alternative hypothesis in most of the examined sample windows. For the full 6/2012–5/2025 sample, the regression explains about 57% of the variation in daily returns (adjusted $R^2 \approx 0.57$; F-statistic $\approx 6{,}188$, $p < 0.001$), and the estimated intercept α is economically and statistically significant at roughly 0.17% per day, with a 95% confidence interval of about 0.12%–0.23% (Annex Table 8). Table 1 reports 13 overlapping regressions, with start dates from June 2012 through June 2024 and a common end date in May 2025. Under conventional OLS inference, the estimated intercept α is positive and statistically significant at the 5% level in 10 of the first 11 windows (6/2012–5/2025 through 6/2022–5/2025), with t-statistics comfortably above the 1.96 threshold and very small p-values (typically below 1%). In the short 6/2021–5/2025 window α remains positive but is not significant at conventional levels, reflecting the reduced number of observations in this subsample. The final two windows (6/2023–5/2025 and 6/2024–5/2025) are also included in Table 1 for transparency. In these most recent periods the strategy and benchmark returns are almost perfectly collinear, so the regression is numerically ill-conditioned: the estimated α is extremely close to zero and the resulting test statistics are not economically meaningful. Rather than omitting these subsamples, they are reported explicitly in Table 1 and Annex Tables 19–20, with standard errors and confidence intervals suppressed and interpreted with caution.

Because the regression windows are overlapping, the estimated α coefficients across the 13 subsamples are not statistically independent. Sequential windows share a large proportion of observations, which induces dependence among their test statistics. For this reason, the overlapping OLS results in Table 1 should be interpreted as descriptive evidence of persistence rather than as a series of independent hypothesis tests. To complement these overlapping regressions with a non-overlapping robustness check, a walk-forward out-of-sample validation is also performed, where each test window uses only data not included in the corresponding training window.

Table 1. Regression results

Period	Coefficient α	Standard Error	t Stat >2	P-value < 2.5%
6/2012 - 5/2025	0.00175	0.000299	5.85111	0.00000001
6/2013 - 5/2025	0.00149	0.000288	5.15492	0.00000026
6/2014 - 5/2025	0.00128	0.000269	4.74974	0.00000211
6/2015 - 5/2025	0.00122	0.000271	4.49184	0.00000728
6/2016 - 5/2025	0.00131	0.000298	4.40390	0.00001097
6/2017 - 5/2025	0.00135	0.000329	4.11187	0.00004034
6/2018 - 5/2025	0.00097	0.000309	3.14394	0.00168621
6/2019 - 5/2025	0.00075	0.000311	2.42628	0.01533538
6/2020 - 5/2025	0.00102	0.000350	2.92183	0.00352306
6/2021 - 5/2025	0.00067	0.000376	1.77202	0.07660227
6/2022 - 5/2025	0.00062	0.000298	2.06180	0.03946733
6/2023 - 5/2025	0.00000	-	-	-
6/2024 - 5/2025	0.00000	-	-	-

Source: Authors' data

Note: During 6/2023–5/2025 and 6/2024–5/2025 the strategy's daily returns are almost perfectly collinear to the benchmark by construction, so the regression is numerically degenerate. In these windows α is mechanically zero and conventional standard errors, t-statistics, p-values and confidence intervals are not reported.

Residual diagnostics and robust inference

To assess whether the OLS assumptions underlying Table 1 are appropriate, residual diagnostics were conducted on the full 6/2012–5/2025 sample. The Durbin–Watson statistic for the regression residuals is 2.10, which is close to the theoretical value of 2 under no first-order autocorrelation. However, a Ljung–Box-type Q-statistic at lag 20 of 50.95 ($p \approx 2.3\times10^{-10}$) indicates that, taken jointly, the residuals exhibit statistically significant autocorrelation at higher lags. This suggests that, while there is no strong single lag-1 effect, serial dependence is present in the error structure.

Heteroskedasticity was examined using both the Breusch–Pagan and White tests. The Breusch–Pagan auxiliary regression of squared residuals on the benchmark return produces $R^2 = 0.000075$, an LM statistic of 0.35 and $p = 0.55$, so a simple linear relationship between the conditional variance and BM% is not supported. In contrast, the White test yields $R^2 = 0.938$, LM = 4424.91 with 2 degrees of freedom and $p < 0.0001$, strongly rejecting homoskedasticity in favor of a more general form of heteroskedasticity. This outcome is consistent with the well-known volatility clustering observed in Bitcoin returns and suggests that OLS standard errors are likely to be understated.

To obtain more reliable inference in the presence of both autocorrelation and heteroskedasticity, Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors were computed for the intercept α in each regression window (Annex Table 5). For the full sample (6/2012–5/2025), the OLS estimate of α is 0.00175 with a t-statistic of 5.85 ($p \approx 1\times10^{-8}$). When Newey–West HAC standard errors are used, the standard error of α increases from 0.000299 to 0.000410 and the t-statistic decreases to 4.27 ($p \approx 2\times10^{-5}$), which still represents strong statistical evidence of a positive intercept. Across the pre-2023 windows (6/2012–5/2025 through 6/2022–5/2025), α remains positive in all cases and statistically significant at the 5% level in 9 out of 11 regressions under HAC inference. The two exceptions are the very short 6/2021–5/2025 and 6/2022–5/2025 samples, where the reduced number of observations and elevated volatility make it more difficult to distinguish α from zero once serial dependence and heteroskedasticity are accounted for. Overall, the HAC results confirm that the main conclusion—a positive and economically meaningful α over the full sample and most subperiods—is robust to more stringent statistical assumptions. Viewed together, the residual diagnostics, HAC-based inference and walk-forward validation indicate that the strategy's excess returns are statistically robust in most of the examined periods, while also making clear that the evidence is sample-specific and that performance varies across market regimes. Overall, these diagnostics, combined with the well-known volatility clustering in Bitcoin returns, are consistent with the view that cryptocurrency markets are non-stationary and subject to frequent external shocks (e.g. regulatory announcements, exchange-specific incidents, and macroeconomic policy shifts), which limits the predictive stability of any single rule-based strategy. This motivates a cautious interpretation: the results provide strong historical evidence consistent with a positive α for this halving-centric strategy, rather than a guarantee of persistent arbitrage or a recommendation of the strategy as investment advice.

Out-of-sample walk-forward validation

In addition to the in-sample regressions, a simple walk-forward analysis was implemented to evaluate the strategy's performance in a genuinely out-of-sample setting. Using the June–May convention for "years", rolling 3-year windows were treated as training periods and the following June–May year as a test period. This procedure yields ten non-overlapping test windows from 2014–2015 up to 2023–2024 (see Annex Table 6). The trading rules themselves are fixed ex ante; the walk-forward split is simply a way of asking how the strategy would have performed if each test year had not been used in calibrating the model. Across these ten out-of-sample test years, the strategy delivers a positive annualized test return in nine out of ten cases. The average annualized out-of-sample return of the strategy is approximately 108.9% per year, compared with about 67.3% for the buy-and-hold benchmark over the same test windows. The largest relative gains occur in the 2017, 2018, 2020 and 2022 test years, where the strategy both amplifies major bull markets and either cushions or reverses benchmark losses. In other years, such as 2015, 2016, 2019, 2023 and 2024, the strategy closely tracks the benchmark, so it does not introduce significant negative drag when its signals are less distinctive. These walk-forward results therefore support the view that the observed outperformance is not solely an artefact of in-sample fitting to a single long window, but persists—albeit with variability—across a sequence of genuinely out-of-sample periods.

Cumulative Return Comparison

When examining the yearly cumulative returns of Benchmark versus the strategy several things can be noticed. The first one, that when BTC rallies, the strategy outperforms the returns of a passive approach, as seen from years 2013, 2017 and 2021. The second notorious is that the strategy is also effective in limiting the negative results, as observed from the results for years 2014, 2018 and 2022. The third thing that can be appreciated from the returns of the benchmark, is a cyclical pattern recurring every four years. This pattern begins with the halving event (years 2012, 2016 and 2020), continues with a bull market phase (years 2013, 2017 and 2021) and ensues with a bear market period (years 2014, 2018 and 2022).

This return behavior is consistent with evidence that momentum factors are strong and persistent drivers of cryptocurrency performance, explaining significant portions of return variation beyond market movements alone (Jia et al. 2022).

Table 2. Cumulative returns

Year	Comp. ret BM	Comp. ret Stg
2012	142.86%	142.86%
2013	5753.34%	8767.95%
2014	-61.37%	-30.23%
2015	34.39%	89.95%
2016	130.66%	130.66%
2017	1435.09%	2012.52%
2018	-72.84%	-3.60%
2019	88.80%	88.80%
2020	289.55%	289.55%
2021	59.90%	117.66%
2022	-63.88%	-23.33%
2023	154.52%	154.52%
2024	122.71%	122.71%
2025	11.93%	11.93%

Source: Authors' data

Equity Curve Analysis

The equity-curve analysis evaluates how a hypothetical trading account would have evolved under the active strategy compared with a passive BTC benchmark. Table 3 reports the end-of-period value of a USD 1,000 account invested in BTC at the start of each sample window (triggered by a "buy" signal), the corresponding benchmark end capital ("BM End capital"), the benchmark return ("BM ROI"), and the excess return generated by the strategy over the benchmark. Across all selected periods, the strategy delivers a higher terminal account value than passive holding.

These findings are consistent with prior evidence that technical, trend-following rules can be profitable in cryptocurrency markets. Empirical studies show that moving-average-based and breakout-style trading systems can generate economically meaningful abnormal returns in Bitcoin, even after accounting for transaction costs and employing robust statistical procedures such as bootstrap inference (Corbet et al. 2019; Gerritsen et al. 2020). The equity-curve results reported here align with this literature by illustrating that a halving-anchored, indicator-driven strategy can systematically outperform a simple buy-and-hold benchmark over multiple overlapping windows.

Table 3. Equity curve comparison

Period	BM End capital (in USD)	BM ROI	Strategy excess return on BM
11/6/2012 - 10/5/2025	19,125,730	1912473%	5379%
2/9/2013 - 10/5/2025	802,212	80121%	4948%
6/6/2014 - 10/5/2025	159,284	15828%	3144%
9/2/2015 - 10/5/2025	468,064	46706%	1362%
31/12/2018 - 10/5/2025	27,358	2636%	192%
16/8/2021 - 10/5/2025	2,229	123%	129%
4/4/2022 - 10/5/2025	2,258	126%	115%

Source: Authors' data

Viewed together with the regression analysis, the equity-curve evidence indicates that the strategy's returns differ from the benchmark in a statistically and economically significant way over most of the examined periods. The estimated intercepts (alphas) are generally positive and significant at conventional levels, while the equity curves show that the active strategy compounds capital more effectively than the passive benchmark. A complementary examination of yearly cumulative returns further suggests that the strategy tends to participate strongly in major BTC bull runs and to limit losses during bear phases, in line with the documented cyclical behavior of cryptocurrency markets.

At the same time, it is important to adopt a cautious interpretation of these results. The documented outperformance is conditional on the specific sample period, the chosen data source, and the particular set of modelling choices and trading rules implemented in this study. Future market regimes—characterized by different volatility, liquidity, regulatory environments, or macroeconomic conditions—may not replicate the historical patterns observed here, and strategy performance could deteriorate accordingly. Consequently, the findings are best viewed as an empirical case study of one halving-centric implementation within the broader family of technical trading strategies, rather than as evidence of persistent arbitrage opportunities or as direct investment advice.

Macroeconomic Correlations

As demonstrated by the statistical analysis, applying the active strategy during the selected period would have outperformed BTC with statistical significance. Although not related to the strategy, there is one question that deserves some consideration. Why has BTC experienced such incredible returns? While not exclusive, some of the arguments as to why BTC could have experienced such phenomenal periods of growth, are the following ones.

Market capitalization (mkt cap)

In July 2010 BTC had a mkt cap of slightly under 250,000 USD, by July 2013 it grew to 1.5 B and by the time of its first massive bull run mkt cap ascend to 13.6 B. Four years later, by the time of the second massive bull run on Dec 2017 mkt cap ascended to 320 B, only to drop to 56.4 B one year later during the bear mkt cycle. At the height of its latest bull run on Nov 2021, mkt cap reached 1.3 T USD for BTC, whereas for the remaining crypto space it amounted to 1.7 T. Current BTC mkt cap, as per the time of writing, is around 2.08 T and remaining crypto assets mkt cap amounts to 1.15 T, 3.24T combined. Whereas just to give a means of comparison, the mkt cap of Microsoft, currently the highest company by mkt cap, is of 3.42 T. Silver stands at 1.86T and Gold at 22.24 T (CompaniesMarketCap n.d.).

Table 4. Market capitalization by market

Markets by mkt cap (in Trillion USD) as of May 2025	
Global Bond (as of 2023 EOY)	140
Global Equity (as of 2023 EOY)	115
S&P 500 (as of May 2025)	49.8
Gold	22.24
Microsoft	3.43
Global crypto	3.23
Silver	1.86
BTC	2.08

Source: Authors' Data

The market cap of the S&P 500 currently stands at about 49.8 T, the global equity market is roughly

115 T (Kolchin et al. 2024) and global bond markets, as of 2023, was 140 T (Neufeld 2023).

It is important to remember that BTC is, after all, a new asset that has been in existence for only 16 years, compared to more mature markets mentioned previously. Given that BTC is an asset that is traded 24/7 and with global exposure it is essential to try to understand how global liquidity could affect the BTC price dynamics. Particularly during earlier phases when mkt cap was relatively small, and could be easily pumped by the inflow of institutional investors or private companies that decided to buy and hold BTC as part of the assets within their balance sheet (Benzinga 2023). This scenario occurred during the last cycle that saw BTC price propelled to 67,000 USD per BTC. Microstrategy (MSTR) is the top reference, currently holding over 580,250 BTC. Also equally important, is the fact that some governments hold BTC in their balance sheet and some countries, such as El Salvador and Central African Republic, have adopted BTC as legal tender currency. Recently the US established a strategic reserve of crypto assets, becoming the government with the largest quantity of BTC holdings (207,189), China follows suit with approximate holdings of 194,000 BTC and other governments are showing interest in doing the same. All of the aforementioned have a direct impact in the demand for BTC and thus have an impact in the price dynamics (Del Castillo 2023).

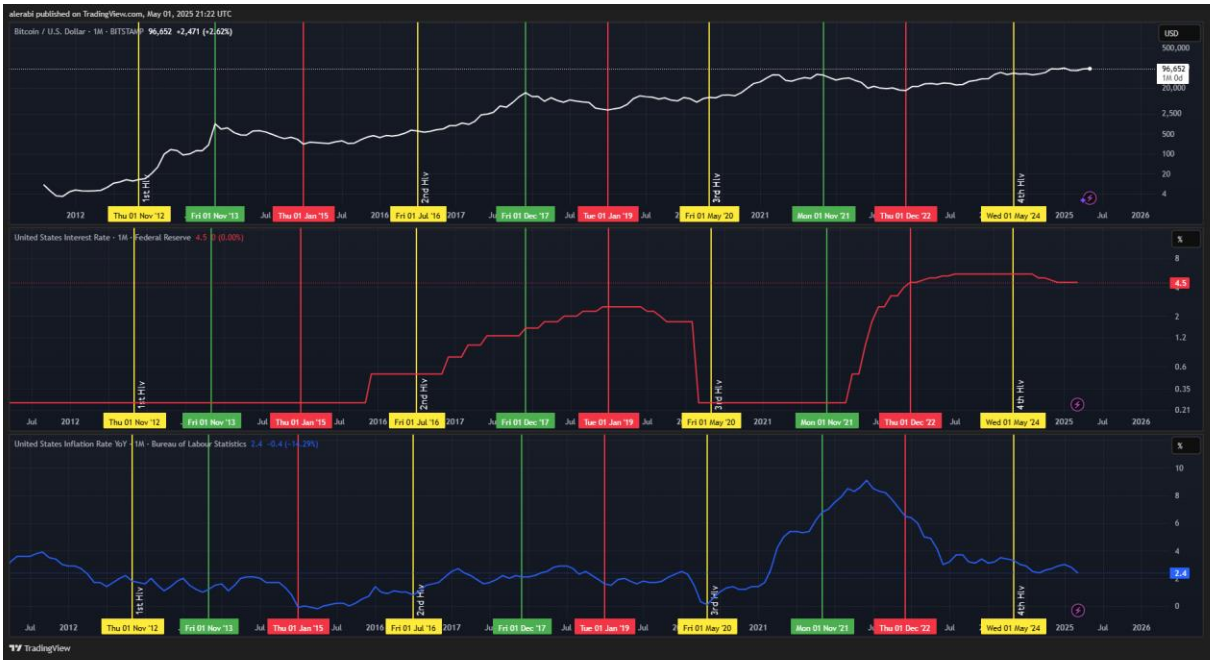
Inflation and interest rates

BTC is a consequence of the financial crisis of 2008, one of its purposes is to be a store of value and a hedge against inflation. Maybe it is a mere coincidence, but it is interesting to observe that the three bull rallies occur while inflation numbers (in the US) were on the rise and that the respective bear cycles take place while inflation numbers decrease. Another possible factor that could have contributed to BTC's growth and the bull periods, are the US Fed's interest rates and its economic impact during these periods. The growth cycles occur while interest rates are at their lowest value in decades, sub 0.5 points. Rates started going up since Nov 2016 till they plateaued at 2.5 on Dec 2018, also marking the bottom for the 2018 bear cycle. Then on Feb 2020, the Covid-19 black swan event triggered the return of low interest rates of 0.25 points. Which could have benefited institutional investors by having access to cheap money for investment purposes.

Expanding on the aforementioned, empirical studies have shown that Bitcoin exhibits time-varying inflation-hedging properties, acting as a partial hedge during periods of monetary expansion and elevated inflation uncertainty (Bouri et al. 2017).

As of time of writing, May 2025, the FED is still applying quantitative tightening but there is increasing pressure to switch towards quantitative easing. When this happens, the crypto markets might benefit from the tail wind and this might translate into appreciation of price (Trading Economics n.d.).

The figure below illustrates in a graphical sense what was happening and when. Yellow indicates the halving event, green the top of cycle and red, the bottom of it.



Source: Authors' data (https://www.tradingview.com/ platform)

Figure 7. BTC's timeline along FED's interest rate & US inflation rate

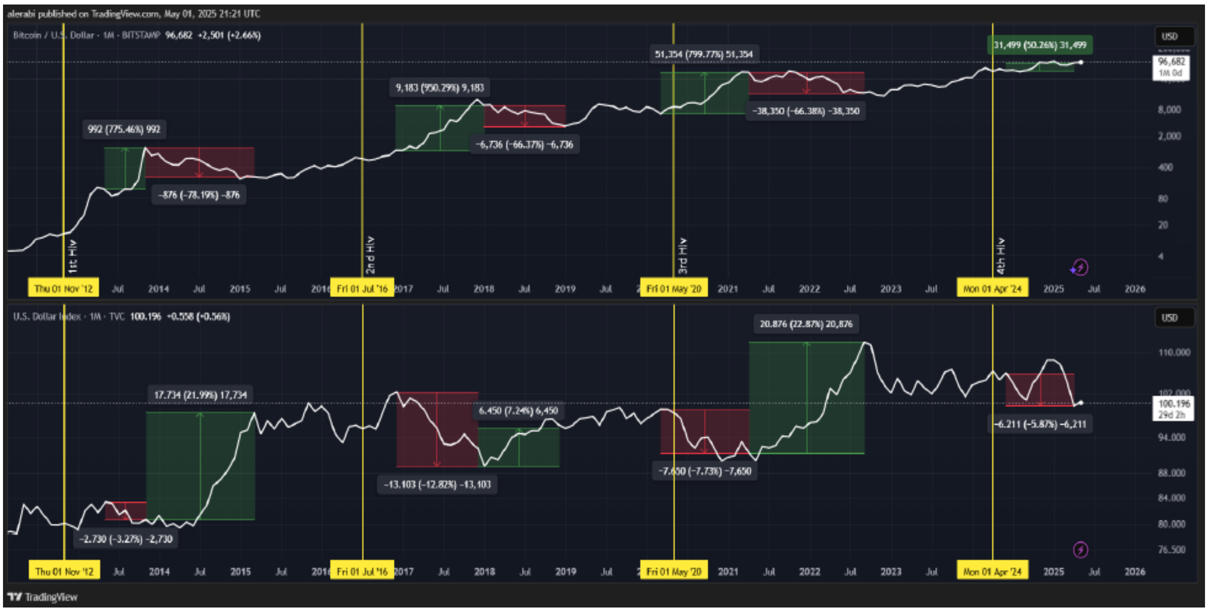
Inverse relation with the DXY U.S. Dollar Index (USDX)

Curiously enough, throughout BTC's history there has been an inverse relationship with the DXY. Whilst also occurring in other periods, this inverse relationship is not as significant as in the months following the halving event. This could well be a mere coincidence, or it could be an indicative of global economic factors. Under this premise, it is of interest studying the relationship between BTC and the DXY, given that the later factors in 7 major currencies: the US dollar, Euro, Japanese Yen, British Pound Sterling, Canadian Dollar, Swedish Krona and Swiss Franc.

At its core the index reflects the appreciation or depreciation of the US dollar versus the other major currencies in the basket, therefore its use as an economic indicator. Under this light, an inverse relation between BTC and the DXY could be explained by some of the objectives of BTC:

- Acting as a safe haven: BTC was conceived as a store of value and a form of digital gold. Inspired by the 2008 financial crisis, it was designed to act as a safe heaven during times of uncertainty when there is a lack of confidence in traditional financial markets.
- Inflation Hedge: Under an inflationary context, when there are doubts about currency devaluation and rising inflation, investors might take shelter in an asset like BTC, that has a capped supply and is not subject to central bank policies.

In line with the discussed, previous research also documents that Bitcoin tends to display a negative correlation with the U.S. Dollar Index, especially in risk-on environments, reinforcing the relevance of dollar-driven macro cycles for BTC valuation (Dyhrberg 2016).



Source: Authors' data (https://www.tradingview.com/ platform)

Figure 8. BTC-DXY inverse relation

Figure 8 illustrates the inverse relationship that has been observed between BTC and the DXY after the halving event or shortly before. The figure plots in yellow the halving event, color green and red are used to show the percentual increases or decreases for the same time window in BTC and DXY.

Halvings effect

The halving might mistakenly be overlooked as a simple event that reoccurs every four years and that just halves BTC's miners reward in half. In fact, the BTC halving is one of, if not, the most important characteristic of the asset, with profound implications for its economic model. The price fluctuations of the asset in the weeks prior and after the halving can be explained by the following:

Supply Reduction: the reward that miners receive for validating and adding new blocks to the blockchain is reduced by half. Initially, when BTC was launched in 2009, miners received 50 BTCs per block. The first halving occurred in 2012, reducing the reward to 25 BTCs. The second halving occurred in 2016, reducing it further to 12.5 BTCs. The third halving occurred in 2020, reducing the reward to 6.25 BTCs. The fourth halving occurred in 2024, reducing the reward to 3.12 BTCs This reduction in the rate of new BTC creation is designed to control its overall supply.

Scarcity and Deflationary Nature: BTC's total supply is capped at 21 million coins. By halving the reward every four years, the rate at which new BTCs are created slows down over time. This controlled issuance creates a sense of scarcity, similar to precious metals like gold. The idea is that as the supply becomes more limited, and if demand remains constant or increases, the value of each BTC could rise.

Market Perception and Speculation: Traders, investors, and the broader market pay close attention to the halving events. The anticipation of reduced new supply often leads to increased speculation about potential price increases. This heightened interest can lead to increased demand in the period leading up to and following a halving, affecting the market dynamics.

Previous empirical halving analyses also document systematic post-halving appreciation cycles, strengthening the argument that Bitcoin's issuance schedule plays a central role in shaping long-term price dynamics (Fabus et al. 2024).

In the figure below, the yellow lines mark when the halving occurred and the consecutive growth in BTC's price after the event.

Source: Authors' data (https://www.tradingview.com/ platform)
Figure 9. BTC's halvings

CONCLUSION

This study has examined whether a halving-anchored, technically driven trading strategy can outperform a passive buy-and-hold exposure to Bitcoin. Using multiple overlapping sample windows, the empirical results indicate that the proposed strategy generates positive and statistically significant alpha relative to a BTC benchmark in most periods, and that the associated equity curves display superior compounded growth. These findings suggest that Bitcoin's protocol-driven supply schedule and its cyclical price behavior can be translated into systematic trading rules with economically meaningful performance over the historical sample considered.

Beyond the strategy itself, the analysis highlights several potential drivers of BTC's long-term growth that warrant further investigation. First, questions remain about market structure and price formation, especially in Bitcoin's early years when market capitalization was low and formal regulation was limited or absent. Under such conditions, the possibility of price manipulation, including pump-and-dump dynamics, cannot be ruled out and deserves dedicated study, particularly in light of the growing influence of large institutional players and the global reach of the asset. Second, macroeconomic forces and investor sentiment appear to interact with Bitcoin's cycles: episodes of elevated inflation, shifting interest-rate regimes, and changing risk appetite may amplify or dampen BTC's performance, suggesting that macro-financial conditions are an important part of the broader narrative. Third, the halving mechanism itself may shape investors' value perceptions and expectations, potentially giving rise to recurring accumulation and distribution phases that extend beyond the immediate supply shock.

From an academic standpoint, the main contribution of this study is to document, over several overlapping windows, that a halving-anchored set of technical rules can generate positive and statistically significant alpha relative to a passive BTC benchmark, and to outline macro-financial channels—such as liquidity conditions, monetary policy regimes, and protocol-driven supply shocks—through which such patterns may arise. Importantly, the analysis is intended as a contribution to the empirical literature on Bitcoin cyclicality and investment strategies, and not as personalized investment advice.

From an institutional portfolio-management perspective, these findings are best interpreted as a case study in designing rule-based, risk-managed crypto exposures that can be slotted into diversified multi-asset portfolios, rather than as a stand-alone trading mandate. The emphasis on transparent rules, explicit drawdown control and long-horizon evaluation is also consistent with the broader sustainable-fintech agenda, in which digital-asset strategies are engineered to balance innovation with risk management, governance and investor protection.

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ANNEXES

```
# Script to fetch data from Bitstamp
import json, requests, datetime
import pandas as pd

#Parameters
currency_pair = "btcusd"
url = f"https://www.bitstamp.net/api/v2/ohlc/{currency_pair}/"

# Convert dates to Unix timestamps
start_date = pd.Timestamp("2012-03-01").timestamp()
end_date = pd.Timestamp("2025-05-10").timestamp()

step = 86400  # 1 day
limit = 1000  # max candles per API call

master_data = []
current_start = int(start_date)
while current_start < end_date:
    current_end = current_start + (step * limit)
    if current_end > end_date:
        current_end = int(end_date)

    print(f"Fetching from {datetime.datetime.utcfromtimestamp(current_start)} "
          f"to {datetime.datetime.utcfromtimestamp(current_end)}")

    params = {"step": step,
        "limit": limit,
        "start": current_start,
        "end": current_end,}

    try:
        response = requests.get(url, params=params)
        if response.status_code != 200:
            print(f"Failed at {current_start}: Status {response.status_code}")
            break
        json_data = response.json()
        ohlc = json_data.get("data", {}).get("ohlc", [])
        master_data += ohlc
    except Exception as e:
        print(f"Exception at {current_start}: {e}")
        break

    current_start = current_end
    time.sleep(1)

# Create DataFrame
df = pd.DataFrame(master_data)
df = df.drop_duplicates()
```

```
# Format date
df["timestamp"] = df["timestamp"].astype(int)
df = df.sort_values(by="timestamp")
df["date"] = pd.to_datetime(df["timestamp"], unit='s').dt.strftime("%d/%m/%Y")
# Save to Drive
output_path = '/content/drive/MyDrive/Data/BTCUSDohlcv.csv'
df.to_csv(output_path, index=False)

print('End of data fetching. Saved to:', output_path)
```

Authors' data (google colabs)

Figure 10. Python script to fetch data

```
# Script for Newey-West HAC
# Drive mount
from google.colab import drive
drive.mount('/content/drive')

import pandas as pd
import datetime as dt
import statsmodels.api as sm

# Adjust path to file directory in Drive
excel_path = "/content/drive/MyDrive/Strategy results 2025.xlsx"
# Load and clean data
raw = pd.read_excel(excel_path, sheet_name="Strat + Acc ret", header=2)
header_row = raw.iloc[0]
col_map = {
    "Benchmark (BTC)": header_row["Benchmark (BTC)"],  # Date
    "Unnamed: 2": header_row["Unnamed: 2"],            # close
    "Unnamed: 3": header_row["Unnamed: 3"],            # open
    "Unnamed: 4": header_row["Unnamed: 4"],            # BM %
    "Strategy": "Long/Sold",
    "Unnamed: 6": header_row["Unnamed: 6"],            # Strategy %
    "Unnamed: 7": header_row["Unnamed: 7"],            # Key event
}
df = raw.iloc[1:].reset_index(drop=True)
df = df.rename(columns=col_map)
df = df[["Date", "BM %", "Strategy %"]].copy()
df["Date"] = pd.to_datetime(df["Date"])
df["BM %"] = pd.to_numeric(df["BM %"], errors="coerce")
df["Strategy %"] = pd.to_numeric(df["Strategy %"], errors="coerce")
df = df.dropna()

df["Date_only"] = df["Date"].dt.date
data_start = df["Date_only"].min()
data_end = df["Date_only"].max()
print("Data from", data_start, "to", data_end, "rows:", len(df))
# Define 13 sampling periods (including 2023 & 2024)
period_specs = [
```

```
        ("6/2012 - 5/2025", dt.date(2012, 6, 1)),
        ("6/2013 - 5/2025", dt.date(2013, 6, 1)),
        ("6/2014 - 5/2025", dt.date(2014, 6, 1)),
        ("6/2015 - 5/2025", dt.date(2015, 6, 1)),
        ("6/2016 - 5/2025", dt.date(2016, 6, 1)),
        ("6/2017 - 5/2025", dt.date(2017, 6, 1)),
        ("6/2018 - 5/2025", dt.date(2018, 6, 1)),
        ("6/2019 - 5/2025", dt.date(2019, 6, 1)),
        ("6/2020 - 5/2025", dt.date(2020, 6, 1)),
        ("6/2021 - 5/2025", dt.date(2021, 6, 1)),
        ("6/2022 - 5/2025", dt.date(2022, 6, 1)),
        ("6/2023 - 5/2025", dt.date(2023, 6, 1)),
        ("6/2024 - 5/2025", dt.date(2024, 6, 1)),
    ]
    desired_end = dt.date(2025, 5, 31)
    period_end = min(data_end, desired_end)
    print("Using period end:", period_end)
    results = []
    # Loop over all 13 periods
    for label, start_cal in period_specs:
        mask_after_start = df["Date_only"] >= start_cal
        if not mask_after_start.any():
            print(f"No data for {label}, skipping.")
            continue

        actual_start = df.loc[mask_after_start, "Date_only"].min()
        mask = (df["Date_only"] >= actual_start) & (df["Date_only"] <= period_end)
        sub = df.loc[mask].copy()
        n = len(sub)
        if n < 50:
            print(f"Period {label} has only {n} rows, skipping regression.")
            results.append({
                "Period": label,
                "N": n,
                "alpha_OLS": None,
                "alpha_se_OLS": None,
                "alpha_t_OLS": None,
                "alpha_p_OLS": None,
                "alpha_HAC": None,
                "alpha_se_HAC": None,
                "alpha_t_HAC": None,
                "alpha_p_HAC": None,
            })
            continue

        y = sub["Strategy %"]
        X = sm.add_constant(sub["BM %"])
        ols = sm.OLS(y, X).fit()
```

```
    maxlags = int(n ** 0.5)
    hac = ols.get_robustcov_results(cov_type="HAC", maxlags=maxlags)
    results.append({
        "Period": label,
        "N": n,
        "alpha_OLS": float(ols.params[0]),
        "alpha_se_OLS": float(ols.bse[0]),
        "alpha_t_OLS": float(ols.tvalues[0]),
        "alpha_p_OLS": float(ols.pvalues[0]),
        "alpha_HAC": float(hac.params[0]),
        "alpha_se_HAC": float(hac.bse[0]),
        "alpha_t_HAC": float(hac.tvalues[0]),
        "alpha_p_HAC": float(hac.pvalues[0]),
    })
# Collect & save
res_df = pd.DataFrame(results)
res_df = res_df[
    [
        "Period",
        "N",
        "alpha_OLS",
        "alpha_se_OLS",
        "alpha_t_OLS",
        "alpha_p_OLS",
        "alpha_HAC",
        "alpha_se_HAC",
        "alpha_t_HAC",
        "alpha_p_HAC",
    ]
]
res_rounded = res_df.round(
    {
        "alpha_OLS": 8,
        "alpha_se_OLS": 8,
        "alpha_t_OLS": 5,
        "alpha_p_OLS": 8,
        "alpha_HAC": 8,
        "alpha_se_HAC": 8,
        "alpha_t_HAC": 5,
        "alpha_p_HAC": 8,
    }
)
print(res_rounded.to_string(index=False))
out_path = "/content/drive/MyDrive/hac_alpha_results_13_periods.csv"
res_rounded.to_csv(out_path, index=False)
print("Saved results to:", out_path)
```

Source: Authors' data (google colabs)

Figure 11. Python script for HAC test

Table 5. Newey–West HAC regression results by sample window

Period	N	α (OLS)	SE (OLS)	t (OLS)	p (OLS)	α (HAC)	SE (HAC)	t (HAC)	p (HAC)
6/2012–5/2025	4717	0.00175	0.00030	5.851	1.00×10^{-8}	0.00175	4.1×10^{-4}	4.267	2.00×10^{-5}
6/2013–5/2025	4362	0.00149	0.00029	5.155	2.60×10^{-7}	0.00149	3.5×10^{-4}	4.228	2.40×10^{-5}
6/2014–5/2025	3997	0.00128	0.00027	4.750	2.11×10^{-6}	0.00128	3.1×10^{-4}	4.117	3.90×10^{-5}
6/2015–5/2025	3632	0.00122	0.00027	4.492	7.28×10^{-6}	0.00122	3.3×10^{-4}	3.595	3.29×10^{-4}
6/2016–5/2025	3266	0.00131	0.00030	4.404	1.10×10^{-5}	0.00131	3.6×10^{-4}	3.641	2.76×10^{-4}
6/2017–5/2025	2901	0.00135	0.00033	4.112	4.03×10^{-5}	0.00135	3.7×10^{-4}	3.585	3.42×10^{-4}
6/2018–5/2025	2536	0.00097	0.00031	3.144	1.69×10^{-3}	0.00097	3.4×10^{-4}	2.838	4.57×10^{-3}
6/2019–5/2025	2171	0.00075	0.00031	2.426	1.53×10^{-2}	0.00075	3.5×10^{-4}	2.132	3.31×10^{-2}
6/2020–5/2025	1805	0.00102	0.00035	2.922	3.52×10^{-3}	0.00102	3.9×10^{-4}	2.602	9.35×10^{-3}
6/2021–5/2025	1440	0.00067	0.00038	1.772	7.66×10^{-2}	0.00067	3.7×10^{-4}	1.768	7.73×10^{-2}
6/2022–5/2025	1075	0.00062	0.00030	2.062	3.95×10^{-2}	0.00062	4.3×10^{-4}	1.402	1.61×10^{-1}

Source: Authors' data

Note: Rows for 6/2023–5/2025 and 6/2024–5/2025 are omitted from this HAC table because, in those short subsamples, the strategy and benchmark returns are nearly collinear and the regression becomes numerically ill-conditioned. The corresponding OLS coefficients and test statistics are nevertheless reported in Table 1 for completeness.

Table 6. **Walk-forward out-of-sample performance (3-year train / 1-year test, June–May years)**

Train start	Train end	Test year	N_test	Test cumulative return (strategy)	Test cumulative return (BM)	Test annualized return (strategy)	Test annualized return (BM)
2012	2014	2015	366	1.311	1.311	0.780	0.780
2013	2015	2016	365	3.598	3.598	1.867	1.867
2014	2016	2017	365	7.614	2.367	3.423	1.312
2015	2017	2018	365	1.232	0.169	0.741	0.114
2016	2018	2019	366	0.032	0.032	0.022	0.022
2017	2019	2020	365	5.323	2.942	2.573	1.578
2018	2020	2021	365	-0.036	-0.134	-0.025	-0.094
2019	2021	2022	365	0.381	-0.147	0.250	-0.104
2020	2022	2023	366	1.498	1.498	0.878	0.878
2021	2023	2024	344	0.550	0.550	0.379	0.379

Mean test annualized return (strategy) = 1.088

Mean test annualized return (benchmark) = 0.673

Share of positive test years (strategy) = 9/10

Share of positive test years (benchmark) = 8/10

Source: Authors' data

Table 7 below shows all the buy and sell signals, defined by the strategy. Note that on the sell signals, the Long/Sold is also 1, that is due to the signal confirming on the trading day end, executing the sell signal on the following day open.

Table 7. Buy and sell signals

	Benchmark + strategy returns					
	Benchmark (BTC)				Strategy	
Date	**close**	**open**	**BM %**	**Long/Sold**	**Strategy %**	**Key event**
11/6/2012	5.5	5.5	0.73%	1	0.73%	Bull mkt crossover
5/4/2013	141.8	134.7	5.29%	1	5.29%	Pi Cycle Top
2/9/2013	130.2	130.7	-0.38%	1	-0.38%	Bull mkt crossover
5/12/2013	1,023.9	1,135.0	-9.79%	1	-9.79%	Pi Cycle Top
9/6/2014	648.8	658.0	-1.39%	1	-1.39%	Bull mkt crossover
17/8/2014	496.9	523.5	-5.08%	1	-5.08%	Bull mkt crossunder
9/2/2015	220.9	223.9	-1.35%	1	-1.35%	RSI bottom
16/12/2017	19,187.8	17,478.0	9.78%	1	9.78%	Pi Cycle Top
31/12/2018	3,693.3	3,831.0	-3.60%	1	-3.60%	RSI Bottom
12/4/2021	59,831.7	59,972.3	-0.23%	1	-0.23%	Pi Cycle Top
16/8/2021	45,930.5	47,025.0	-2.33%	1	-2.33%	Bull mkt crossover
5/12/2021	49,463.2	49,240.8	0.45%	1	0.45%	Bull mkt crossunder
4/4/2022	46,598.2	46,414.9	0.39%	1	0.39%	Bull mkt crossover
10/4/2022	42,133.9	42,774.9	-1.50%	1	-1.50%	Bull mkt crossunder
29/8/2022	20,302.0	19,571.0	3.74%	1	3.74%	RSI Bottom
10/5/2025	104,809.0	102,992.0	1.76%	1	1.76%	dataset end

Source: Authors' data

Table 8. Regression results for the period June 2012 – May 2025

Regression Statistics	
Multiple R	0.7534
R Square	0.5676
Adjusted R Square	0.5675
Standard Error	0.0205
Observations	4717

ANOVA 6/2012 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.590723	2.590723	6188.022	0
Residual	4715	1.974017	0.000419		
Total	4716	4.564739			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00175	0.00030	5.85111	5.2133E-09	0.00116	0.00233	0.00116	0.00233
X Variable 1	0.56662	0.00720	78.66	0	0.55250	0.58074	0.55250	0.58074

Source: Authors' data

Table 9. Regression results for the period June 2013 – May 2025

Regression Statistics	
Multiple R	0.7822
R Square	0.6118
Adjusted R Square	0.6117
Standard Error	0.0190
Observations	4362

ANOVA 1/6/2013 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.479121	2.479121	6870.217	0
Residual	4360	1.573308	0.000361		
Total	4361	4.052428			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00149	0.00029	5.15492	2.64976E-07	0.00092	0.00205	0.00092	0.00205
X Variable 1	0.61064	0.00737	82.89	0	0.59620	0.62509	0.59620	0.62509

Source: Authors' data

Table 10. Regression results for the period June 2014 – May 2025

Regression Statistics	
Multiple R	0.8199
R Square	0.6723
Adjusted R Square	0.6722
Standard Error	0.0170
Observations	3997

ANOVA 1/6/2014 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.360475	2.360475	8195.721	0
Residual	3995	1.150612	0.000288		
Total	3996	3.511087			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00128	0.00027	4.74974	2.10827E-06	0.00075	0.00180	0.00075	0.00180
X Variable 1	0.67103	0.00741	90.53	0	0.65650	0.68556	0.65650	0.68556

Source: Authors' data

Table 11. Regression results for the period June 2015 – May 2025

Regression Statistics	
Multiple R	0.8447
R Square	0.7135
Adjusted R Square	0.7134
Standard Error	0.0163
Observations	3632

ANOVA 1/6/2015 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.408330	2.408330	9038.519	0
Residual	3630	0.967220	0.000266		
Total	3631	3.375550			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00122	0.00027	4.49184	7.28097E-06	0.00069	0.00175	0.00069	0.00175
X Variable 1	0.71226	0.00749	95.07	0	0.69757	0.72695	0.69757	0.72695

Source: Authors' data

Table 12. Regression results for the period June 2016 – May 2025

Regression Statistics	
Multiple R	0.8339
R Square	0.6953
Adjusted R Square	0.6952
Standard Error	0.0170
Observations	3266

ANOVA 1/6/2016 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.150193	2.150193	7448.660	0
Residual	3264	0.942214	0.000289		
Total	3265	3.092406			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00131	0.00030	4.40390	1.09735E-05	0.00073	0.00190	0.00073	0.00190
X Variable 1	0.69403	0.00804	86.31	0	0.67826	0.70979	0.67826	0.70979

Source: Authors' data

Table 13. Regression results for the period June 2017 – May 2025

Regression Statistics	
Multiple R	0.8175
R Square	0.6683
Adjusted R Square	0.6682
Standard Error	0.0177
Observations	2901

ANOVA 1/6/2017 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.824587	1.824587	5842.049	0
Residual	2899	0.905415	0.000312		
Total	2900	2.730002			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00135	0.00033	4.11187	4.0337E-05	0.00071	0.00200	0.00071	0.00200
X Variable 1	0.66705	0.00873	76.43	0	0.64994	0.68416	0.64994	0.68416

Source: Authors' data

Table 14. Regression results for the period June 2018 – May 2025

Regression Statistics	
Multiple R	0.8442
R Square	0.7127
Adjusted R Square	0.7126
Standard Error	0.0155
Observations	2536

ANOVA 1/6/2018 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.518074	1.518074	6287.112	0
Residual	2534	0.611855	0.000241		
Total	2535	2.129929			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00097	0.00031	3.14394	0.001686206	0.00037	0.00158	0.00037	0.00158
X Variable 1	0.71183	0.00898	79.29	0	0.69422	0.72943	0.69422	0.72943

Source: Authors' data

Table 15. Regression results for the period June 2019 – May 2025

Regression Statistics	
Multiple R	0.8763
R Square	0.7678
Adjusted R Square	0.7677
Standard Error	0.0145
Observations	2171

ANOVA 1/6/2019 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.498918	1.498918	7173.241	0
Residual	2169	0.453234	0.000209		
Total	2170	1.952152			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00075	0.00031	2.42628	0.015335382	0.00014	0.00136	0.00014	0.00136
X Variable 1	0.76721	0.00906	84.69	0	0.74944	0.78497	0.74944	0.78497

Source: Authors' data

Table 16. Regression results for the period June 2020 – May 2025

Regression Statistics	
Multiple R	0.8218
R Square	0.6754
Adjusted R Square	0.6752
Standard Error	0.0149
Observations	1805

ANOVA 1/6/2020 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.828433	0.828433	3751.438	0
Residual	1803	0.398158	0.000221		
Total	1804	1.226591			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00102	0.00035	2.92183	0.003523064	0.00034	0.00171	0.00034	0.00171
X Variable 1	0.67444	0.01101	61.25	0	0.65285	0.69604	0.65285	0.69604

Source: Authors' data

Table 17. Regression results for the period June 2021 – May 2025

Regression Statistics	
Multiple R	0.8045
R Square	0.6473
Adjusted R Square	0.6470
Standard Error	0.0142
Observations	1440

ANOVA 1/6/2021 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.535521	0.535521	2638.808	0
Residual	1438	0.291829	0.000203		
Total	1439	0.827350			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00067	0.00038	1.77202	0.076602273	-0.00007	0.00140	-0.00007	0.00140
X Variable 1	0.64687	0.01259	51.37	0	0.62217	0.67157	0.62217	0.67157

Source: Authors' data

Table 18. Regression results for the period June 2022 – May 2025

Regression Statistics	
Multiple R	0.9216
R Square	0.8494
Adjusted R Square	0.8492
Standard Error	0.0098
Observations	1075

ANOVA 1/6/2022 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.577390	0.577390	6049.540	0
Residual	1073	0.102411	0.000095		
Total	1074	0.679801			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.00062	0.00030	2.06180	0.039467333	0.00003	0.00120	0.00003	0.00120
X Variable 1	0.84837	0.01091	77.78	0	0.82697	0.86977	0.82697	0.86977

Source: Authors' data

Table 19. Regression results for the period June 2023 – May 2025

Regression Statistics	
Multiple R	1
R Square	1
Adjusted R Square	1
Standard Error	0
Observations	710

ANOVA 1/6/2023 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.474147869	0.474147869	-	-
Residual	708	2.36968E-32	3.34701E-35		
Total	709	0.474147869			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0	-	-	-	-	-	-	-
X Variable 1	1	-	-	-	-	-	-	-

Source: Authors' data

Table 20. Regression results for the period June 2024 – May 2025

Regression Statistics	
Multiple R	1
R Square	1
Adjusted R Square	1
Standard Error	0
Observations	344

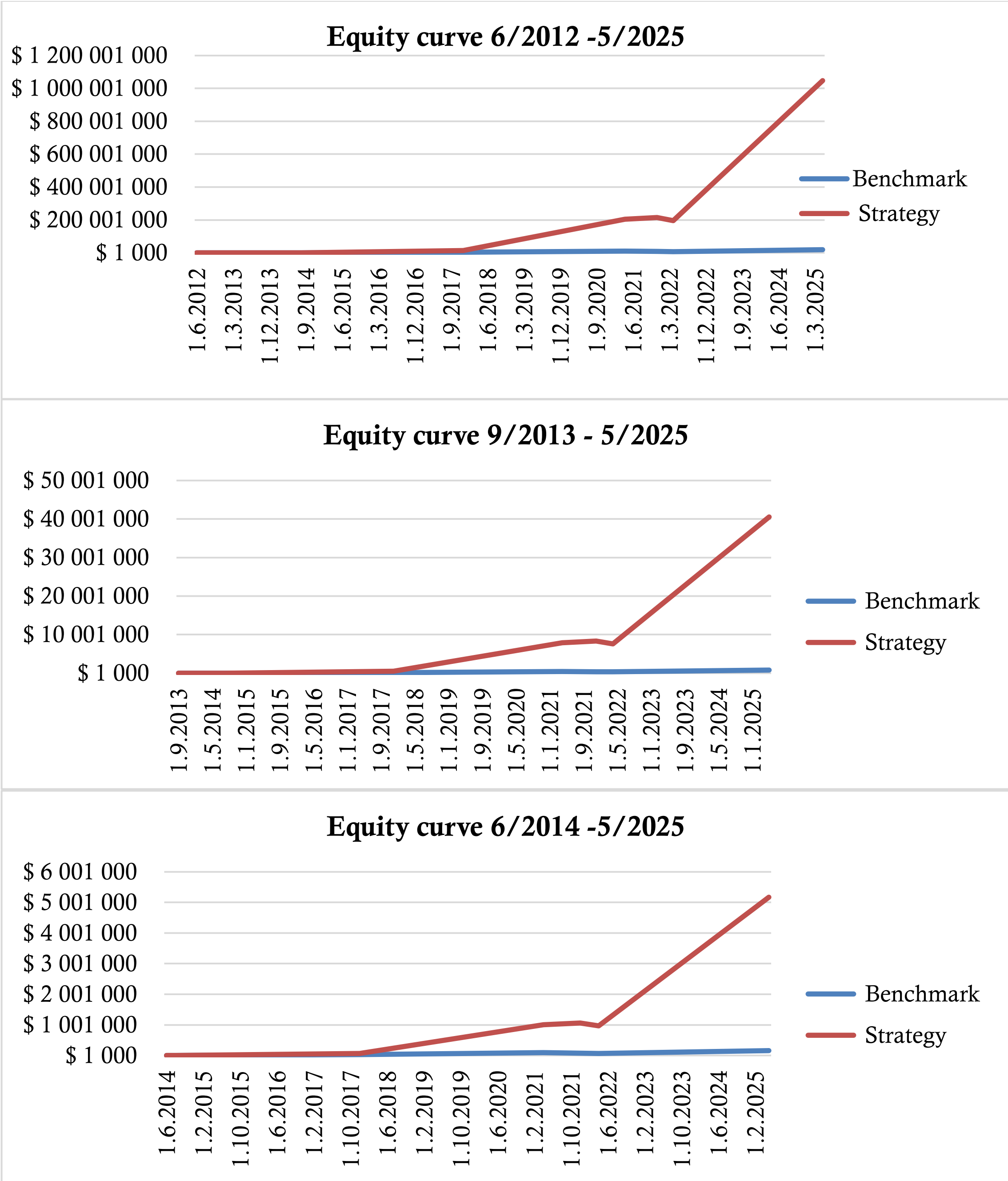
ANOVA 1/6/2024 - 10/5/2025

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.240305728	0.240305728	-	-
Residual	342	0	0		
Total	343	0.240305728			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0	-	-	-	-	-	-	-
X Variable 1	1	-	-	-	-	-	-	-

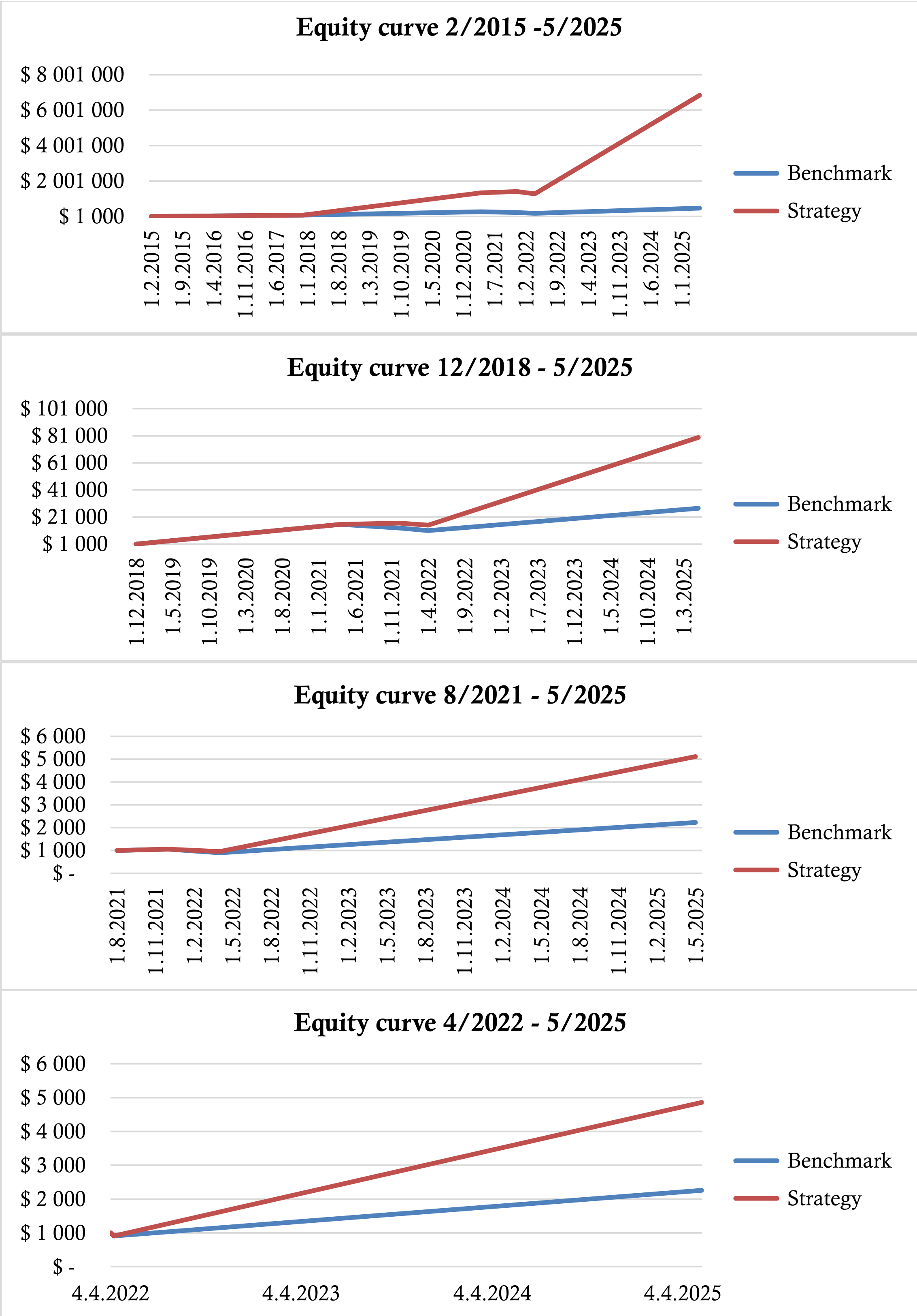
Source: Authors' data

Note: In the periods June 2023–May 2025 and June 2024–May 2025 (Tables 19 and 20), the strategy and benchmark returns are almost perfectly collinear, so the regression is degenerate. $\alpha = 0$ and $\beta = 1$ are implied mechanically; residual variance is effectively zero, and standard errors, test statistics and confidence intervals are therefore not reported.



Source: Authors' data

Figure 12. Equity curves



Source: Authors' data

Figure 13. Equity curves pt 2