Theory and Practice of Econometrics I Project

2861F

May 2025

Q4. Bitcoin Halving and the Rainbow Chart

The biggest cryptocurrency, Bitcoin (BTC), has two important features: a fixed supply and decreasing block rewards, which occur about every four years. This periodic decrease in the rate of Bitcoins issued into circulation is called halving. There have been four halvings to date: on 28 November 2012, 9 July 2016, 11 May 2020, and 20 April 2024. Some analysts believe that halving causes a significant increase in the price of Bitcoin, due to higher demand and the corresponding increase in value. To assess this claim empirically, you are tasked with conducting an event study of abnormal returns to BTC/USD rate around the dates of the halving events.

Plagiarism Declaration
I confirm that this is entirely my own work and has not previously been submitted for assessment, and I have read and understood the University's and Faculty's definition of Plagiarism.

Anonymisation of Work Declaration
I confirm that I have taken all reasonable steps to ensure that all submitted files for assessment have been anonymised and do not contain any identifiable information to me.

2000 words, including 4 tables, 4 figures and equations

1 Introduction

Bitcoin's halving events are widely speculated to increase its price. Empirically, I tested the above hypothesis using event study methodology, estimating expected returns using capital asset pricing models (CAPM) and constant-mean models. I find no immediate price reaction to halvings and suggest that significant post-halving price increases are better explained by regime changes linked to macroeconomic conditions.

2 Data

2.1 Data Limitations

The cryptocurrency market capitalisation series begins after the first halving, with no reliable data available for 2012.

Bitcoin prices are reported daily, whereas Treasury yields and the S&P 500 index are only available on business days. I address this mismatch by forward filling the missing values.

Measurement errors in the *crypto_cap* and *btc_cap* series introduce attenuation bias. As Bitcoin constitutes a subset of the total cryptocurrency market, instances where *btc_cap* exceeded *crypto_cap* reflected measurement errors and were corrected by setting *crypto* to zero.

Finally, discrepancies in Bitcoin closing prices across data providers (Yahoo Finance, CoinGecko, and the dataset used) indicate the presence of noise, which increases the variance of regression coefficient estimates.

Variable	Description	Source
close	Daily closing prices of Bitcoin	Moodle
btc_d	Calculated as first difference of log daily closing prices of Bitcoin	Moodle
btc_m	Calculated as first difference of log monthly closing prices of Bitcoin	Moodle
blocks	Daily number of Bitcoin blocks mined	bitcoinvisuals.com
height	Daily total number of blocks in the chain	bitcoinvisuals.com
rfr	Calculated as the implied daily rate by taking the 365^{th} root of the market yield of U.S. treasury securities at 1-month constant maturity	FRED
crypto_cap	Daily global cryptocurrency market capitalisation	coingecko.com
btc_cap	Daily Bitcoin market capitalisation	coingecko.com
crypto	Calculated as first difference of log $(crypto\_cap_t - btc\_cap_t)$	Author
sp500	Calculated as first difference of log daily closing prices of the S&P 500 index	investing.com
spgsci	Calculated as first difference of log monthly S&P Goldman Sachs Commodity Index	investing.com
vix	Monthly CBOE Volatility Index	FRED
usd	Calculated as first difference of log monthly Nominal Broad U.S. Dollar Index	FRED
gepu	Calculated as first difference of log monthly Global Economic Policy Uncertainty Index	GEPU

Table 1: Data Description

3 Methodology

According to the semi-strong form of the efficient market hypothesis (EMH), prices should reflect all publicly available information (Fama, 1970). Hence, under the semi-strong form of EMH, predictable halving events should not generate any abnormal returns. Otherwise, market participants could preempt halving-induced price increases by buying in advance. Thus, significant price increases resulting from predictable halvings necessarily imply violation of the semi-strong form of EMH.

Alternatively, if halving events are unpredictable ex-ante, Bitcoin's price could be significantly affected by the halving. Under EMH, the price response should be immediate. If Bitcoin markets were inefficient, market participants may be slow to act upon the information, and price changes would be observed with a lag.

Under the null hypothesis that halving does not affect the price of Bitcoin, cumulative abnormal returns (CAR) should not be statistically significant. However, if significant CAR are observed, and given that halving dates are known in advance, EMH and the null hypothesis may only be consistent if the returns are attributable to confounding events or represent statistical coincidence.

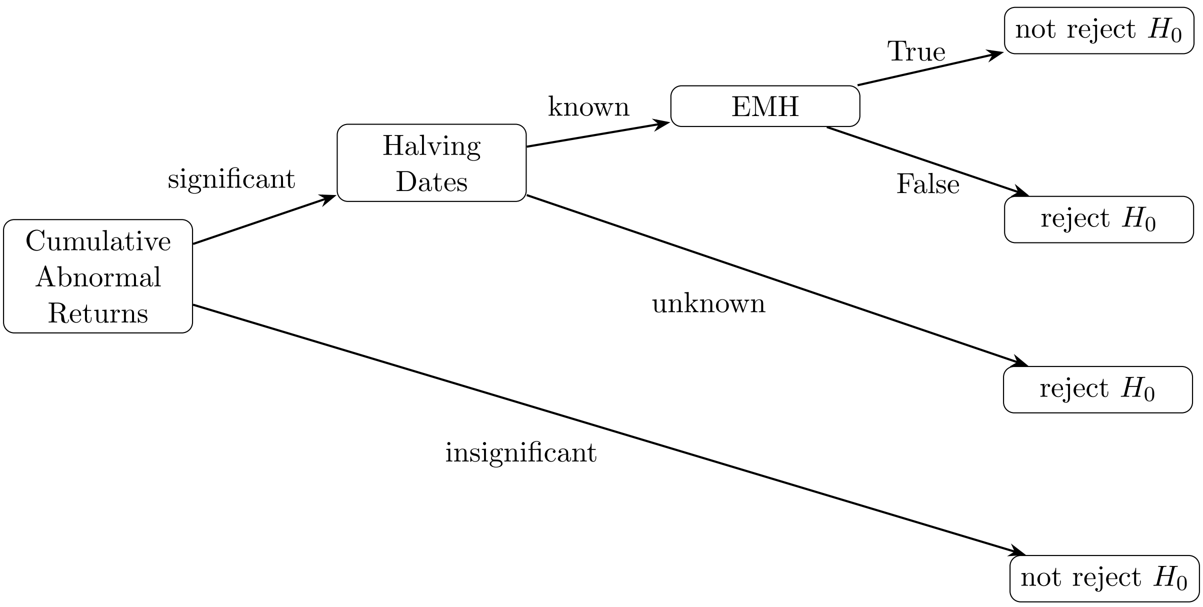


Figure 1: Hypothesis Testing Procedure

3.1 Predicting Halving Dates

The expected number of days until the next Bitcoin halving was calculated by dividing the number of blocks remaining until the next halving by the 100-day rolling average of blocks mined:

$$\mathbb{E}[Days] = \frac{210000 - height_t \bmod 210000}{\frac{1}{100}\sum_{i=0}^{99} blocks_{t-i}}$$

The prediction errors were calculated by subtracting $\mathbb{E}[Days]$ from the actual days until halving. Prediction errors were plotted against days to halving. Low variance and mean-zero prediction errors would indicate high predictability.

3.2 Testing EMH

The weak form of EMH was evaluated using the Augmented Dickey-Fuller (ADF) test with lags selected by minimising the Akaike Information Criterion (AIC). Rejection of the unit root null indicates stationarity in Bitcoin prices, violating the weak, and by extension, the semi-strong form of EMH. However, it is worth noting that the semi-strong form may fail even if the weak form holds.

3.3 Modelling Cumulative Abnormal Returns

3.3.1 Estimation, Event, and Post-Event Windows

I employed the event study methodology outlined by MacKinlay (1997) to examine the effects of halving events on Bitcoin's price. An estimation window prior to the event was used to model expected returns $\mathbb{E}[btc\_d]$ using CAPM or a constant-mean model. A post-event window was included to allow for market inefficiencies, where the market has a delayed reaction. Calculation of CAR follows the equation below, where n represents the length of the window.

$$CAR = \sum_{i=0}^{n-1} btc\_d_{t+i} - \mathbb{E}[btc\_d_{t+i}]$$

Event windows last for 5 days, centred on the halving event. Estimation windows span 180 days and end right before the event window, ensuring no overlap. Meynkhard (2019) suggested that the market requires an interim period of 5 months for the onset of reactions to halving, and 17 months until the market reacts fully. Therefore, two post-event windows were set up after the event window. They are 160 and 550 days long, to capture both the proposed onset of reactions, and the full reaction.

3.3.2 Model Selection

Three models were considered to estimate expected returns in the estimation window. The models are specified as follows and estimated using ordinary least squares (OLS):

1. **Constant Mean**

$$btc\_d_t = \alpha + u_t$$

2. **CAPM (Cryptocurrency Index as Market Proxy)**

$$btc\_d_t - rfr_t = \beta_c \left(crypto_t - rfr_t\right) + u_t$$

3. **CAPM (S&P 500 Index as Market Proxy)**

$$btc\_d_t - rfr_t = \beta_s \left(sp500_t - rfr_t\right) + u_t$$

The cryptocurrency CAPM follows the specification of Dunbar and Owusu-Amoako (2022), excluding Bitcoin to avoid endogeneity.

The S&P 500 CAPM serves as a complementary benchmark, given the considerable noise in the *crypto* series and the absence of reliable data for the first halving.

Heteroskedasticity and serial correlation were tested; robust (HAC) standard errors were applied where necessary. Models with insignificant β were rejected for that halving.

Following Liu (2024), the applicability of the CAPM models was further assessed by estimating the regression with an intercept and testing its significance. CAPM models with significant intercepts were also rejected for that halving. If both CAPMs were rejected, then the constant mean model was selected to forecast expected returns for that halving period.

3.3.3 Statistical Inference

For post-event windows, statistical inference for CAR was conducted using t-tests, as justified by asymptotic normality via the Central Limit Theorem. As event-windows are short, it was instead assumed that errors follow a Gaussian white noise process where $u_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_u^2)$. This can be corroborated by Sharpiro-Wilk tests.

In both cases, the test statistic was assumed to have the following distribution under H_0:

$$\frac{\widehat{CAR}}{\sqrt{n\hat{\sigma}_u^2}} \sim t_n$$

3.4 Testing EMH-consistent CAR Explanations

Significant CAR during event and post-event windows may result from a violation of the semi-strong form of EMH. However, a plausible alternative is that halving events coincide with broader shifts in return regimes that are driven by macroeconomic conditions. It has been shown that Bitcoin exhibits clear bull, neutral, and bear markets (Bruzge *et al.*, 2024).

First, to examine whether macroeconomic variables directly explain Bitcoin returns, an ordinary least squares (OLS) regression of daily Bitcoin returns on macroeconomic variables and their lags was conducted.
The model is specified as: ($\boldsymbol{X}_t = [spgsci_t \quad vix_t \quad usd_t \quad gepu_t]$)

$$btc\_m_t = \alpha + \boldsymbol{X}_t\boldsymbol{\beta_1} + \boldsymbol{X}_{t-1}\boldsymbol{\beta_2} + \upsilon_t$$

Assuming persistent regimes, the 30-day rolling average of daily Bitcoin returns (btc_d) was used to classify the Bitcoin market into three distinct constant-mean regimes using a Markov-switching (MS) model, corresponding to a bear, neutral, and bull regime.
The MS model is specified as:

$$btc\_d_t = \mu_{S_t} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2_{S_t})$$

with regime states $S_t \in \{0, 1, 2\}$, following a 3-state first-order Markov chain:

$$\mathbb{P}(S_t = j \mid S_{t-1} = i) = p_{ij}, \quad \forall i, j \in \{0, 1, 2\}$$

Each date was assigned to the regime with the highest smoothed probability for that day. To reduce noise, regimes lasting fewer than 50 consecutive days were discarded and merged with the preceding dominant regime.

Regime dummies θ_t^i were constructed to equal 1 if that date t is of regime i. Chow tests were conducted to test the presence of structural breaks between regimes, with the 0^{th} regime as the baseline:

$$btc\_d = \alpha_0 + \alpha_1\theta_t^1 + \alpha_2\theta_t^2 + v_t$$

It has been suggested that Bitcoin regime changes may be influenced by factors such as USD strength (*usd*) and stock market volatility (*vix*) (Shih *et al.*, 2024). Global economic policy uncertainty (*gepu*), commodity indices (*spgsci*), and USD strength (*usd*) have also been identified as significant drivers of Bitcoin volatility regimes (Wang *et al.*, 2022).

In order to test this, a probit model was estimated to examine whether macroeconomic factors explain regimes in the Bitcoin market.
The probit model is specified as:

$$P(\theta_t^i = 1 \mid \boldsymbol{X}_t, \boldsymbol{X}_{t-1}) = \Phi\left(\alpha + \boldsymbol{X}_t\boldsymbol{\gamma_1} + \boldsymbol{X}_{t-1}\boldsymbol{\gamma_2}\right)$$

The probit model was tested using a likelihood ratio test. Additionally, each variable and its lag are jointly tested to assess their joint significance.

Finally, Granger-causality tests were conducted. Assuming EMH and that regimes are determined by macroeconomic factors, it is expected that x_t Granger-causes regimes but not returns, as public information should be instantly incorporated into prices.
The following model specifications are used:

$$btc\_m_t = \alpha + \phi btc\_m_{t-1} + \beta x_{t-1} + \varepsilon_t$$

$$\theta_t^i = \alpha + \phi\theta_{t-1}^i + \beta x_{t-1} + \varepsilon_t$$

4 Diagnostic Tests

Issue	Test	Model	Results	
Misspecification	Ramsey RESET	*btc_m* OLS:**	$F_{1,150} = 5.300$	$p = 0.023$
Heteroskedasticity	Breush-Pagan	Crypto CAPM (2):***	$\chi^2_1 = 7.539$	$p = 0.006$
		Crypto CAPM (3):	$\chi^2_1 = 0.063$	$p = 0.802$
		Crypto CAPM (4):	$\chi^2_1 = 0.824$	$p = 0.364$
		S&P CAPM (1):	$\chi^2_1 = 0.000$	$p = 0.986$
		S&P CAPM (2):**	$\chi^2_1 = 4.447$	$p = 0.035$
		S&P CAPM (3):***	$\chi^2_1 = 10.93$	$p = 0.001$
		S&P CAPM (4):	$\chi^2_1 = 1.921$	$p = 0.166$
		btc_m OLS:	$\chi^2_8 = 6.739$	$p = 0.565$
Heteroskedasticity	White	Crypto CAPM (2):***	$\chi^2_2 = 12.90$	$p = 0.002$
		Crypto CAPM (3):	$\chi^2_2 = 0.373$	$p = 0.830$
		Crypto CAPM (4):	$\chi^2_2 = 1.674$	$p = 0.433$
		S&P CAPM (1):	$\chi^2_2 = 1.096$	$p = 0.578$
		S&P CAPM (2):*	$\chi^2_2 = 5.346$	$p = 0.069$
		S&P CAPM (3):***	$\chi^2_2 = 37.25$	$p = 0.000$
		S&P CAPM (4):	$\chi^2_2 = 2.106$	$p = 0.349$
		btc_m OLS:	$\chi^2_{43} = 46.1$	$p = 0.384$
Serial Correlation	Ljung-Box	Crypto CAPM (2):*	$Q = 17.98$	$p = 0.055$
		Crypto CAPM (3):***	$Q = 26.52$	$p = 0.003$
		Crypto CAPM (4):	$Q = 7.801$	$p = 0.648$
		S&P CAPM (1):	$Q = 7.84$	$p = 0.644$
		S&P CAPM (2):*	$Q = 16.83$	$p = 0.078$
		S&P CAPM (3):***	$Q = 29.80$	$p = 0.001$
		S&P CAPM (4):	$Q = 9.35$	$p = 0.499$
		btc_m OLS:***	$Q = 25.81$	$p = 0.004$
Non-normality of Errors	Sharpiro-Wilk	Constant Mean (1):***	$W = 0.660$	$p = 0.000$
		Constant Mean (2):***	$W = 0.828$	$p = 0.000$
		S&P CAPM (3):***	$W = 0.749$	$p = 0.000$
		Crypto CAPM (4):***	$W = 0.964$	$p = 0.000$
Unit Roots	ADF	*close*	$\tau = -0.437$	$p = 0.904$
		*btc_d****	$\tau = -13.66$	$p = 0.000$
		*btc_m***	$\tau = -2.995$	$p = 0.035$
		$btc\_d - rfr^{***}$	$\tau = -13.66$	$p = 0.000$
		$crypto - rfr^{***}$	$\tau = -16.38$	$p = 0.000$
		$sp500 - rfr^{***}$	$\tau = -13.83$	$p = 0.000$
		$spgsci^{***}$	$\tau = -10.43$	$p = 0.000$
		vix^{***}	$\tau = -5.186$	$p = 0.000$
		usd^{***}	$\tau = -0.609$	$p = 0.000$
		$gepu^{***}$	$\tau = -10.47$	$p = 0.000$

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2: Diagnostic Table

5 Results and Discussion

5.1 Predictability of Halving Dates

Figure 2 illustrates that prediction errors converge towards zero and are consistently small, especially for later halvings. I interpret this as evidence that halving dates are highly predictable in advance and provide little informational surprise.

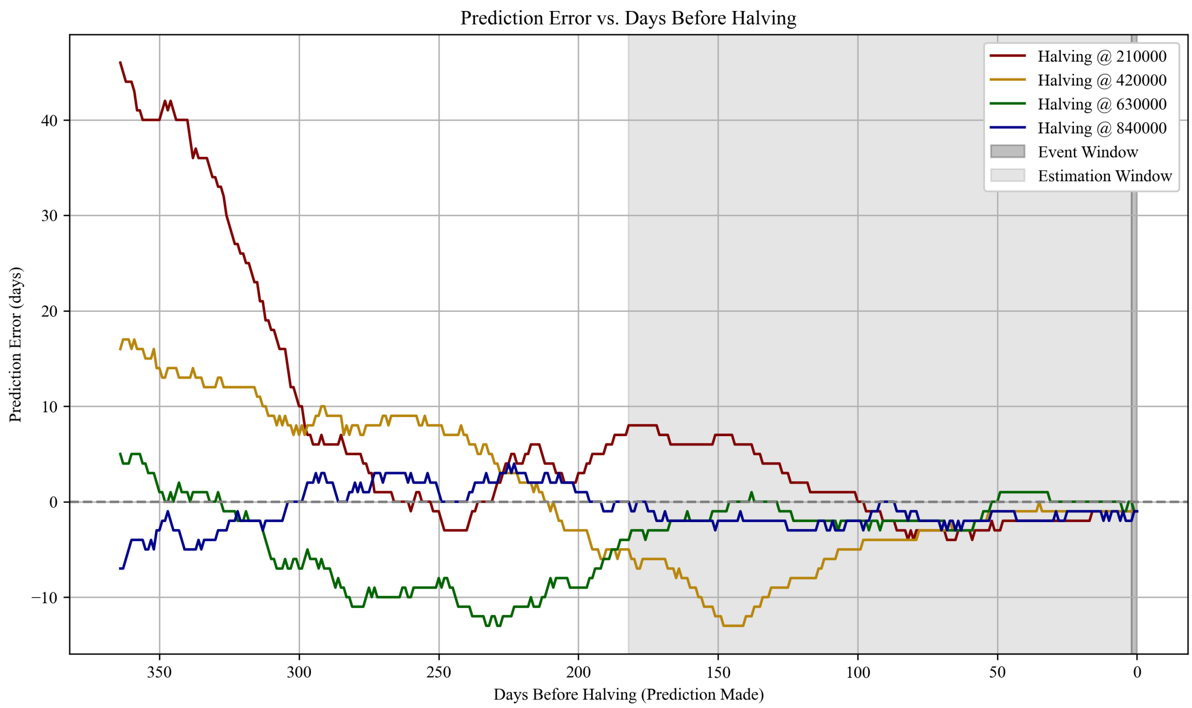


Figure 2: Halving Dates Prediction Errors

5.2 Testing EMH

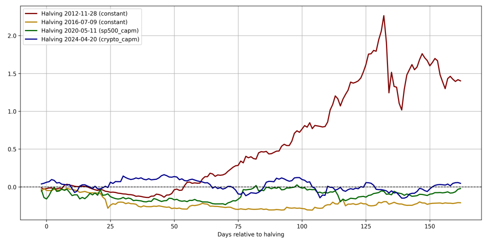
From Table 2, Bitcoin's prices follow a random walk. As such, I do not reject the weak form of EMH. However, that does not confirm the semi-strong form. EMH is notoriously hard to falsify, due to the joint hypothesis problem in accurately estimating expected returns.

5.3 Cumulative Abnormal Returns

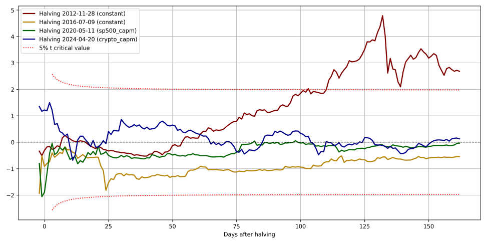
Referring to Table 3 on the next page, I selected the constant-mean model for the first two halvings, the S&P 500 CAPM for the third halving, and the cryptocurrency CAPM for the fourth halving. No models were rejected based on a significant intercept.

My findings replicate Meynkhard (2019), showing significant CAR after 5 and 17 months for the first and second halvings. However, I find no significant CAR across all post-event windows for the third and fourth halvings. For all event windows, CAR are insignificant. Despite evidence of residual non-normality in Table 2, the high excess kurtosis (exceeding 10) of the errors supports the robustness of the insignificance of CAR.

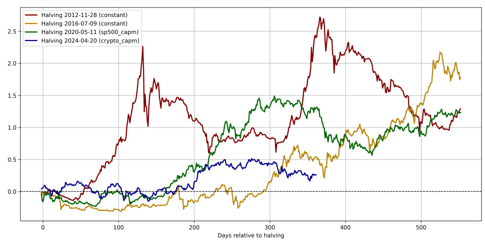
Robustness checks by varying post-event windows show significant but non-persistent CAR for the first and second halvings. The results are plotted in Figure 3.



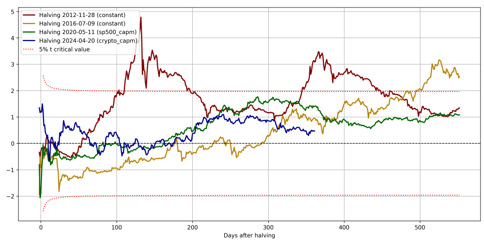
(a) CAR (160 days)



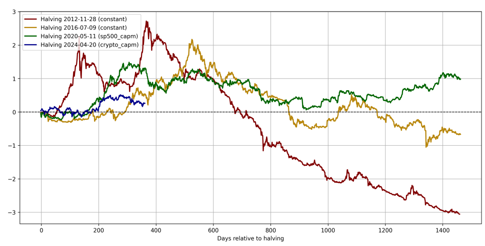
(b) t-values (160 days)



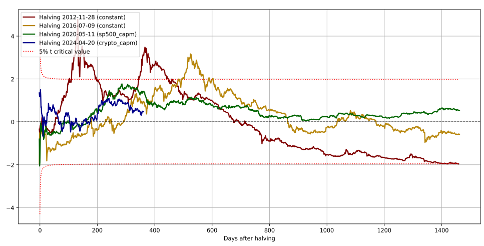
(c) CAR (550 days)



(d) t-values (550 days)



(e) CAR (1460 days)



(f) t-values (1460 days)

Note: the 4^{th} post-event window only lasts for 358 days, as *btc_d* ends on 16/4/2025.

Figure 3: Cumulative Abnormal Returns

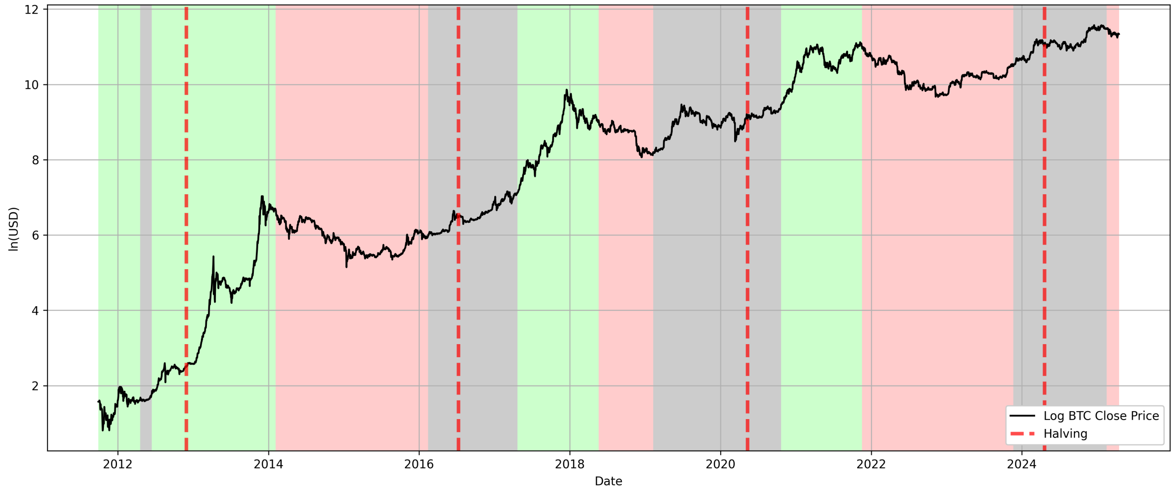
Halving	(1)	(2)	(3)	(4)
Constant Mean Model	✓	✓		
α	**0.0049**	**0.0022**	0.0004	0.0039*
	(0.003)	**(0.002)**	(0.004)	(0.002)
CAPM (Crypto)				✓
crypto-rfr	N/A	-0.0023	0.0082*	0.0762**
	N/A	(0.012)†	(0.005)†	(0.036)
Constant	N/A	0.0022	0.0004	0.0037*
	N/A	(0.002)†	(0.004)†	(0.002)
crypto-rfr	N/A	-0.0021	0.0082*	**0.0785****
	N/A	(0.0118)†	(0.0049)†	**(0.037)**
CAPM (S&P 500)			✓	
sp500-rfr	0.0148	-0.0302	0.7643**	0.2669
	(0.321)	(0.225)†	(0.296)†	(0.304)
Constant	0.0049	0.0022	0.0008	0.0036
	(0.003)	(0.002)†	(0.004)†	(0.002)
sp500-rfr	0.0753	-0.0224	**0.7636****	0.3491
	(0.320)	(0.2240)†	**(0.2980)**†	(0.301)
Cumulative Abnormal Returns with Best Model				
Event Window	-0.0147	-0.0494	-0.0472	0.0968
	(0.0911)	(0.0668)	(0.1082)	(0.0640)
Post-event Window (160 days)	1.4166***	-0.1604	0.0253	-0.0500
	(0.5151)	(0.3777)	(0.6123)	(0.3619)
Post-event Window (550 days)	1.3015	1.8291***	0.9369	0.1629
	(0.9551)	(0.7003)	(1.0823)	(0.5421)

Notes: Standard errors in parentheses, † indicates HAC errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

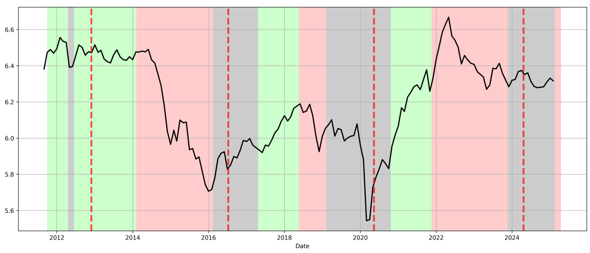
Table 3: Model Selection and CAR Significance

5.4 Regime Classification

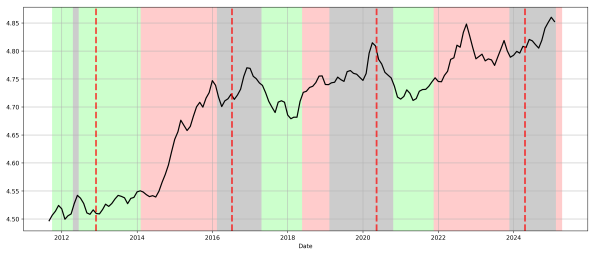
Significant CAR observed after the first and second halvings remain to be explained. Meynkhard (2019) attributed price peaks to the halving events. Although it is possible that the Bitcoin market became more efficient between the second and third halving, I propose an alternative explanation based on EMH-consistent regime switching, as shown in Figure 4.



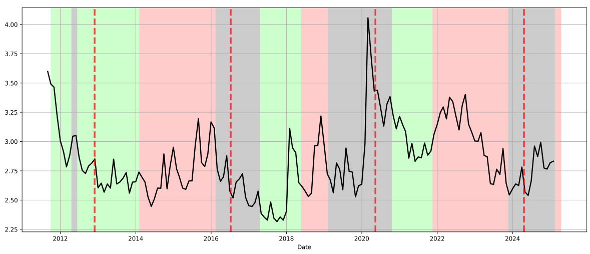
(a) Log of Bitcoin's Daily Closing Prices



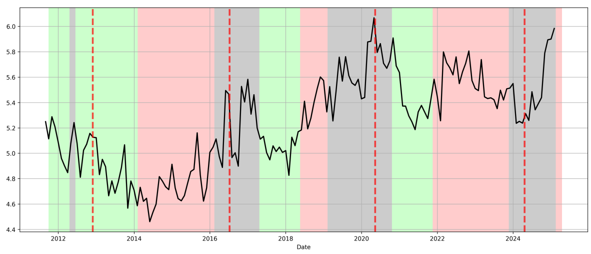
(b) Log of S&P GS Commodity Index



(c) Log of USD Index



(d) Log of CBOE Volatility Index



(e) Log of GEPU Index

Notes: The colours red, grey, and green correspond to regimes 0, 1, and 2

Figure 4: Variables with Regime Backgrounds

The results in Table 4 on the next page confirm this narrative. Chow tests confirm significant structural breaks between regimes identified by the MS model. The probit regression shows that commodity markets significantly explain bull market regimes, and macroeconomic factors jointly explain regime transitions at $p < 0.01$.

The fact that the same macroeconomic variables fail to explain monthly Bitcoin returns in the OLS model highlights the central role of regimes in accounting for significant CAR; however, this may reflect model misspecification or omitted variable bias, as shown by the RESET test.

Granger causality tests provide weak evidence of predictive relationships between macroeconomic variables and regimes or returns. Predictive power over returns could indicate a potential violation of EMH. This weakens but does not conclusively refute my hypothesis.

Nonetheless, periods of low economic uncertainty tend to coincide with bull regimes. This pattern reflects Bitcoin's role as a risky asset, with investors allocating capital during stable macroeconomic conditions, leading to both higher expected returns and higher volatility, consistent with the MS model results. Such dynamics are compatible with EMH, as abnormal returns reflect time-varying risk premia rather than market inefficiency. Significant CAR coincide with bull markets following the first and second halvings, and the lack of abnormal returns after the fourth halving is explained by the absence of a bull regime. However, the lack of abnormal returns after the third halving, despite a subsequent bull regime, remains unexplained.

6 Conclusion

I find limited empirical evidence that halving events directly increase Bitcoin's price. My analysis instead indicates that regime shifts driven by macroeconomic factors offer a more plausible explanation for significant post-event abnormal returns.

(a) MS Model Results

	coef	std err	z	P> |z|
μ_0	-0.0045***	0.000	-32.300	0.000
σ_0^2	7.527e-06***	4.35e-07	17.320	0.000
μ_1	0.0021***	0.000	17.423	0.000
σ_1^2	5.088e-06***	2.59e-07	19.680	0.000
μ_2	0.0082***	0.000	21.714	0.000
σ_2^2	0.0002***	7.21e-06	0.000	0.000

(b) Chow Test Results

	coef	std err	t	P> |t|
α_0	-0.0403	0.033	-1.216	0.226
α_1	0.1051**	0.048	2.183	0.031
α_2	0.1987***	0.048	4.168	0.000

(c) Probit Model Results / **(d) OLS Model Results**

Regime 2	(c) coef	(c) std err	(c) LR-stat	(c) p-value	(d) coef	(d) std err	(d) F-stat	(d) p-value
α	0.1242	0.695†			0.218***	0.076†		
$spgsci_t$	3.9928	2.489†	6.507**	0.039	-0.0896	0.357†	0.348	0.707
$spgsci_{t-1}$	3.8170**	1.814†			0.237	0.286†		
vix_t	-0.0481	0.039†	2.635	0.268	-0.009	0.006†	2.376*	0.096
vix_{t-1}	0.0123	0.044†			0.001	0.005†		
usd_t	-3.2080	8.557†	1.228	0.541	-2.848	1.774†	1.321	0.270
usd_{t-1}	-10.5632	10.918†			2.064	2.448†		
$gepu_t$	-0.5027	0.603†	1.664	0.435	0.062	0.123†	1.979	0.1417
$gepu_{t-1}$	-0.8834	0.607†			-0.253	0.199†		
All			22.026***	0.005			1.734*	0.095

(e) Granger Causality Test Results p-values in parentheses

spgsci Granger-cause *btc_m*?	No	(0.105)	*spgsci* Granger-cause θ^0?	No	(0.315)
vix Granger-cause *btc_m*?	Yes	(0.037)	*vix* Granger-cause θ^0?	No	(0.976)
usd Granger-cause *btc_m*?	No	(0.460)	*usd* Granger-cause θ^0?	Yes	(0.005)
gepu Granger-cause *btc_m*?	Yes	(0.022)	*gepu* Granger-cause θ^0?	No	(0.487)

Notes: † indicates HAC errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: MS Model, Chow Test, Probit, OLS, and Granger Causality Results

7 Bibliography

Literature

Bruzge, Rasa and Šapkauskienė (2024), 'Bitcoin Economics in Bull and Bear Phases.', *SSRN Electronic Journal* [Preprint].

Dunbar, K. and Owusu-Amoako, J. (2022) 'Cryptocurrency returns under empirical asset pricing', *International Review of Financial Analysis*, 82, p. 102216.

Fama, E.F. (1970) 'Efficient Capital Markets: A review of theory and empirical work', *The Journal of Finance*, 25(2), p. 383.

Liu, Y. (2024) 'Applicability analysis of cryptocurrency market based on Capital Asset Pricing Model', *Highlights in Business, Economics and Management*, 24, pp. 923–928.

MacKinlay, A.C. (1997) 'Event Studies in Economics and Finance', *Journal of Economic Literature*, Vol. 35, pp. 13–39.

Meynkhard, A. (2019) 'Fair market value of bitcoin: Halving effect', *Investment Management and Financial Innovations*, 16(4), pp. 72–85.

Shih, Y.-C., Huang, W.-T. and Hsu, P.-P. (2024) 'Bitcoin cycle through Markov regime-switching model', *IEEE ICEIB 2024*, p. 12.

Wang, J., Bouri, E. and Ma, F. (2022) 'Which factors drive bitcoin volatility: Macroeconomic, technical, or both?', *SSRN Electronic Journal* [Preprint].

Data Sources

Daily number of Bitcoin blocks mined
The total number of blocks in the chain
https://bitcoinvisuals.com/chain-height

Daily market yield on U.S. treasury securities at 1-month constant maturity
https://fred.stlouisfed.org/series/DGS1MO

Daily global cryptocurrency market capitalisation
https://www.coingecko.com/en/global-charts

Daily Bitcoin market capitalisation
https://www.coingecko.com/en/coins/bitcoin

Daily closing prices of the S&P500 index
https://uk.investing.com/indices/us-spx-500

S&P Goldman Sachs Commodity Index
https://uk.investing.com/indices/s-p-goldman-sachs-commodity-index

CBOE Volatility Index
https://fred.stlouisfed.org/series/VIXCLS

Nominal Broad U.S. Dollar Index
https://fred.stlouisfed.org/series/DTWEXBGS

Global Economic Policy Uncertainty Index
https://www.policyuncertainty.com/global_monthly.html