Why Feature Selection Still Matters in Bitcoin Return Forecasting[⋆]

Huei-Wen Teng[a,*], Yen-Ting Chen[a], Yen-Chang Lee[a]

[a]*Department of Information Management and Finance, National Yang Ming Chiao Tung University, 1001 University Road, Hsinchu, 30010, , Taiwan*

Abstract

Bitcoin's volatility and complex market drivers make return prediction a challenging task, even for advanced machine learning models such as XGBoost. While ensemble methods are often considered robust to irrelevant variables, this study demonstrates that feature selection remains essential for improving predictive performance and model interpretability. We apply a statistically grounded feature selection technique, PowerSHAP, to a rich dataset of 22 technical, macroeconomic, and market indicators spanning 2014–2023 (Verhaeghe et al, 2022). Using a rolling-window design across multiple forecast horizons, we find that applying PowerSHAP significantly reduces prediction error and enhances out-of-sample Sharpe ratios, even for XGBoost. Our results show that technical indicators and exchange rates are consistently selected as informative features, while macroeconomic variables contribute little to daily BTC return forecasts. This study highlights the continuing value of variable selection in modern machine learning pipelines, particularly for volatile financial assets like Bitcoin.

Keywords:
Bitcoin returns, Feature selection, Machine learning, XGBoost, Shapley values, Predictive modeling, Trading strategy
JEL: C45, C53, G11, G17

[⋆]This paper is supported by the National Science and Technology Council of Taiwan under Grant No. 112-2118-M-A49-001-MY2; the Higher Education Sprout Project of the Ministry of Education of Taiwan, ROC; the European Cooperation in Science & Technology COST Action grant CA19130 - Fintech and Artificial Intelligence in Finance - Towards a transparent financial industry; the project "IDA Institute of Digital Assets", CF166/15.11.2022, contract number CN760046/ 23.05.2024 financed under the Romania's National Recovery and Resilience Plan, Apel nr. PNRR-III-C9-2022-I8; and the Marie Skłodowska-Curie Actions under the European Union's Horizon Europe research and innovation program for the Industrial Doctoral Network on Digital Finance, acronym DIGITAL, Project No. 101119635.

[*]Corresponding author
Email address: `hwteng@nycu.edu.tw` (Huei-Wen Teng)

1. Introduction

Bitcoin has become an increasingly important financial asset, known for its high volatility, decentralized nature, and growing institutional adoption. The approval of spot Bitcoin Exchange-Traded Funds (ETFs) in countries such as Canada, Brazil, Australia, and European nations like Germany and Switzerland has elevated Bitcoin's accessibility to investors. Most notably, on January 10, 2024, the U.S. Securities and Exchange Commission (SEC) approved a spot Bitcoin ETF (Gensler, 2024), highlighting Bitcoin's mainstream status in global financial markets. Despite this growth, understanding and predicting Bitcoin returns remains a formidable challenge (Liu and Tsyvinski, 2021; Liu et al., 2022).

Extensive literature has explored the determinants of Bitcoin returns (Panagiotidis et al., 2018), investigating a wide range of features. Technical indicators such as MACD, RSI, CCI, and ADX have been widely used for predictive modeling (Bâra and Oprea, 2024; Orte et al., 2023; Liu and Huang, 2024). Ghosh et al. (2022) incorporate historical return structures across varying holding periods to improve prediction. Stock market indices and volatility metrics, such as the VIX and US equity uncertainty index, have also shown predictive power (Bouri et al., 2017; Zhu et al., 2017; Panagiotidis et al., 2019). On the commodity side, Catania et al. (2019) highlight the role of gold, while Salisu et al. (2023) find links between oil prices and Bitcoin dynamics.

Macroeconomic variables have also been examined. Pyo and Lee (2020) report that employment rates and the Producer Price Index (PPI) affect Bitcoin prices, while Li and Wang (2017) emphasize long-term effects of CPI and GDP. Monetary policy and exchange rates are found to play roles as well (Schilling and Uhlig, 2019; Panagiotidis et al., 2018). With the advent of natural language processing and alternative data, researchers have also turned to media sentiment and online behavior. For example, Polasik et al. (2015) and Kim et al. (2016) use Google search and forum sentiment to forecast crypto prices, while recent work by Sockin and Xiong (2023), Cong and He (2019), and King et al. (2024) study blockchain and smart contract activity as predictors.

While these studies have advanced the understanding of Bitcoin return drivers, a common limitation is the reliance on large feature sets without systematic variable filtering. Including too many features can lead to multicollinearity, overfitting, and decreased out-of-sample prediction accuracy. Although tree-based ensemble models like XGBoost are known for handling irrelevant features to some extent, recent findings suggest that feature selection still offers measurable gains in performance and interpretability (Verhaeghe et al., 2022).

To mitigate feature redundancy and improve generalization, researchers have explored a variety of feature selection approaches. Filter methods evaluate statistical properties of features independently of learning algorithms (Ferreira and Figueiredo, 2012; Sánchez-Maroño et al., 2007; Yu and Liu, 2003), while wrapper methods assess feature subsets using predictive models and search heuristics (Kabir et al., 2010; Kohavi and John, 1997; Leardi et al., 1992). Embedded methods integrate selection within the model training process itself (Battiti, 1994; Blum and Langley, 1997; Gurdgiev and O'Loughlin, 2020).

In this study, we investigate the importance of feature selection for Bitcoin return forecasting using machine learning models. Specifically, we apply *PowerSHAP*, a recently proposed wrapper method that combines Shapley value-based interpretability with statistical hypothesis testing (Verhaeghe et al., 2022). By comparing the explanatory power of each feature against randomized benchmarks, PowerSHAP selects only those features that significantly contribute to prediction. This framework is model-agnostic and helps identify stable, informative drivers of returns in a data-driven yet interpretable manner.

We apply PowerSHAP to a comprehensive dataset containing 22 features across five categories: technical indicators, macroeconomic variables, commodities, exchange rates, and stock market indexes. Using a rolling-window forecasting framework, we evaluate Bitcoin return predictions at multiple horizons (1-day, 7-day, 14-day, 28-day) and compare models trained with and without feature selection. Our analysis includes both statistical evaluation (e.g., MSPE) and economic performance (e.g., Sharpe ratio, drawdown) through a simple trading strategy.

The results highlight that feature selection remains valuable even for robust models like XGBoost. PowerSHAP-selected models consistently outperform their unfiltered counterparts in both forecast accuracy and trading outcomes. Technical indicators and exchange rates emerge as consistently informative, while macroeconomic indicators provide limited value at the daily frequency.

To summarize, this study makes three key contributions. First, it provides empirical evidence that feature selection improves predictive performance for Bitcoin returns, even when using ensemble learning algorithms. Second, it introduces PowerSHAP as a powerful, interpretable, and statistically principled selection method. Third, it identifies a stable set of return predictors with consistent explanatory value across time and forecast horizons.

The remainder of this paper is organized as follows: Section 2 outlines the PowerSHAP methodology. Section 3 describes our dataset and variable construction. Section 4 details the rolling-window experimental design and prediction framework. Section 5 reports the empirical results, while Section 6 introduces a trading strategy to demonstrate the practical value of our prediction framework. Section 7 concludes with implications and suggestions for future research.

2. Methodology: PowerSHAP Feature Selection

To enhance prediction accuracy and interpretability in forecasting Bitcoin returns, we employ *PowerSHAP*, a recent wrapper-based feature selection method that combines Shapley value explanations with formal hypothesis testing (Verhaeghe et al., 2022). The central idea is to retain only those features that consistently and significantly contribute to model predictions, relative to a baseline of random noise.

The intuition is straightforward: a meaningful feature should yield higher Shapley values — a measure of its contribution to model output — compared to an uninformative, randomly generated feature. PowerSHAP operationalizes this through a statistical testing framework and automates the selection process with a sequence of four core algorithms: `Explain`, `Core`, `Analysis`, and `Auto`. The official code and documentation are publicly available at `https://github.com/predict-idlab/PowerSHAP`.

We begin by introducing notation. Let M be the predictive model (e.g., XGBoost), trained on dataset D composed of n observations and p features. Denote the feature matrix as $F \in \mathbb{R}^{n \times p}$, with $F_j \in \mathbb{R}^n$ representing the j-th feature. Let α and β denote the false positive and false negative rates, respectively. Our goal is to select a subset of features $\mathcal{I} \subseteq \{1, \ldots, p\}$ that pass a statistical threshold for relevance.

The `Explain` algorithm generates Shapley values across multiple resampled validation sets:

$$[PV] = \texttt{Explain}(I, M, D, rs),$$

where I is the number of Monte Carlo iterations and rs the random seed. For each iteration $i = 1, \ldots, I$, a random feature $F_{p+1} \sim \mathcal{U}(-1, 1)$ is appended to F, and the model M is trained on an 80:20 train-validation split. The absolute Shapley values of all $p + 1$ features on the validation set are averaged, producing row vectors $PV_i \in \mathbb{R}^{p+1}$. These are collected into a matrix $PV \in \mathbb{R}^{I \times (p+1)}$.

Next, the `Core` algorithm compares each feature's average Shapley value to that of the random benchmark:

$$[\mathcal{I}] = \texttt{Core}(I, M, D, \alpha, \beta),$$

1. Compute $PV = \texttt{Explain}(I, M, D, rs)$.
2. Let μ_r denote the mean absolute Shapley value of the random feature:

$$\mu_r = \frac{1}{I} \sum_{i=1}^{I} PV_{i,(p+1)}.$$

3. For each real feature j, calculate

$$P_j = \frac{1}{I} \sum_{i=1}^{I} \mathbf{1}(PV_{ij} < \mu_r),$$

   where P_j is the proportion of iterations in which the j-th feature's Shapley value falls below that of the random feature.

4. Features with $P_j \leq \alpha$ are selected:

$$\mathcal{I} = \{j : P_j \leq \alpha\}.$$

To ensure statistical rigor, PowerSHAP calibrates the number of iterations I required to achieve power $1 - \beta$ under the alternative hypothesis. The effect size d between a true feature and a random feature is computed as:

$$d = \frac{\mu(u) - \mu(v)}{\sqrt{(\sigma^2(u) + \sigma^2(v))/2}},$$

where u and v are vectors of Shapley values for the feature and the random benchmark, respectively. The statistical power is approximated using a non-central t-distribution:

$$\texttt{TTestPower}(\alpha, I, d) = F_{\text{NCT}}\left(F_{\text{CT}}^{-1}(\alpha, \kappa = I - 1, \delta = -d\sqrt{I})\right),$$

and the minimum number of iterations I required is chosen to solve:

$$(1 - \beta) = \texttt{TTestPower}(\alpha, I, d).$$

Given matrix PV, the `Analysis` algorithm evaluates P and the iteration thresholds N for each feature:

$$[P, N] = \texttt{Analysis}(\alpha, \beta, PV).$$

Then, the `Auto` algorithm starts with $I = 10$ and automatically expands the sample until the desired power threshold is satisfied for all features:

$$[\mathcal{I}] = \texttt{Auto}(M, D, \alpha, \beta).$$

In our empirical implementation, we use significance level $\alpha = 0.01$ and power target $1 - \beta = 0.99$. These thresholds ensure that only the most statistically informative features are selected each month before rolling-window predictions.

3. Data and Feature Engineering

This section introduces the data used for Bitcoin return prediction and outlines the feature engineering process applied to construct explanatory variables. We begin with a description of the BTC price and return dynamics over the study period, followed by the construction and categorization of predictive features.

3.1. BTC Prices and Returns

Figure 1 presents the daily time series of Bitcoin (BTC) prices and corresponding log returns spanning from April 1, 2014, to April 26, 2023. During the initial years, particularly from 2014 to 2017, BTC prices exhibited relatively low volatility with gradual appreciation. A notable price surge occurred in late 2017, reaching a then-record high near USD 20,000, followed by a pronounced correction in 2018. Subsequent years were characterized by cyclical fluctuations and increased trading activity, reflecting heightened investor interest and market evolution.

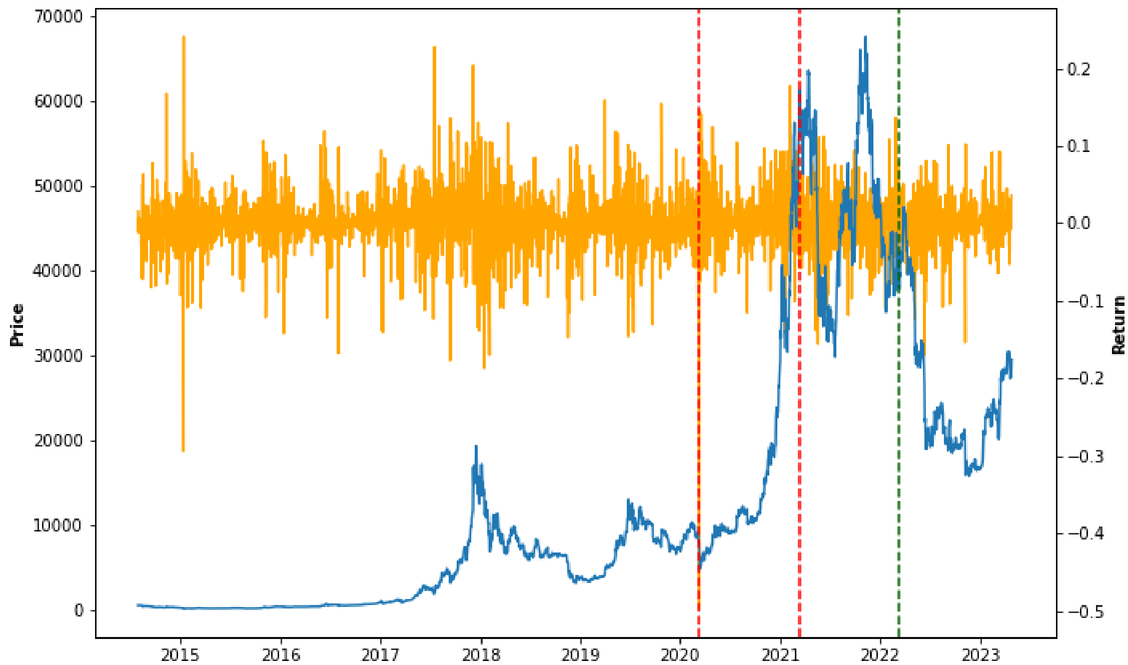
To analyze the predictive performance of explanatory variables under different market conditions, we segment the sample period into three sub-periods, following the approach in Barak and Parvini (2023). These sub-periods are defined with reference to key pandemic-related milestones:

- *COVID-19 outbreak period* (March 11, 2020 to March 11, 2021): This period begins with the World Health Organization's declaration of COVID-19 as a global pandemic. During this time, Bitcoin prices experienced a sustained upward trend, supported by expansionary monetary policies and increased institutional participation.

- *COVID-19 stability period* (March 12, 2021 to March 11, 2022): This period starts one year after the European Medicines Agency granted marketing authorization for the Janssen COVID-19 vaccine. While broader pandemic conditions stabilized, BTC prices displayed significant volatility—initially declining by half, then recovering to reach new all-time highs in late 2021.

- *Post-COVID-19 period* (March 12, 2022 to April 26, 2023): The final sub-period covers the post-pandemic normalization phase. Bitcoin prices generally trended downward amid tightening financial conditions and global macroeconomic uncertainty, although signs of recovery emerged in early 2023.

Segmenting the data in this manner allows us to assess whether the relevance and predictive power of explanatory variables differ across distinct phases of the pandemic, each associated with different macro-financial environments and investor behaviors.



BTC price *log return*

Figure 1: Time series plot of BTC price and its log daily return

3.2. Five Categories of Explanatory Variables

Table 1 presents the 22 explanatory variables used in our study, grouped into five broad categories: technical indicators, stock market indexes, commodities, macroeconomic indicators, and exchange rates. These variables are selected based on their relevance to financial markets and their documented associations with cryptocurrency dynamics in prior studies.

Technical indicators are widely used in financial forecasting and trading strategies (Neely et al., 2014; Fang et al., 2014). We include four indicators: the Moving Average Convergence Divergence (MACD), which captures momentum and trend reversals (Chio, 2022); the Relative Strength Index (RSI), which evaluates recent price gains and losses to assess potential overbought or oversold conditions; the Commodity Channel Index (CCI), which measures the deviation of price from its moving average; and the Average Directional Index (ADX), which quantifies the strength of a prevailing trend.

Stock market indexes provide insights into broader market sentiment and volatility. The Dow Jones Industrial Average (DJIA) tracks 30 large U.S. firms and serves as a proxy for overall equity market performance. The CBOE Volatility Index (VIX), derived from S&P 500 option prices, captures market expectations of future volatility. The US Equity Uncertainty

Index (USUI) aggregates data from trading volumes and derivatives markets to quantify economic uncertainty. Additionally, we include the NASDAQ Composite Index and the CBOE DJIA Volatility Index (DJVIX) to reflect technology sector trends and DJIA-related sentiment, respectively.

In the commodity category, we consider the daily prices of gold and crude oil. Gold is traditionally viewed as a safe-haven asset, while oil prices reflect global economic activity and energy market dynamics.

Macroeconomic indicators are included to account for fundamental economic conditions. These include the Consumer Price Index (CPI), Unemployment Rate, and Producer Price Index (PPI), all of which capture inflationary trends and labor market status. We also include the monthly USD Money Supply (mSup), Monthly Inflation Rate (IFR), Gross Domestic Product (GDP), and the Federal Funds Effective Rate (FFR), which influences short-term interest rates and liquidity conditions.

Finally, exchange rate variables include the US Dollar Index (USDX), along with bilateral exchange rates of EUR/USD, GBP/USD, and CNY/USD. These reflect the relative strength of the U.S. dollar and potential capital flow pressures affecting cryptocurrency markets.

We note that GDP is reported quarterly, while CPI, the Unemployment Rate, PPI, Monthly USD Money Supply, and Monthly Inflation Rate are released on a monthly basis. To align these lower-frequency macroeconomic variables with the daily frequency of Bitcoin returns, we apply a forward imputation strategy, carrying forward the most recently reported value until the next observation becomes available. This allows us to construct a unified dataset with consistent daily frequency across all explanatory variables.

Table 1: Variables

Variable	Description	Abbreviation	Source	Frequency
Technical Indicators				
x_1	MACD	MACD		Daily
x_2	RSI	RSI		Daily
x_3	CCI	CCI		Daily
x_4	ADX	ADX		Daily
Stock Market Indexes				
x_5	Dow Jones Industrial Average	DJ	Yahoo Finance	Daily
x_6	VIX	VIX	Yahoo Finance	Daily
x_7	US Equity Uncertainty Index	USUI	Economic Policy Uncertainty	Daily
x_8	NASDAQ Index	Nasdaq	Yahoo Finance	Daily
x_9	CBOE DJIA Volatility Index	DJVIX	CBOE	Daily
Commodities				

(continued)

Table 1 – continued from previous page

Variable	Description	Abbreviation	Source	Frequency
x_{10}	Gold Price	GP	Kaggle	Daily
x_{11}	Oil Price	OP	MarketWatch	Daily
Macroeconomic Data				
x_{12}	CPI	CPI	FRED Economic Research	Monthly
x_{13}	The Unemployment Rate	Unemp	OECD.org	Monthly
x_{14}	PPI	PPI	FRED Economic Research	Monthly
x_{15}	Monthly USD Money Supply	mSup	FRED Economic Research	Monthly
x_{16}	Monthly Inflation Rate	IFR	US Inflation Calculator	Monthly
x_{17}	GDP	GDP	FRED Economic Research	Quarterly
x_{18}	Federal Funds Effective Rate	FFR	FRED Economic Research	Daily
Exchange Rates				
x_{19}	US Dollar Index	USDX	MarketWatch	Daily
x_{20}	EUR/USD	EUR/USD	investing.com	Daily
x_{21}	GBP/USD	GBP/USD	investing.com	Daily
x_{22}	CNY/USD	CNY/USD	investing.com	Daily

Figure 2 displays the time series plots of Bitcoin alongside the twenty-two explanatory variables summarized in Table 1. Two broad trend patterns are observed. The first pattern is characterized by a rise during the pandemic followed by a decline, and is typical of variables such as VIX, USUI, DJVIX, and the Unemployment Rate—indicators that reflect market uncertainty and labor conditions. The second pattern resembles Bitcoin's own trajectory, with a steady increase during the pandemic. This is seen in variables such as the Gold Price (GP) and the Monthly Inflation Rate (IFR), which may reflect broader inflationary pressures and safe-haven demand.

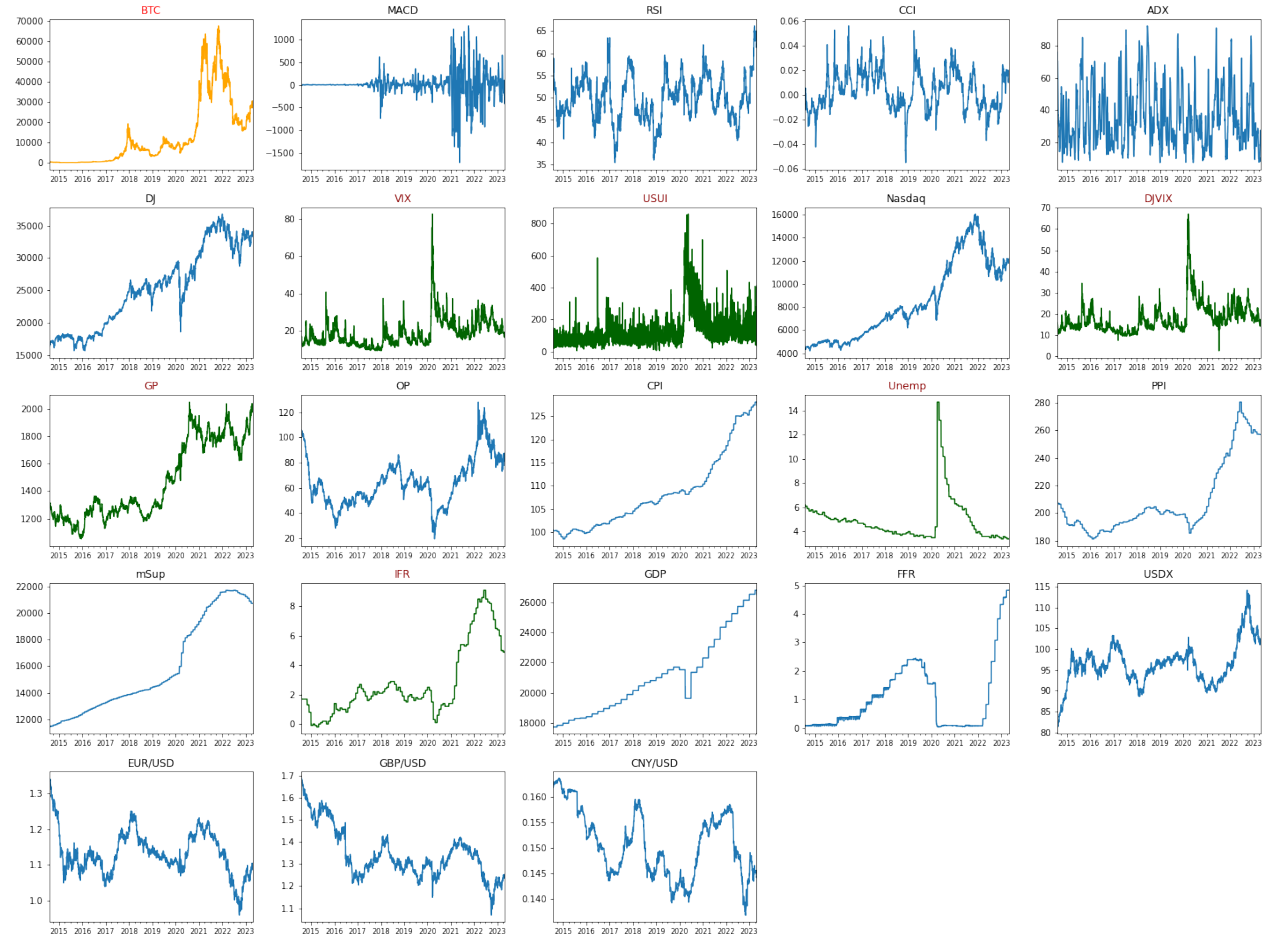


Figure 2: Time series plot of all explanatory variables

Since the time series of many explanatory variables exhibit non-stationary behavior, we additionally analyze their percentage changes, as defined in Equation (4.1). Figure 3 displays the time series plots of these percentage changes. Given Bitcoin's inherently high volatility, technical indicators derived from price dynamics show pronounced fluctuations. In particular, variables such as RSI, DJIA, NASDAQ, DJVIX, Oil Price (OP), Unemployment Rate (Unemp), Monthly Inflation Rate (IFR), and Federal Funds Rate (FFR) exhibit elevated volatility during the COVID-19 period relative to non-pandemic intervals. Moreover, Figure 3 highlights that the volatility of Bitcoin returns generally exceeds that of traditional financial variables, including equity indexes, exchange rates, and commodity prices.

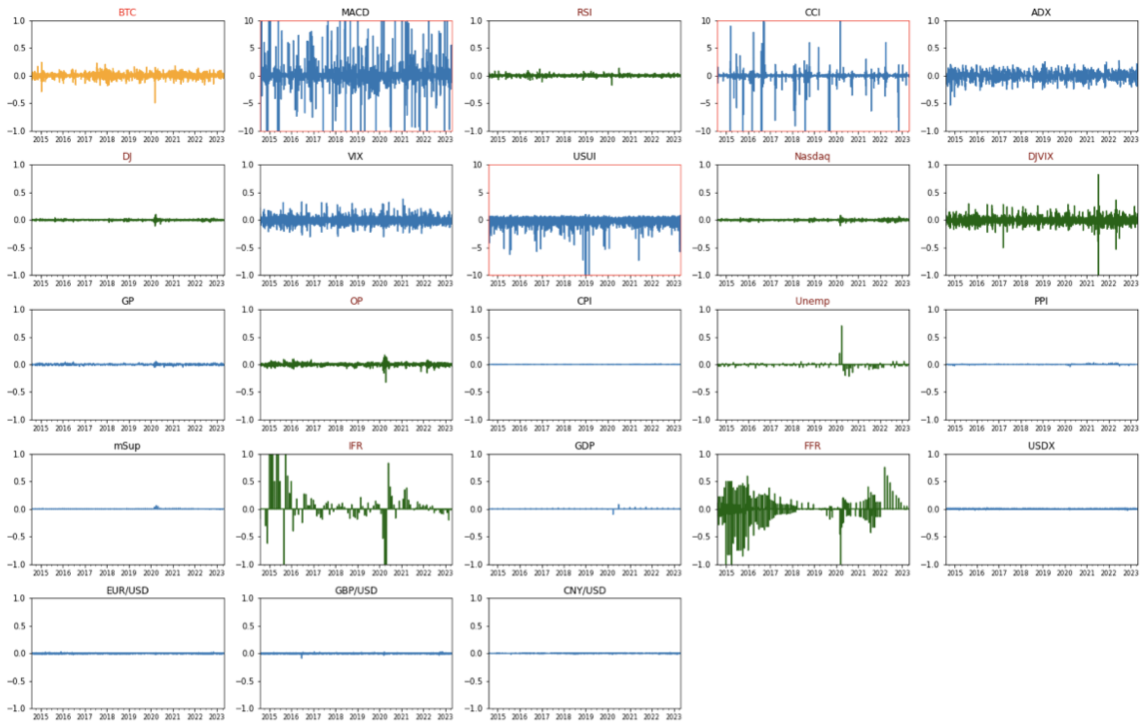


Figure 3: Percentage change plot of all explanatory variables

4. Study Plan

This section outlines the framework of our empirical analysis, including the notational setup, the definition of target and feature variables, and the design of the rolling-window approach used for model training and evaluation.

4.1. Notations

Let P_t denote the closing price of Bitcoin on day t, where $t = 1, \ldots, T$. We define the h-day ahead log return based on continuously compounded returns as follows:

$$r_t(h) = \ln P_{t+h} - \ln P_t.$$

This quantity, $r_t(h)$, serves as the response variable to be predicted in our study.

Assume there are p explanatory variables. Let $x_{i,t}$ denote the value of the i-th explanatory variable on day t, for $i = 1, \ldots, p$ and $t = 1, \ldots, T$. To capture relative changes and mitigate non-stationarity, we compute the percentage change of each variable:

$$\Delta x_{i,t} = \frac{x_{i,t} - x_{i,t-1}}{x_{i,t-1}}.$$

For notational convenience, we define the p-dimensional vector of explanatory variables on day t as

$$x_t = \{x_{1,t}, \ldots, x_{p,t}\},$$

and the corresponding vector of percentage changes as

$$\Delta x_t = \{\Delta x_{1,t}, \ldots, \Delta x_{p,t}\}.$$

4.2. Historical Returns

To construct a feature set based on historical price dynamics, we follow the methodology proposed by Ghosh et al. (2022), with adaptation to the nature of Bitcoin trading. Unlike their approach, which uses both opening and closing prices, we rely exclusively on daily closing prices to accommodate the continuous 24-hour nature of cryptocurrency markets.

Let H denote the hyperparameter specifying the historical window length used to compute past return features. We define the single-day log returns at day $(t - w)$ as:

$$lr_{t,w} = \log(p_{t-w}) - \log(p_{t-w-1}), \quad \text{for } w = 0, \ldots, H - 1,$$

where p_t denotes the closing price of Bitcoin on day t.

Similarly, we define the w-day cumulative return at day t as:

$$hr_{t,w} = \log(p_t) - \log(p_{t-w}), \quad \text{for } w = 0, \ldots, H - 1.$$

For notational simplicity, we collect the return features as vectors:

$$lr_t = \{lr_{t,0}, \ldots, lr_{t,H-1}\},$$
$$hr_t = \{hr_{t,0}, \ldots, hr_{t,H-1}\}.$$

The complete set of historical return features at time t is then defined as the union of these two vectors:

$$\mathbf{r}_t = \{lr_t, hr_t\} = \{lr_{t,0}, \ldots, lr_{t,H-1}\} \cup \{hr_{t,0}, \ldots, hr_{t,H-1}\}.$$

4.3. Rolling-Window Approach

Since both the response and explanatory variables form time series, their relationships may evolve over time. To account for this potential non-stationarity, we adopt a rolling-window framework that enables re-estimation of the model parameters in each subsample. This approach allows the predictive model to adapt dynamically to changing market conditions.

Several hyperparameters must be specified for the rolling-window procedure:

- T: the total number of time steps in the full sample period.
- H: the window length used for computing historical return features.
- M: the number of observations used for model training in each subsample.
- δ: the number of days between successive rolling windows (i.e., the step size).
- $K = \texttt{floor}\left(\frac{T-(M+H+2h)}{\delta}\right)$: the total number of rolling-window iterations.
- M_k, for $k \in \{1, \ldots, K\}$: the model trained in the k-th rolling window.

The rolling-window subsampling and prediction procedure proceeds as follows. Let $\boldsymbol{x}_t$ denote the feature vector at time t, and initialize the time index at $t = 1$. For each iteration $k = 1, \ldots, K$:

1. Use the training set $\{(\boldsymbol{x}_t, r_t(h)), \ldots, (\boldsymbol{x}_{t+M-1}, r_{t+M-1}(h))\}$ to estimate model M_k.
2. Generate predictions for the test set $\{\boldsymbol{x}_{t+M+h}, \ldots, \boldsymbol{x}_{t+M+h+\delta-1}\}$, yielding

$$\{\hat{r}_{t+M+h}(h), \ldots, \hat{r}_{t+M+h+\delta-1}(h)\}.$$

3. Update the time index: $t \leftarrow t + \delta$.

Note that in the training phase, the final return observation $r_{t+M-1}(h)$ is computed using the future price $P_{t+M+h-1}$. To avoid data leakage, the test set is strictly separated and begins at $t + M + h$, rather than $t + M$. A schematic illustration of the rolling-window structure is provided in Figure 4.

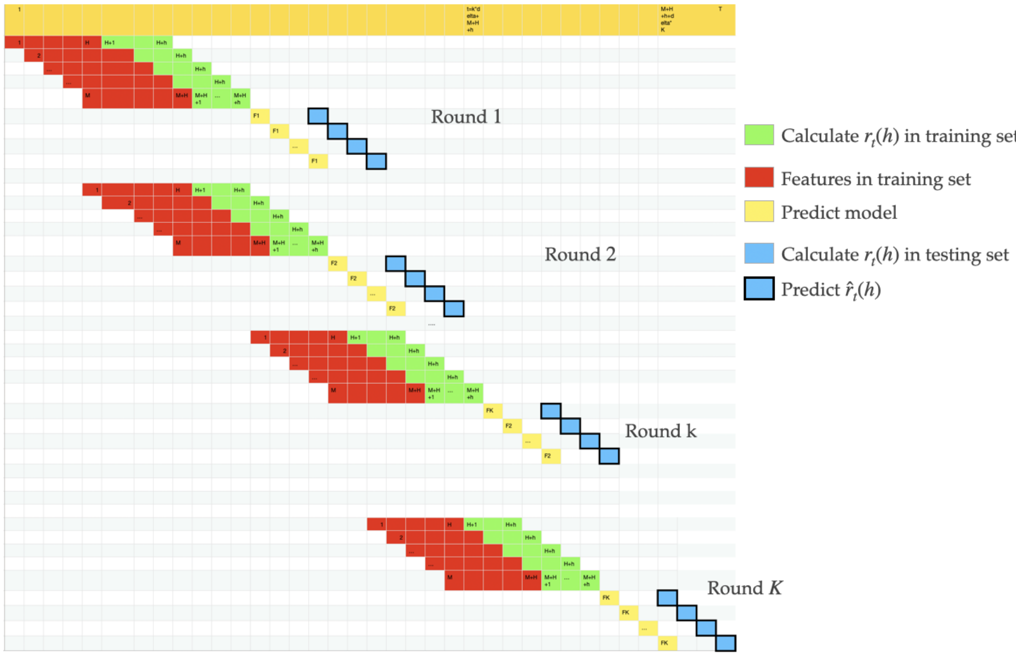


Figure 4: Diagram of rolling window subsample

4.4. Design of Analysis

We consider two values for the historical window length: $H = \{30, 90\}$. Each rolling-window subsample contains 336 observations, of which the first $M = 335$ are used for model training. The rolling step is set to one day ($\delta = 1$), implying that one new prediction is generated per day.

Our prediction target is the future log return of Bitcoin over various horizons. Specifically, we consider four forecast periods: one day ($h = 1$), one week ($h = 7$), two weeks ($h = 14$), and one month ($h = 28$), where a month is operationally defined as 28 days. Hence, the response variable $r_t(h)$ is evaluated for $h \in \{1, 7, 14, 28\}$.

To capture different forms of information, we construct five distinct feature sets. Let

$$\boldsymbol{x}_t = \{x_t, x_{t-1}, \ldots, x_{t-H+1}\}$$

denote the original features over a rolling horizon of length H, and

$$\boldsymbol{\Delta x}_t = \{\Delta x_t, \Delta x_{t-1}, \ldots, \Delta x_{t-H+1}\}$$

denote the corresponding percentage changes. The feature sets are defined as follows:

1. Original feature set: $\boldsymbol{x} = \{\boldsymbol{x}_H, \ldots, \boldsymbol{x}_T\}$

2. Percentage change feature set: $\boldsymbol{\Delta x} = \{\boldsymbol{\Delta x}_H, \ldots, \boldsymbol{\Delta x}_T\}$
3. Historical returns feature set: $\boldsymbol{r} = \{\boldsymbol{r}_H, \ldots, \boldsymbol{r}_T\}$
4. Combined feature set (original + historical returns): $\boldsymbol{x} \cup \boldsymbol{r}$
5. Combined feature set (percentage change + historical returns): $\boldsymbol{\Delta x} \cup \boldsymbol{r}$

Each feature set is used to predict Bitcoin returns at the four horizons mentioned above. We implement two supervised learning algorithms: linear regression and XGBoost. To enhance model interpretability and reduce overfitting, we perform variable selection using the PowerSHAP algorithm. This selection is conducted monthly—on the first trading day of each month—and the selected features are held fixed for the entire month before re-evaluation in the next cycle.

Our full experimental design spans 40 configurations, considering combinations of: historical window length $H \in \{30, 90\}$; five feature sets; two modeling approaches (Regression, XGBoost); variable selection applied or not (Yes/No); and four forecast horizons $h \in \{1, 7, 14, 28\}$. After completing all K rounds of rolling-window iterations, we aggregate daily prediction results and record the variables selected each month. This comprehensive design enables a systematic evaluation of model performance across multiple dimensions of temporal resolution, feature construction, and algorithmic complexity.

5. Empirical Results

This section presents our empirical findings. We begin by comparing the mean squared prediction errors (MSPE) of regression and XGBoost models, both with and without feature selection, across multiple forecast horizons. We then examine the characteristics and frequency of selected features over time. Finally, we evaluate the economic value of the predictions through a trading strategy based on the forecasted returns.

5.1. Mean squared prediction errors

Table 2 reports the mean squared prediction errors (MSPE) under a rolling-window configuration with $H = 30$, comparing the performance of Regression and XGBoost models, both with and without feature selection, across forecast horizons $h = \{1, 7, 14, 28\}$. Overall, XGBoost consistently outperforms Regression across all scenarios. Furthermore, feature selection significantly improves prediction accuracy for both models, regardless of the feature set or forecast horizon. The gains in predictive performance are most pronounced when combining XGBoost with variable selection. In particular, the feature set based on percentage changes, denoted by $\boldsymbol{\Delta x}$, coupled with XGBoost and PowerSHAP-based selection, achieves the lowest MSPE across all forecast horizons.

Table 2: Relative MSPE with $H = 30$, with $\delta = 1$, $M = 335$

h	Model	Variable selection	Benchmark MSPE	$\mathbf{x}$	$\Delta\mathbf{x}$	$\mathbf{r}$	$\mathbf{x} \cup \mathbf{r}$	$\Delta\mathbf{x} \cup \mathbf{r}$
1	Regression	No	0.0015	35.95	2895.00	1.56	27.00	1646.00
		Yes		1.01	1.28	1.00	1.02	1.07
	XGBoost	No		1.78	1.22	1.36	1.71	1.20
		Yes		0.99	0.99	0.99	0.99	0.99
7	Regression	No	0.011	21.10	4291.00	2.48	14.97	3011.00
		Yes		1.39	1.05	1.03	1.47	1.39
	XGBoost	No		1.63	1.26	1.40	1.63	1.29
		Yes		1.00	0.99	1.00	1.01	0.99
14	Regression	No	0.0236	19.88	2693.00	2.64	16.11	2935.00
		Yes		1.65	1.07	1.05	1.95	1.09
	XGBoost	No		1.62	1.23	1.40	1.62	1.26
		Yes		1.08	1.00	1.00	1.09	1.01
28	Regression	No	0.0539	15.55	7065.00	1.97	12.84	4561.00
		Yes		2.59	53.81	1.10	2.86	55.80
	XGBoost	No		1.66	1.20	1.45	1.69	1.31
		Yes		1.22	1.02	1.05	1.30	1.07

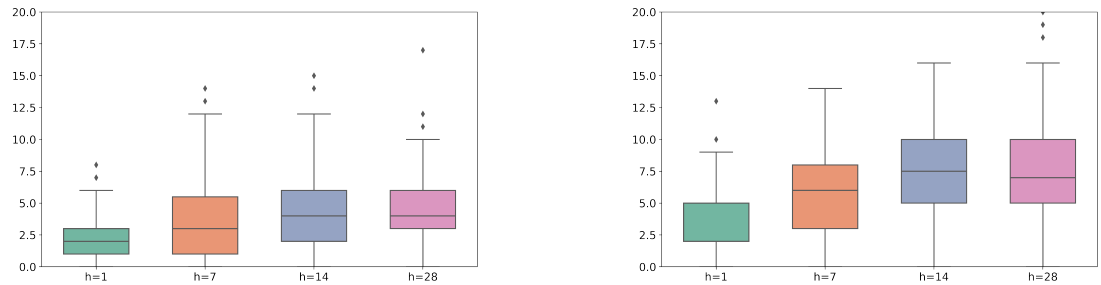
Similarly, Table 3 presents the MSPE results under a longer historical window with $H = 90$. The findings are consistent with those observed for $H = 30$. XGBoost continues to outperform Regression across all forecast horizons and feature sets. Additionally, feature selection enhances predictive accuracy for both models. Notably, the combination of XGBoost with PowerSHAP-based feature selection using the percentage change feature set $\boldsymbol{\Delta x}$ yields the best performance across all forecast horizons.

Table 3: Relative MSPE with $H = 90$: $\delta = 1$, $M = 335$

h	Model	Variable selection	Benchmark MSPE	$\mathbf{x}$	$\Delta\mathbf{x}$	$\mathbf{r}$	$\mathbf{x} \cup \mathbf{r}$	$\Delta\mathbf{x} \cup \mathbf{r}$
1	Regression	No	0.0015	8.37	5064.00	1.71	8.26	9619.00
		Yes		1.01	1.35	1.02	1.03	1.33
	XGBoost	No		1.82	1.18	1.30	1.73	1.19
		Yes		0.99	0.99	0.99	0.99	0.99
7	Regression	No	0.011	8.70	2133.00	2.52	8.66	6011.00
		Yes		1.20	24.49	1.16	1.29	25.31
	XGBoost	No		1.63	1.24	1.56	1.59	1.38
		Yes		1.01	1.00	1.00	1.01	0.99
14	Regression	No	0.0236	8.16	2328.00	2.85	8.15	4572.00
		Yes		1.78	20.35	1.30	1.64	16.93
	XGBoost	No		1.56	1.19	1.54	1.59	1.39
		Yes		1.07	0.99	1.05	1.07	1.04
28	Regression	No	0.0539	9.15	1608.00	2.64	0.14	1498.00
		Yes		2.34	50.49	1.53	1.89	53.32
	XGBoost	No		1.58	1.24	1.64	1.64	1.47
		Yes		1.29	1.04	1.15	1.15	1.13

5.2. Selected variables

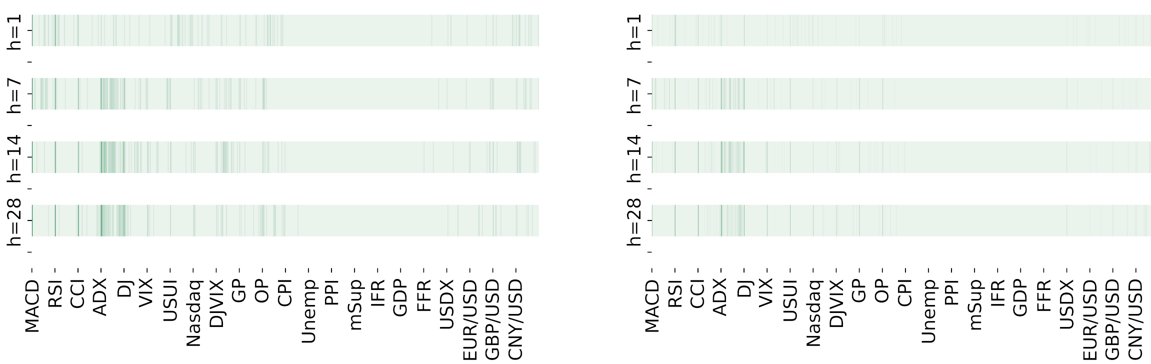
This subsection presents our analysis of the predictive relevance of features in the percentage change set $\boldsymbol{\Delta x}$. The investigation is organized into three parts: (1) an overview of monthly variable selection outcomes, (2) a detailed examination of the variables selected over time, and (3) a ranking of the most frequently selected features, both over the full sample and across distinct market sub-periods.



(a) $H = 30$ (b) $H = 90$

Figure 5: Number of variables selected

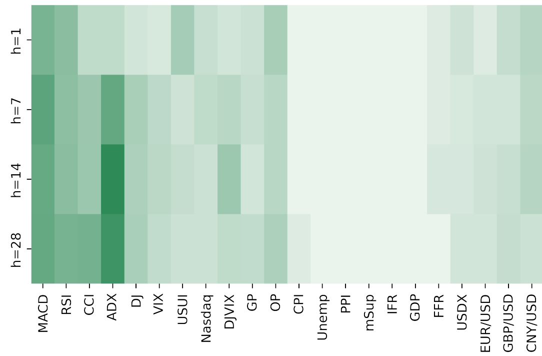
Figure 5 illustrates the distribution of the number of selected variables. Initially, the feature space is large, comprising 660 variables for $H = 30$ and 1980 for $H = 90$. However, after applying the PowerSHAP selection procedure with stringent thresholds ($\alpha = 0.01$ and $\beta = 0.01$), the number of retained features is reduced to single digits on average. This substantial reduction reflects the effectiveness of our filtering strategy. Additionally, we



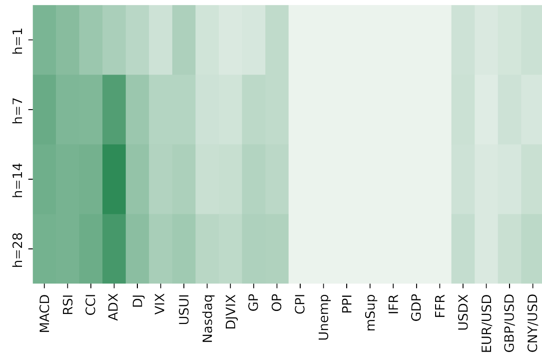
(a) $H = 30$ (b) $H = 90$

Figure 6: Heatmap plots of variable selection proportions

The heatmap plot in Figure 6 shows the proportions of selected variables for $H = 30$ and $H = 90$. The y-axis arranged for $h = 1, 7, 14, 28$. The x-axis lists features with darker colors indicating higher proportions of Selected variables. Technical indicators such as ADX and DJ are frequently selected, along with exchange rates and other technical indicators like MACD, CCI, and RSI. Conversely, macroeconomic indicators such as PPI, mSup, IFR, GDP, and FFR are selected less frequently.



(a) $H = 30$



(b) $H = 90$

Figure 7: Heatmap plots of variable selection proportions averaged over window length H

Figure 6 presents heatmaps of the selection proportions for each feature under $H = 30$ and $H = 90$. The y-axis corresponds to the forecast horizons $h = \{1, 7, 14, 28\}$, while the x-axis lists the explanatory variables. Darker shading indicates a higher frequency of selection. Technical indicators such as ADX, DJ, MACD, CCI, and RSI are among the most frequently selected features. In contrast, macroeconomic indicators—including PPI, mSup, IFR, GDP, and FFR—are selected less frequently, suggesting a more limited role in short-term Bitcoin return prediction.

Table 4: Variable importance when $H = 30$

	1st	2nd	3rd	4th	5th
ALL period					
h=1	MACD	RSI	USUI	OP	CNY/USD
h=7	MACD	ADX	RSI	CCI	DJ
h=14	ADX	MACD	RSI	CCI	DJVIX
h=28	ADX	MACD	CCI	RSI	DJ
COVID-19 pandemic outbreak period					
h=1	MACD	RSI	ADX	USUI	GBP/USD
h=7	ADX	MACD	OP	RSI	CCI
h=14	ADX	MACD	RSI	CCI	OP
h=28	ADX	MACD	RSI	CCI	OP
COVID-19 pandemic stability period					
h=1	OP	MACD	CNY/USD	Nasdaq	USUI
h=7	MACD	RSI	CCI	DJ	
h=14	ADX	MACD	RSI	DJVIX	CNY/USD
h=28	ADX	MACD	RSI	CCI	DJ
Post COVID-19 pandemic period					
h=1	MACD	USUI	RSI	CNY/USD	GBP/USD
h=7	MACD	ADX	DJVIX	RSI	CCI
h=14	ADX	DJVIX	MACD	CCI	RSI
h=28	CCI	MACD	RSI	ADX	DJ

Table 4 presents the top-ranked variables most frequently selected under the setting $H = 30$. Over the full sample period, technical indicators consistently occupy the highest ranks. For forecast horizons of $h = 7$, 14, and 28, technical indicators dominate the top four positions, with stock market indices such as the Dow Jones Index typically ranking fifth. In the case of daily returns ($h = 1$), technical indicators remain prominent in the top two positions, while variables such as the US Equity Uncertainty Index (USUI), oil price (OP), and the CNY/USD exchange rate also emerge as important predictors.

Under the $H = 30$ setting, technical indicators consistently play a dominant role across all forecast horizons and market periods. Exchange rate variables also demonstrate stable importance throughout the sample. Oil prices contribute significantly to p

During the COVID-19 outbreak period, technical indicators remain dominant across all forecast horizons. For $h = 1$, GBP/USD and USUI are among the top-ranked variables, whereas oil price (OP) does not appear. However, for longer horizons ($h = 7$, 14, and 28), OP becomes more prominent, replacing Dow Jones Index-related variables in importance. In the COVID-19 stability period, OP ranks first for $h = 1$, marking the only instance where a non-technical indicator tops the list. CNY/USD continues to exhibit strong predictive power, and stock market variables—including Nasdaq, USUI, DJVIX, and DJ—are consistently selected across all horizons. In the post-COVID-19 period, technical indicators remain consistently important regardless of the forecast horizon. Volatility indicators, such as USUI and DJVIX, gain prominence, while exchange rates (CNY/USD and GBP/USD) and the Dow Jones Index (DJ) maintain relevance. In contrast, OP no longer ranks among the top features.

Table 5 presents the variable ranking results for $H = 90$. Over the entire study period, technical indicators occupy the top four positions, with stock market indicators—such as the Dow Jones Index (DJ)—ranking fifth. Compared to the $H = 30$ setting, the influence of exchange rates and commodity variables is notably reduced, while stock market indicators like DJ and USUI maintain modest importance.

During the COVID-19 outbreak period, technical indicators consistently dominate across all forecast horizons, and stock market indicators—including DJ—retain significant relevance. In the COVID-19 stability period, volatility indicators gain greater prominence. Notably, for $h = 1$, USUI ranks third, surpassing traditional technical indicators such as CCI and ADX, while DJ remains influential for longer horizons. In the post-COVID-19 period, technical indicators continue to lead in predictive power. USUI and DJ also rank among the top features, with USUI reaching the fifth position for $h = 28$.

In summary, the results underscore the persistent dominance of technical indicators in forecasting Bitcoin returns. The relative importance of exchange rates, commodities, and stock market variables varies across different forecast horizons and economic periods.

Table 5: Variable importance when $H = 90$

	1st	2nd	3rd	4th	5th
ALL period					
h=1	MACD	RSI	CCI	ADX	USUI
h=7	ADX	MACD	RSI	CCI	DJ
h=14	ADX	MACD	CCI	RSI	DJ
h=28	ADX	CCI	MACD	RSI	DJ
COVID-19 pandemic outbreak period					
h=1	MACD	RSI	CCI	ADX	DJ
h=7	ADX	MACD	RSI	CCI	DJ
h=14	ADX	CCI	MACD	RSI	DJ
h=28	ADX	CCI	MACD	RSI	DJ
COVID-19 pandemic stability period					
h=1	MACD	RSI	USUI	CCI	ADX
h=7	MACD	RSI	CCI	ADX	DJ
h=14	ADX	MACD	RSI	CCI	DJ
h=28	ADX	CCI	MACD	RSI	DJ
Post COVID-19 pandemic period					
h=1	MACD	RSI	ADX	CCI	DJ
h=7	ADX	MACD	CCI	RSI	DJ
h=14	ADX	MACD	CCI	RSI	DJ
h=28	ADX	CCI	RSI	MACD	USUI

6. A Trading Strategy

To illustrate the practical implications of our Bitcoin return predictions, we construct a simple trading strategy. We assume access to unlimited capital and restrict the strategy to long positions only—short selling is not permitted. Each time a position is opened, the strategy invests exactly one million USD worth of Bitcoin. We also specify a rebalancing frequency denoted by h. That is, when a position is initiated at the opening of day $(t + 1)$, it is held for h trading days and liquidated at the closing price on day $(t + h)$.

The execution of this trading strategy is driven by the predicted Bitcoin returns. We focus specifically on the feature set $\boldsymbol{\Delta x}$ and set the historical window length to $H = 90$, as this configuration yields the lowest mean squared prediction errors (MSPE) across forecast horizons, as demonstrated in Section 5.1.

When no Bitcoin position is held at the end of day t, the condition for initiating a new long position is determined by the predicted return $\hat{r}_t(h)$. Specifically, a position is opened if the predicted return at time t exceeds a dynamic threshold, denoted by $\theta_t(h)$. Formally, a buy signal is triggered when

$$\hat{r}_t(h) > \theta_t(h). \tag{1}$$

If condition (1) is satisfied, a long position worth one million USD is initiated using the opening price of Bitcoin on day $(t + 1)$.

The dynamic threshold $\theta_t(h)$ is defined as the 15th percentile of predicted returns from the past 365 days, including day t:

$$\theta_t(h) = \text{15th percentile of } \{\hat{r}_{t-364}(h), \dots, \hat{r}_t(h)\}. \tag{2}$$

For example, if the 15th percentile of the predicted returns in the past 365 days is 10%, the strategy initiates a buy on day $(t + 1)$ if today's predicted return exceeds this 10% threshold. Once a long position is established, it is held for h days and closed at the end of day $(t + h)$. A new position is only considered after the previous one has been closed.

Table 6 summarizes the timeline of the trading strategy. As noted in Section 4.4, the first day of the study period is July 2, 2015. Given that 365 predicted return values are needed to calculate the dynamic threshold, the first decision date occurs on June 30, 2016. If the condition in (1) is met on this day, the strategy initiates a buy using the opening price on July 1, 2016.

Table 6: Trading timeline with Predicted Returns. * indicates the first trading date.

Day	Date	Prediction	Action
$t - 364$	2015-07-02	$\hat{r}_{t-364}(h)$	
⋮	⋮	⋮	
$t - 1$	2016-06-29	$\hat{r}_{t-1}(h)$	
t	2016-06-30	$\hat{r}_t(h)$	Calculate $\theta_t(h)$ in (2).
$t + 1$	2016-07-01*	$\hat{r}_{t+1}(h)$	If $\hat{r}_t(h) > \theta_t(h)$, open a position using the open price at day $(t + 1)$
$t + 2$	2016-07-02	$\hat{r}_{t+2}(h)$	
⋮	⋮	⋮	
⋮	⋮	⋮	
⋮	⋮	⋮	
	2023-04-25		

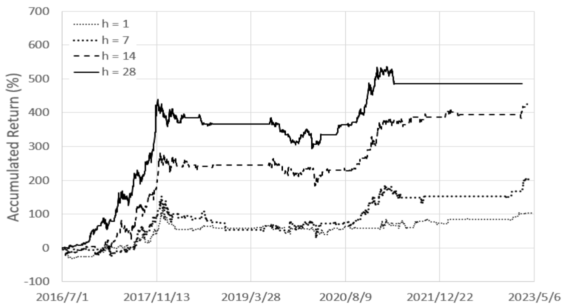
Table 7 reports the annualized returns, standard deviations, Sharpe ratios, and maximum drawdowns (MDDs) of portfolio returns generated by our trading strategy, which is based on BTC return forecasts from Regression and XGBoost models, both with and without variable selection. As established in Section 5.1, XGBoost with variable selection yields the most accurate predictions, achieving the lowest MSPE values. The results in Table 7 further demonstrate that incorporating more accurate predictions leads to superior trading performance, characterized by higher cumulative returns and reduced portfolio risk.

Across all rebalancing horizons, XGBoost consistently outperforms Regression in terms of annualized return, Sharpe ratio, and MDD—regardless of whether variable selection is employed. The addition of variable selection improves risk-adjusted performance for both models, reflected in higher Sharpe ratios and lower MDDs, except for the case of $h = 1$ under Regression, where performance slightly deteriorates. Furthermore, for both models and variable selection settings, annualized returns generally increase with longer holding periods. Most notably, XGBoost with variable selection achieves the highest annualized Sharpe ratio of 1.501 when rebalancing occurs every 14 days.

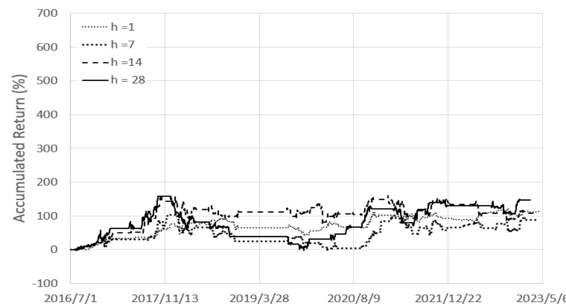
Table 7: Trading performance

h	Model	variable selection	Annualized Return	Annualized Std	Sharpe ratio	MDD
1	Regression	No	10.8%	14.9%	0.724	26.9
		Yes	13.8%	22.9%	0.604	31.9
	XGBoost	No	9.1%	18.2%	0.46	28.4
		Yes	13.3%	14.5%	0.92	24.7
7	Regression	No	11.0%	23.8%	0.46	56.3
		Yes	18.2%	29.1%	0.625	50.7
	XGBoost	No	18.2%	22.4%	0.814	33.7
		Yes	21.1%	24.7%	0.855	51.6
14	Regression	No	11.9%	21.9%	0.543	31.2
		Yes	24.0%	24.6%	0.978	31.4
	XGBoost	No	21.4%	19.2%	1.118	22.8
		Yes	25.5%	17.0%	1.501	21.2
28	Regression	No	14.4%	23.2%	0.623	62.0
		Yes	24.6%	17.4%	1.411	26.9
	XGBoost	No	26.2%	21.9%	1.198	29.4
		Yes	24.8%	18.7%	1.327	29.0

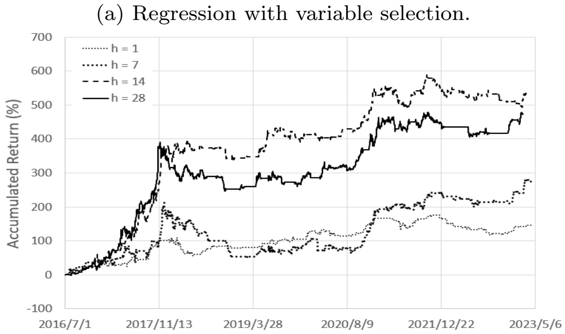
Figure 8 illustrates the cumulative returns of our trading strategy using BTC return forecasts generated by Regression and XGBoost models, both with and without variable selection. The results reveal a steady increase in accumulated returns over the study period. More importantly, strategies that incorporate variable selection—whether using Regression or XGBoost—consistently outperform those that do not, underscoring the critical role of feature selection in enhancing predictive accuracy and trading performance.



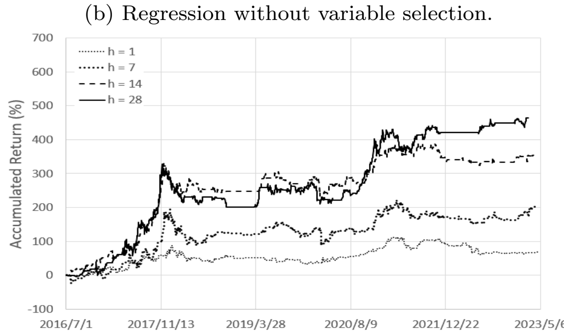
(a) Regression with variable selection.



(b) Regression without variable selection.



(c) XGBoost with variable selection.



(d) XGBoost without variable selection.

Figure 8: Accumulative returns of trading strategies based on BTC returns predicted by Regression and XGBoost, with and without variable selection, using the feature set $\boldsymbol{\Delta x}$

7. Conclusion and Future Work

This study offers new insights into the forecasting of Bitcoin returns by exploring the role of variable selection and feature interpretability. Our empirical investigation reveals that even with powerful machine learning algorithms such as XGBoost, proper feature selection remains crucial for enhancing predictive accuracy. Specifically, we introduce PowerSHAP—a statistically grounded, model-agnostic feature selection method based on Shapley values—which substantially reduces feature dimensionality while preserving or improving forecast performance.

Our findings highlight three key contributions. First, we demonstrate that feature selection improves Bitcoin return prediction across various forecast horizons, even when employing ensemble learning methods. Second, we validate PowerSHAP as an interpretable and statistically principled approach that selects a concise set of features with consistent explanatory power. Third, we identify a core group of predictive variables—primarily technical indicators and selected exchange rate and market sentiment measures—that remain robust across different market regimes, including various phases of the COVID-19 pandemic.

Finally, we implement a trading strategy based on our predictive model and demonstrate its potential for generating superior risk-adjusted returns, especially when feature selection is applied.

Future work may extend our framework by incorporating alternative data sources, such as sentiment from social media and blockchain activity metrics. These sources may provide valuable complementary signals to traditional financial and macroeconomic indicators, further enhancing our understanding of return drivers in cryptocurrency markets (Cheng et al., 2022; King et al., 2024).

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT and Grok, developed by OpenAI and xAI, respectively, in order to improve the clarity, precision, and overall quality of the writing. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

References

Bâra, A., Oprea, S.V., 2024. An ensemble learning method for bitcoin price prediction based on volatility indicators and trend. Engineering Applications of Artificial Intelligence 133, 107991.

Barak, S., Parvini, N., 2023. Transfer-entropy-based dynamic feature selection for evaluating bitcoin price drivers. Journal of Futures Markets 43, 1695–1726.

Battiti, R., 1994. Using mutual information for selecting features in supervised neural net learning. IEEE Transactions on Neural Networks 5, 537–550.

Blum, A.L., Langley, P., 1997. Selection of relevant features and examples in machine learning. Artificial Intelligence 97, 245–271.

Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D., 2017. Does bitcoin hedge global uncertainty? evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters 23, 87–95.

Catania, L., Grassi, S., Ravazzolo, F., 2019. Forecasting cryptocurrencies under model and parameter instability. International Journal of Forecasting 35, 485–501.

Cheng, D., Yang, F., Xiang, S., Liu, J., 2022. Financial time series forecasting with multi-modality graph neural network. Pattern Recognition 121, 108218.

Chio, P.T., 2022. A comparative study of the macd-base trading strategies: evidence from the US stock market. arXiv preprint arXiv:2206.12282 .

Cong, L.W., He, Z., 2019. Blockchain disruption and smart contracts. The Review of Financial Studies 32, 1754–1797.

Fang, J., Qin, Y., Jacobsen, B., 2014. Technical market indicators: An overview. Journal of Behavioral and Experimental finance 4, 25–56.

Ferreira, A.J., Figueiredo, M.A., 2012. Efficient feature selection filters for high-dimensional data. Pattern Recognition Letters 33, 1794–1804.

Gensler, G., 2024. Statement on the approval of spot bitcoin exchange-traded products. https://www.sec.gov/news/statement/gensler-statement-spot-bitcoin-011023.

Ghosh, P., Neufeld, A., Sahoo, J.K., 2022. Forecasting directional movements of stock prices for intraday trading using LSTM and random forests. Finance Research Letters 46, 102280.

Gurdgiev, C., O'Loughlin, D., 2020. Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty. Journal of Behavioral and Experimental Finance 25, 100271.

Kabir, M.M., Islam, M.M., Murase, K., 2010. A new wrapper feature selection approach using neural network. Neurocomputing 73, 3273–3283.

Kim, Y.B., Kim, J.G., Kim, W., Im, J.H., Kim, T.H., Kang, S.J., Kim, C.H., 2016. Predicting fluctuations in cryptocurrency transactions based on user comments and replies. PloS one 11, e0161197.

King, J.C., Dale, R., Amigó, J.M., 2024. Blockchain metrics and indicators in cryptocurrency trading. Chaos, Solitons & Fractals 178, 114305.

Kohavi, R., John, G.H., 1997. Wrappers for feature subset selection. Artificial Intelligence 97, 273–324.

Leardi, R., Boggia, R., Terrile, M., 1992. Genetic algorithms as a strategy for feature selection. Journal of Chemometrics 6, 267–281.

Li, X., Wang, C.A., 2017. The technology and economic determinants of cryptocurrency exchange rates: The case of bitcoin. Decision Support Systems 95, 49–60.

Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. The Review of Financial Studies 34, 2689–2727.

Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. The Journal of Finance 77, 1133–1177.

Liu, Y.H., Huang, J.K., 2024. Cryptocurrency trend forecast using technical analysis and trading with randomness-preserving. Computers and Electrical Engineering 118, 109368.

Neely, C.J., Rapach, D.E., Tu, J., Zhou, G., 2014. Forecasting the equity risk premium: the role of technical indicators. Management Science 60, 1772–1791.

Orte, F., Mira, J., Sánchez, M.J., Solana, P., 2023. A random forest-based model for crypto asset forecasts in futures markets with out-of-sample prediction. Research in International Business and Finance 64, 101829.

Panagiotidis, T., Stengos, T., Vravosinos, O., 2018. On the determinants of bitcoin returns: A LASSO approach. Finance Research Letters 27, 235–240.

Panagiotidis, T., Stengos, T., Vravosinos, O., 2019. The effects of markets, uncertainty and search intensity on bitcoin returns. International Review of Financial Analysis 63, 220–242.

Polasik, M., Piotrowska, A.I., Wisniewski, T.P., Kotkowski, R., Lightfoot, G., 2015. Price fluctuations and the use of bitcoin: An empirical inquiry. International Journal of Electronic Commerce 20, 9–49.

Pyo, S., Lee, J., 2020. Do fomc and macroeconomic announcements affect bitcoin prices? Finance Research Letters 37, 101386.

Salisu, A.A., Ndako, U.B., Vo, X.V., 2023. Oil price and the bitcoin market. Resources Policy 82, 103437.

Sánchez-Maroño, N., Alonso-Betanzos, A., Tombilla-Sanromán, M., 2007. Filter methods for feature selection–a comparative study, in: International Conference on Intelligent Data Engineering and Automated Learning, Springer. pp. 178–187.

Schilling, L., Uhlig, H., 2019. Some simple bitcoin economics. Journal of Monetary Economics 106, 16–26.

Sockin, M., Xiong, W., 2023. A model of cryptocurrencies. Management Science 69, 6684–6707.

Verhaeghe, J., Van Der Donckt, J., Ongenae, F., Van Hoecke, S., 2022. Powershap: A power-full shapley feature selection method, in: Joint European Conference on Machine Learning and Knowledge Discovery in Databases, Springer. pp. 71–87.

Yu, L., Liu, H., 2003. Feature selection for high-dimensional data: A fast correlation-based filter solution, in: Proceedings of the 20th International Conference on Machine Learning, pp. 856–863.

Zhu, Y., Dickinson, D., Li, J., 2017. Analysis on the influence factors of bitcoin's price based on vec model. Financial Innovation 3, 1–13.