The University of Oklahoma

Bitcoin and U.S. Financial Confidence: A Regression Analysis

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Executive Summary

Research Objective:

Bitcoin has several value propositions. This study aims to evaluate its proposition to as an investment “safe haven” during economic turmoil due to its decentralization from intermediaries and transparent peer-to-peer transaction methodology. A summary of this paper’s specific tasks and assumptions are as follows:

- Bitcoin’s goal may be evaluable as a function of global confidence in the US economy
- An aggregation of US economic indicators can serve as proxies for global confidence in the US economy

Summary of Findings:

After visualizing several variable relationships, it was clear that strong correlations and non-linearities existed. To account for non-linear relationships, a MARS model was constructed in addition to OLS and ElasticNet models, where the MARS model performed the best ($R^2 = 0.945$, *RMSE* = 0.295) against the testing data. The MARS model presented several key insights, in addition to the finding that Bitcoin may indeed be effectively modeled as a function of US economic indicators:

- Bitcoin prices and the S&P 500 index are *tightly* and positively correlated when the S&P 500 is underperforming
- Bitcoin prices tend to fall when the S&P 500 is strong and gold is underperforming

The above bullet points seem to indicate that two differing types of Bitcoin investors exist: speculative investors that invest during times of high economic confidence, and “digital gold” investors that see Bitcoin as a hedge alternative against economic downturns.

Recommendations:

Because this study resulted in a well-performing model utilizing US economic indicators, it could be useful to extend this approach to chronological time series analysis. This model could be applied in subsequent time periods to generate both accurate and interpretable predictions of Bitcoin behavior that can be communicated to investors as a useful decision-making tool.

I. Problem Background

a. Background

Bitcoin has fascinated investors, economists, and technologists since its conception. There have been several proposed value propositions to explain its adoption. Energy arbitrage to capitalize on underutilized energy resources, censorship resistance to nation-states, and a digital gold-like safe haven during periods of global financial instability. The focus of this research project is on the third value proposition. Particularly, considering the United States' role as the most influential financial institution in global stability, this research focuses on analyzing Bitcoin’s relationship with proxies for confidence in the US financial system. The metrics are focused on fundamental economic indicators, with examples such as the consumer price index (CPI), 10-year bond yields, foreign purchases of US securities, and average prices of the S&P 500.

Investigating Bitcoin’s potential as a safe haven asset, prior research has sought to disentangle its behavior under conditions of economic and political uncertainty. Studies using proxies like the Partisan Conflict Index (PCI) and Economic Policy Uncertainty (EPU) index reveal Bitcoin’s mixed responses to instability, with its price oscillating between stabilizing tendencies and speculative, bubble-like behavior during heightened uncertainty [3]. Complementing this, investigations into Bitcoin’s classification suggest it is best understood as a new technology product diffusing through society or an emerging asset class, rather than a traditional currency or security [4]. Furthermore, modeling efforts have demonstrated that volatility metrics—particularly the VIX index and Bitcoin’s own price volatility—hold the greatest explanatory power for short-term price dynamics [1]. In addition, attempts to model next-day pricing of Bitcoin led researchers to examine the performance between an autoregressive integrated moving average model (ARIMA) and a neural network autoregressive model, where ARIMA was found to perform better. [2]. This underscores the value of simpler, more interpretable models, which not only achieve better accuracy but also elucidate complex relationships between Bitcoin and its explanatory variables.

To the research team's knowledge, no existing work has used this specific feature set to model Bitcoin. The potential novel contributions to the literature include new insights into how trust in traditional financial systems affects cryptocurrency markets, a comprehensive view of how macroeconomic influences impact Bitcoin, and a novel perspective on modeling Bitcoin as a function of trust in the US financial system. This approach fills a gap in the literature which typically focuses on price prediction using complex models with limited interpretability, short-term price movements as opposed to insight into long-term economic insights, and technical analysis which might not emphasize relationships with fundamental economic factors.

b. Data Description

The dataset utilized in this analysis is a collection of United States economic indicators (i.e., gold price, US dollar index, 10-Year Bond Yields) that were modeled as proxies for global confidence in the US economy. The response variable in this study is the natural log of Bitcoin (BTC) Price.

- $N = 118$ observations (July 2014 – October 2024, sampled monthly)
- $p = 50$ variables (all of which can be found in **Appendix B)**

Data was collected and aggregated by date through various historical databases which can be found. in **Appendix A**. There were no missing data points; however, there may exist relevant bias in the data affecting the interpretation of outcomes. These biases could arise from the exclusion of time-series adjustments, such as detrending or accounting for the adoption and growth of the financial assets being modeled (e.g., Bitcoin, S&P 500).

An outlier was identified within the data, August 2020, and was assumed to be a mistake (order of magnitude error), which was corrected using data from another source. A boxplot of each variable was created to investigate possible skewness in the data to understand where transformations would be required.

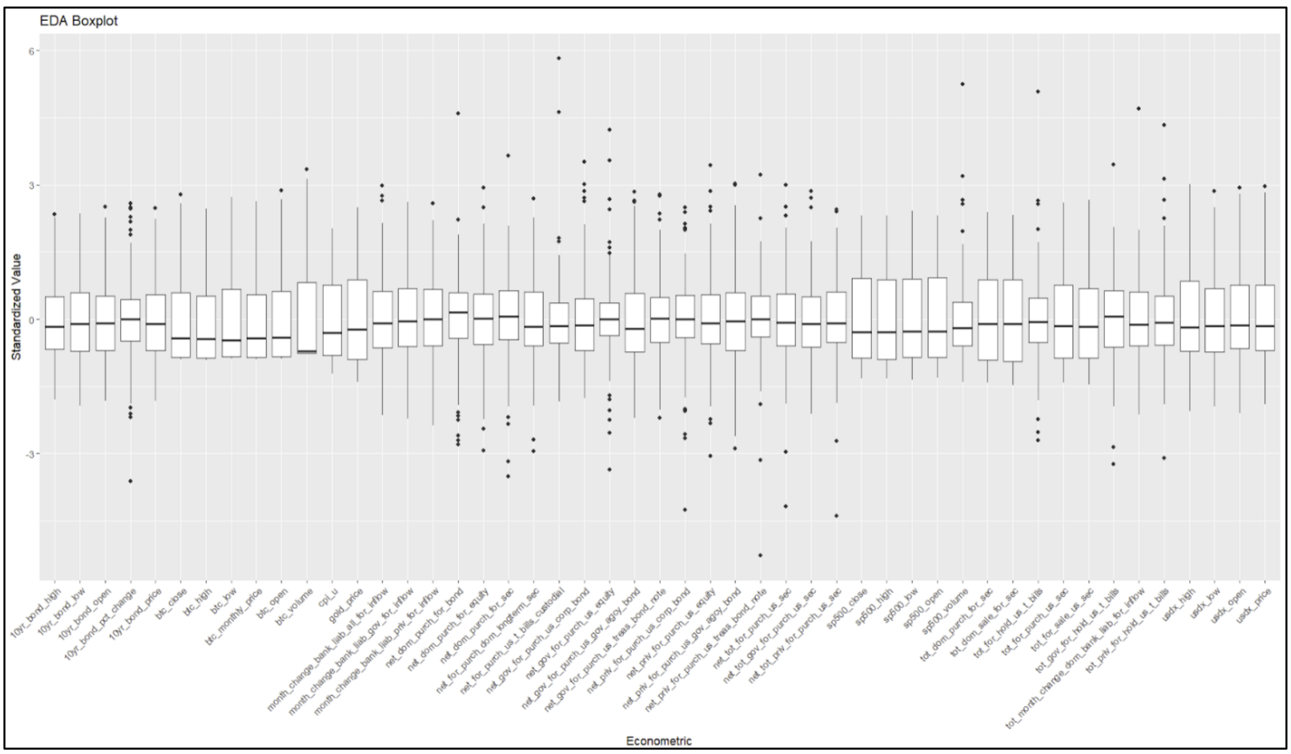

Figure 1: Boxplot of all variables

Most of the outliers are in Bonds and Treasury notes. This indicates that the US government rapidly issues "quick fixes" and changes bond and treasury rates. Also, Bitcoin has extremely high volatility in terms of buying or holding. These sources of volatility are further explored in the correlation plot.

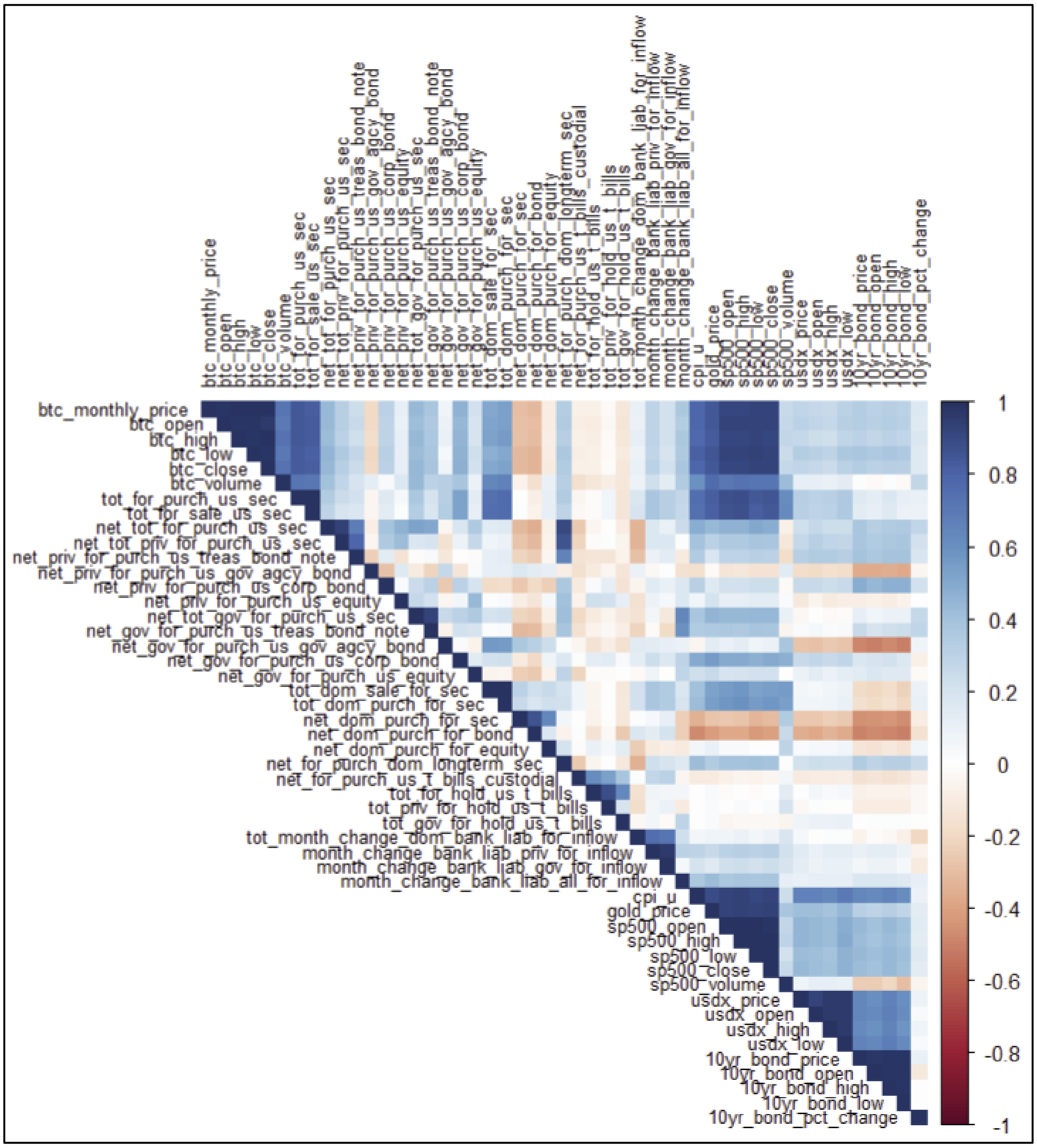

Figure 2: Correlation plot of variables

c. Exploratory Analysis

The figure above highlights that Bitcoin is negatively correlated with US purchases of bonds and securities. This provides evidence for the hypothesis that Bitcoin prices rise as US trust falls. However, there are some weak correlations (-0.3). This may not be significant.

Bitcoin, gold, and S&P 500 prices are strongly positively correlated with a strength of .8 or above. This provides stronger preliminary evidence against the hypothesis that Bitcoin prices rise as US trust falls.

This is a surprising result. It could be that Bitcoin price is positively correlated with US trust; or there is simply no causal relationship here. Bitcoin grows, the US economy grows, and they are independent processes. To better understand this result, the relationship between Bitcoin, gold, and S&P 500 prices were investigated.

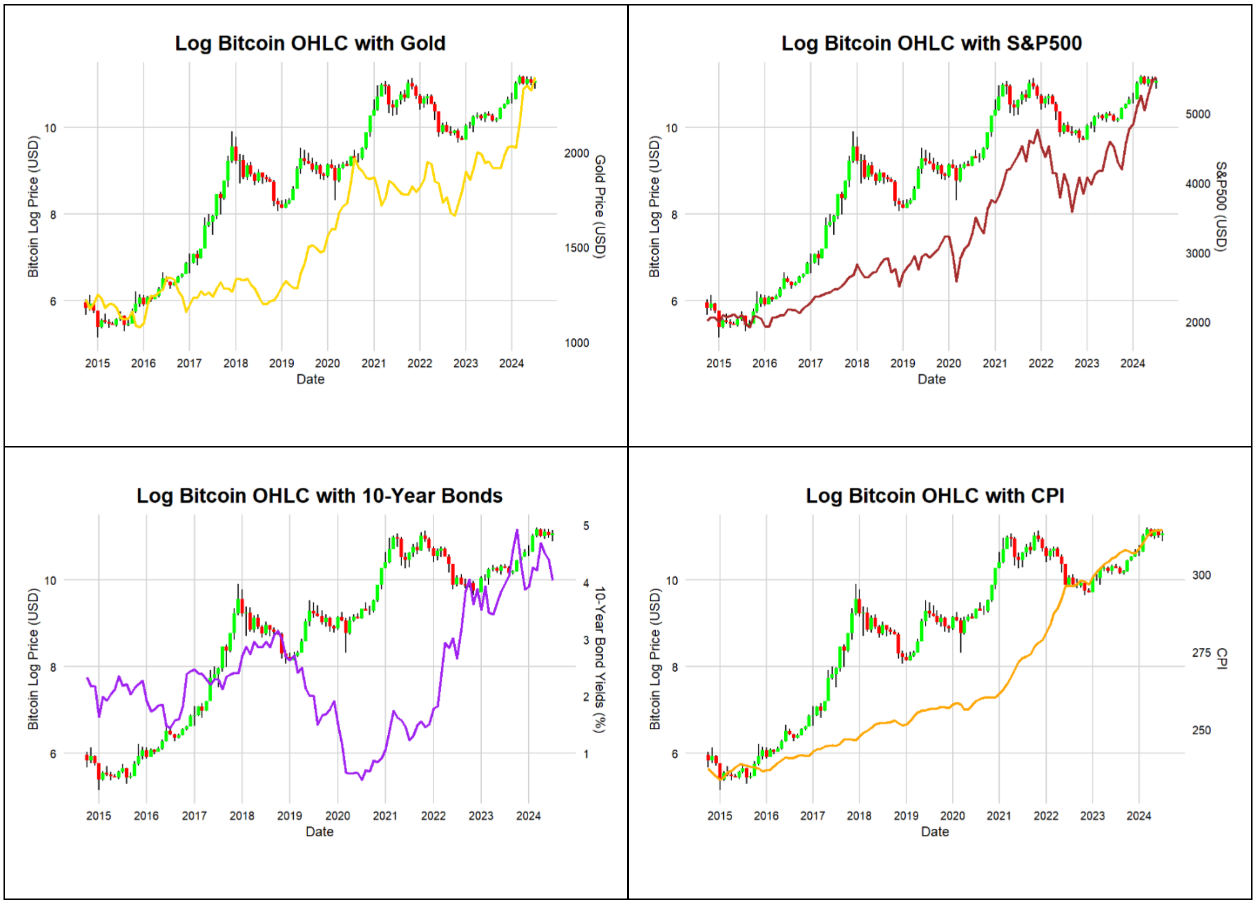

Figure 3: Relationship between Log(BTC Price) and Gold, S&P 500 Index, and Bond % Change

Interestingly, Bitcoin price is more correlated with S&P500 prices than it is with gold prices. This is reflected in Figure 2 as well. It shows that the correlation coefficient for gold is about 0.7, and the correlation coefficient for S&P500 is about 0.9. Again, this suggests that, if anything, Bitcoin price and US Economic performance are either casually or incidentally positively correlated. To investigate further nuance, there may be a positive correlation between the *volume* of Bitcoin trade and US Economic slowdowns. This is investigated below.

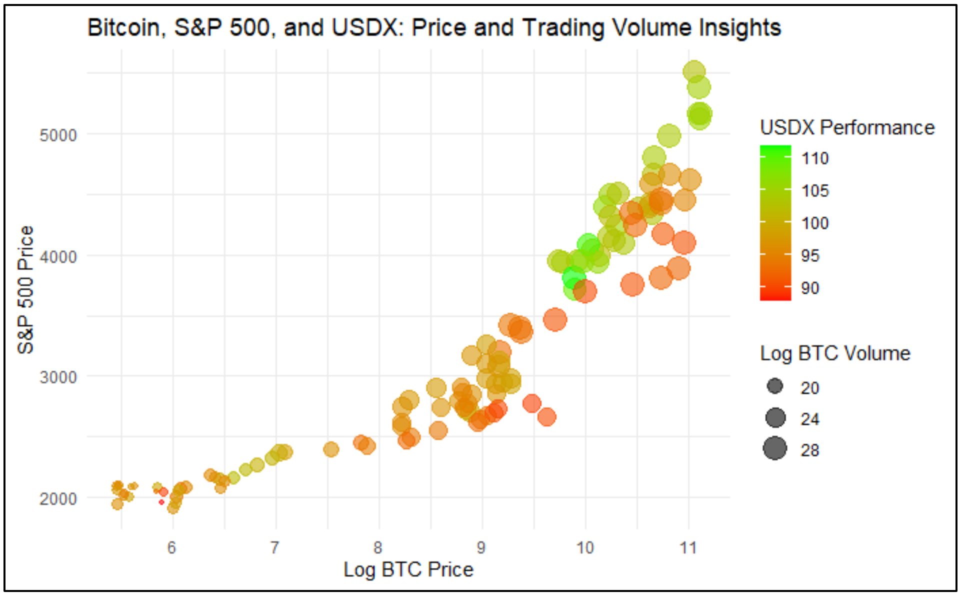

Figure 4: Log(BTC Price) with S&P 500 Index, USDX, and Log(BTC Volume)

Figure 4 indicates a few important insights: when the US Dollar Index is performing higher, the S&P 500 Index performs higher, BTC trading volume is higher, and BTC price tends to be higher; also, this graph seems to present that non-linear relationships may exist between present variables. Additionally, this figure demonstrates that BTC trading volume is always high when there is low currency instability (high USDX), as well as a high positive correlation between BTC Price and S&P 500 Index.

II. Methodology

a. Pre-Processing

The preprocessing steps taken were transforming Bitcoin price, OHLC feature engineering, variable scaling, and an 80/20 split into training and testing data.

First, Bitcoin price was transformed. In order to take advantage of the nice properties of the natural log in linear regression models, Bitcoin's monthly price was transformed into natural log of Bitcoin's price. This was then designated as the variable the regression models were trying to predict.

$$\log\left(btc_{monthly_{price}}\right) \leftarrow btc_{monthly_{price}}$$

Equation 1: Bitcoin Log Transformation

Second, OHLC feature engineering was conducted. OHLC stands for Open, High, Low, Close and refers to the price of the stock, commodity, or bond at the beginning of the trading period, highest price during the trading period, lowest price during the trading period, and the closing price during the trading period. In this analysis, the trading period was months. With this context in mind, new variables from the averages of the open, high, low, and close price for the S&P500 data, US dollar index, and10 year bonds, were respectively created. These aggregated variables were kept, and the intermediary OHLC variables were justly omitted from the analysis.

$$S\&P500 \leftarrow \frac{S\&P500_{open} + S\&P500_{high} + S\&P500_{low} + S\&P500_{low}}{4}$$

Equation 2: OHLC transformation example

Third, all input variables were scaled. This wase done by using the sample mean($\bar{x}$) and sample standard deviation(s) of the variable(x), as shown in **Eq. 3.** This allowed each of the input variables to be on the same scale, thereby reducing the variability inherent in each financial index having a different scale. The response variable of log(btc_monthly_price) was not scaled.

$$Z_x = \frac{x - \bar{x}}{s}$$

Equation 3: Scaling method

Finally, an 80/20 split of the data into training and testing sets was conducted. In order to pair nicely with the 10-fold cross validation for the regression models, a random sample of 94 months to train on, and 24 months to test on was created. This made the training dataset non-chronological, and the testing dataset non-chronological. The reason for a non-chronological testing and training dataset was to prevent the data from being extremely skewed and allowed it to be amenable to subsequent 10-fold cross validation. Overall, by preprocessing the data, it was more amenable for use in OLS, ElasticNet, and MARS.

b. Model Selection & Validation

i. OLS

Potential multicollinearity was addressed first by using the alias function to detect and exclude variables that were linearly dependent. After removing these variables, remaining predictors were examined for high multicollinearity using Variance Inflation Factor (VIF) scores. Variables with VIF values greater than 5 were excluded to improve model stability and interpretability. Finally, 10-fold cross-validation was applied to the training data to evaluate model performance. This model was included as a baseline to assess how a simple, statistically sound approach without interaction terms or derived variables would perform, serving as a control for comparison against more sophisticated models.

ii. ElasticNet

10-fold cross-validation was used with an alpha parameter of 0.9 to heavily incentivize dimension reduction. This hyperparameter was chosen to discourage the model from relying on more predictors than necessary, addressing the high correlation observed during exploratory analysis (see **Fig. 2**). The strong regularization was motivated by the issues encountered in OLS, where collinearity was abundant. By using ElasticNet, the aim was to evaluate how the model could prioritize the most influential variables while maintaining linearity and balancing the trade-offs between interpretability and complexity.

iii. MARS

Manual feature selection was not required, as the model incorporates automatic pruning through forward stepwise selection. Scaling was conducted prior to model development, and 10-fold cross-validation was applied to ensure robust performance evaluation. The inclusion of MARS was motivated by exploratory analysis, which indicated potential non-linear relationships in the data (see **Fig. 4**). This approach was used to investigate how accounting for non-linear effects could enhance model performance and influence the dimension reduction compared with ElasticNet and OLS.

III. Results

a. Model Results

Model	Hyperparameters	Adjusted R^2	AIC	RMSE	Rank
MARS	nprune = 15 degree = 2	0.945	-38.60	0.295	#1
ElasticNet	λ = 0.028 α = 0.9	0.440	13.93	0.606	#2
OLS	N/A	0.374	334.55	1.397	#3

Table 1. Performance metrics of regression models.

MARS had the highest overall performance, which supports the belief that there are several non-linear relationships within the data that strictly linear models like ElasticNet and OLS would not be able to capture.

b. MARS Analysis

As discussed, the best performing model across all metrics was MARS. The coefficients of the model can be found in **Appendix F**. The reason MARS performed the best was due to nonlinear trends in the data, as shown in **Fig. 4** and **5**.

In this analysis, the testing dataset was comprised of 24 randomly selected months. These datapoints were selected from anywhere in the entire analysis period from July 2014 – October 2024. As described in the Methodology pre-processing section, this was in order to prevent skewing in both the testing and training dataset, as well as for amenability to cross validation.

This made the testing dataset non-chronological, which was initially suspected to pose a problem to the predictive accuracy of the model. However, based on the results as shown in **Figure 5**, the MARS model did surprisingly well handling non-chronological data.

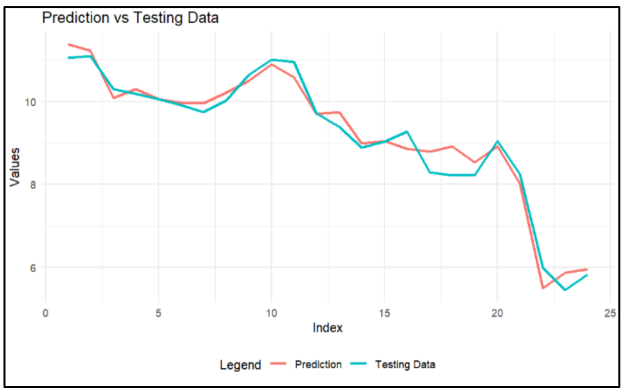

Figure 5: MARS performance against testing data

As can be seen in **Fig. 5**, the MARS model, for only having been trained on 94 observations, did remarkably well in predicting the log of the price over the 24-month non-chronological timespan. This is

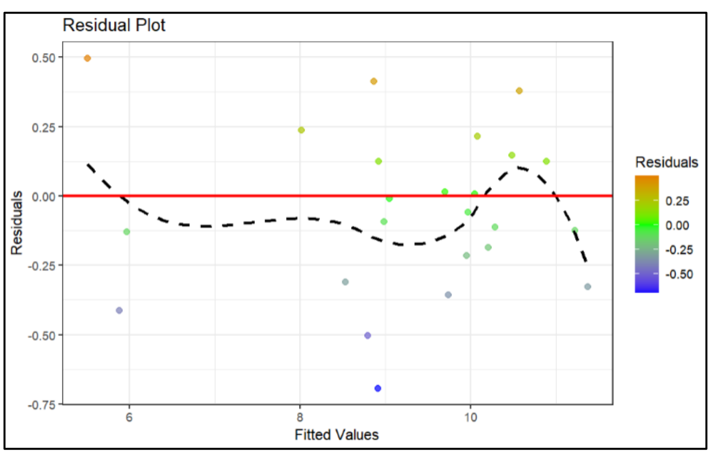

Figure 6: MARS residuals against fitted values

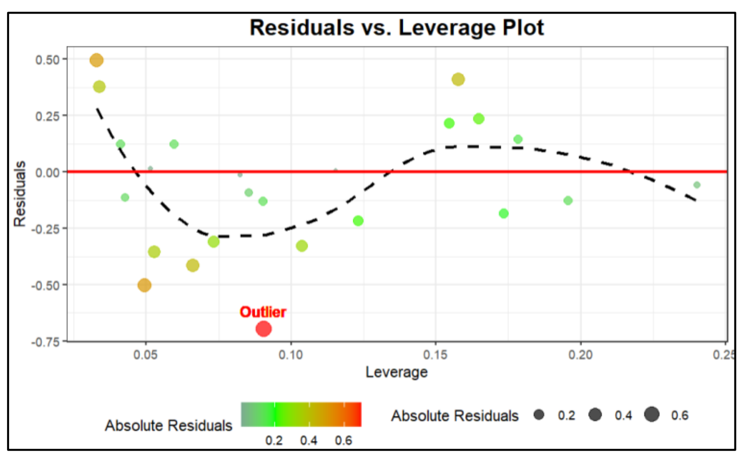

Figure 7: MARS residuals vs. leverage

with the exception of one point, which represented an outlier. This is shown in both **Figures 6** and **7** as the lowest point on the graph.

Outliers were ascertained using the standard two sample standard deviations away from the mean rule.

$$\{Outliers\} = x \text{ such that } |x - \bar{x}| > 2s$$

Equation 4: OHLC transformation example

Because of the non-chronological nature of the sampling method, residuals were also contingent upon the time frame in which the datapoint was selected. This resulted in the general trend shown in both **Figures 6** and **7**. This trend is generally flat, and deviations are largely due to sampling non-chronological data and a small testing data set. Although further information could be obtained from using a dedicated time series model, a substantial number of insights can be gained with the current non-chronological modeling approach.

c. Key Insights

The variable with the largest coefficient weight was the S&P 500 average price. MARS found two knots to be most effective when modeling the effect the S&P 500 had on the price of Bitcoin (**Figure 8**).

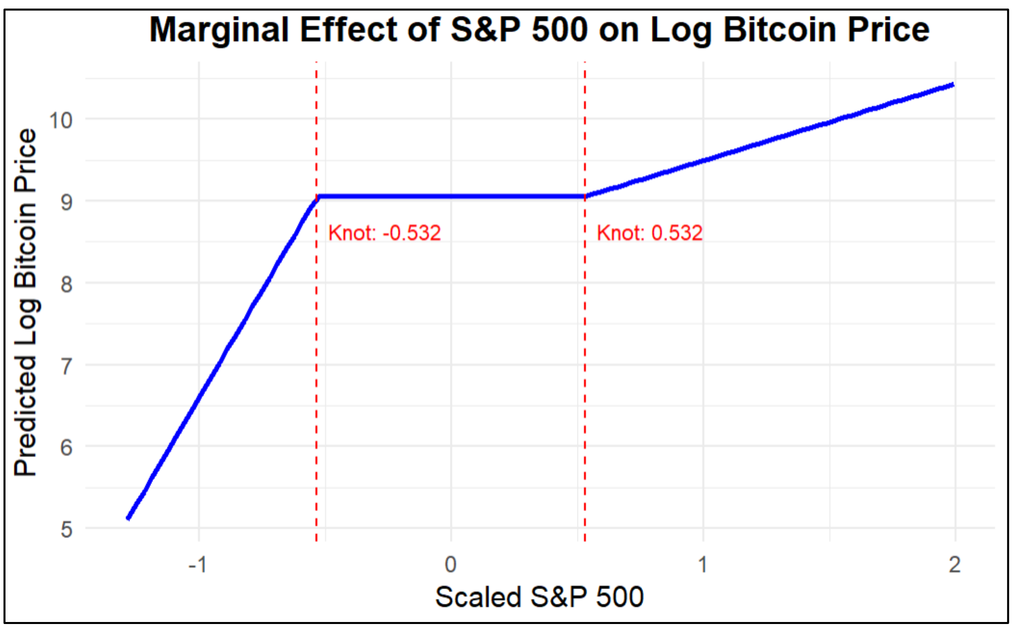

Figure 8: Marginal effects of S&P 500 has on Bitcoin Price

The S&P 500 price is scaled, so the knots are -0.5 and 0.5 standard deviations away from the mean price of the S&P 500. Essentially, whenever the S&P 500 had values -0.5 standard deviations away from the mean, there was a strong, positive linear relationship between the S&P 500 and Bitcoin. Likewise, when the S&P 500 was 0.5 standard deviations away from the mean, there was a linear relationship, but not as strong as the other knot.

The asymmetric influence on the price of Bitcoin depending on the S&P 500's values were of great interest to the research team, particularly the influence the model gave to the first (-0.5) knot. Two potential conjectures were generated as potential directions for further inquiry. The first is that within the data, most of the prices that fell below the mean of the S&P 500 were earlier on with respect to time. Simultaneously, Bitcoin was much lower in price and experienced rapid, unparalleled adoption speed. In essence, the model may have picked up on the disproportionately quick growth of Bitcoin relative to S&P 500 earlier in the data. The second conjecture is derived from the fact some data points with low S&P 500 values could be from recessions. In periods of relative economic recession or rebounding (referring to periods where the S&P 500 falls below the mean), the amplified influence the S&P 500 has on Bitcoin might indicate high-growth, tech stock-like behavior that reacts disproportionately to shifts in the equity market sentiments. In addition, the right knot (0.5) also shows a tight correlation found within the data, although not as strong as the left knot. These findings suggest that Bitcoin's price is asymmetrically influenced by the S&P 500, particularly when the S&P 500 is below the mean. This could reflect Bitcoin's increased sensitivity to broader market conditions during periods of relative economic recovery or recession. While the data provides evidence for Bitcoin's speculative, tech-like behavior under such conditions, further research is needed to explore the interplay between historical timing, market adoption, and investor sentiment.

The term with the second largest coefficient weight was the interaction effect between the S&P 500 and gold on Bitcoin. The interaction effect is plotted in **Figure 9**.

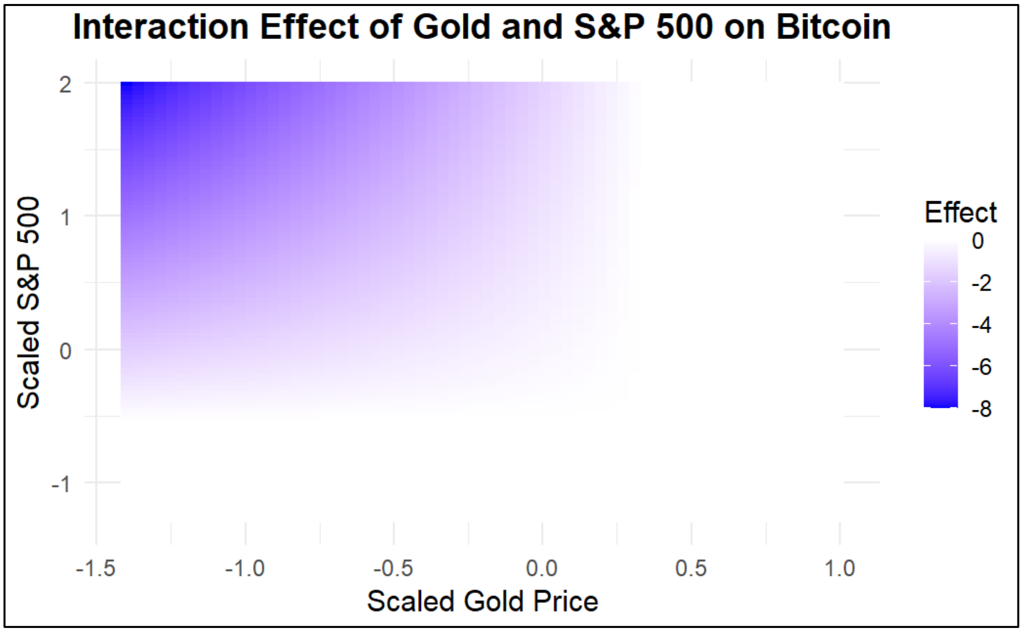

Figure 9: Interaction effect between Gold and S&P 500 on log(BTC Price)

The price of gold and the S&P 500 are scaled to be standard deviations away from their respective means. The behavior described above is when the S&P 500 is high, gold and Bitcoin are positively correlated and move opposite to that of the S&P 500. This is contrary to **Figure 3**, which suggests a scenario where gold and Bitcoin could potentially serve the same economic purpose outside of Bitcoin's relationship with the S&P 500. This may suggest that the model captured an underlying pattern in the data, highlighting a segment of the market where Bitcoin aligns more closely with gold-like behavior. Essentially, when the S&P 500 and Bitcoin are decoupled, gold becomes the strongest influence, suggesting a market segmentation that categorizes Bitcoin as a digital-gold-like asset under these conditions.

The trends shown in the data are similar to those expected if two dominant groups existed that invest in Bitcoin. One group in which investors see it as a more speculative technology stock, and another group that might view Bitcoin within the same category as gold. It is possible that the interactions between these two groups define the market value of Bitcoin. If so, the unique property of Bitcoin having no fundamental backing in physical assets or government fiat leaves open the possibility that Bitcoin could be more purely represented by the views and beliefs of its strongest investors. Consequently, the price of Bitcoin could be seen as a measure of the investor's beliefs in the stability of U.S. financial institutions. This is purely correlational evidence, and more research needs to be done to fully understand with statistical confidence the impact or extent of these claims.

IV. Conclusion

In this paper, an exploration of the value proposition of Bitcoin as a digital gold-like safe haven was conducted. The hypothesis that US Economic performance and Bitcoin price are inversely correlated was investigated. A surprisingly strong positive correlation (.8) was found, but with some interesting caveats related to the interaction effects of S&P500 and gold prices.

To explore Bitcoin's value proposition, an interpretable numeric dataset of proxies of trust in US Economic performance was combined with a MARS model. In doing this, it was possible to elucidate the relationships between trust in US Economic performance and its relationship with Bitcoin's price. This was through looking at the coefficients of each of the predictors in the MARS model as they relate to the log of Bitcoin's price. To do this, an 80/20 split of training and testing data was used, followed by a 10-fold cross validation approach. This resulted in a non-chronological modeling approach designed to mitigate time-biased skewness.

From this, the important findings were that Bitcoin price and the S&P500 are tightly correlated, and S&P500 price is the most important predictor of Bitcoin price, followed by the interaction effect between the S&P500 and gold prices. Further, a division was found in the model between the effect of Bitcoin purchased earlier in the decade, and Bitcoin purchased later in the decade. This finding suggests that Bitcoin has two main segments of investors: those who view Bitcoin as a "digital gold" safe haven for economic uncertainty, while others view it analogous to a high growth tech stock.

A non-chronological random sampling approach was used instead of a time series approach. Despite this, the MARS model featured an impressive adjusted R^2 of 0.945 and RMSE of 0.295. This suggests there is not overfitting and a model reasonably capable of predicting Bitcoin price has been created. Further, the model could be extended to chronological data sets to inform real time predictions of Bitcoin price in a way that is explainable to investors.

Overall, Bitcoin represents a unique asset class. Some view it as a tech stock, others as digital gold. So long as the S&P500 continues to rise, it is suspected that the erratic rise of Bitcoin has no sign of stopping anytime soon.

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Appendix

Appendix A - Sources and Descriptions of the Data

Metric	Data URL	Brief Description
Bitcoin	https://coinmarketcap.com/currencies/bitcoin/historical-data/	Bitcoin price history (USD) from October 2014 to now.
Gold	https://github.com/datasets/gold-prices/blob/main/data/monthly.csv	Gold price data (USD) from
Consumer Price Index	Consumer Price Index (CPI) Databases : U.S. Bureau of Labor Statistics	Consumer Price Index data from January 2014 to Now. Covers CPI for All Urban Consumers. This explains inflation trends within the U.S.
S&P 500	https://finance.yahoo.com/quote/%5EGSPC/history/?form=MG0AV3	S&P 500 index time series data from October 2014 to Now. This data explains how the top 500 publicly traded companies are performing.
10-year yields	https://www.investing.com/rates-bonds/u.s.-10-year-bond-yield-historical-data?form=MG0AV3	10-year Bond Yield history from October 2014 to Now. This serves as an economic indicator of citizen confidence.
Gross Foreign Investors Purchases (LT-Securities)	https://home.treasury.gov/archives-of-tic-monthly-data-releases	Total value of long-term U.S. securities (maturity of more than one year i.e. bonds, notes, equities) purchased by foreign investors.
Gross Foreign Investors Sales (LT-Securities)	https://home.treasury.gov/archives-of-tic-monthly-data-releases	Total value of long-term securities sold by foreign investors in the U.S. market,
Gross Foreign Purchase of Foreign LT-Securities	https://home.treasury.gov/archives-of-tic-monthly-data-releases	Total value of long-term foreign securities purchased by foreign investors.
Gross Foreign Sales of Foreign LT-Securities	https://home.treasury.gov/archives-of-tic-monthly-data-releases	Total value of long-term foreign securities sold by foreign investors.
US dollar index	https://www.investing.com/indices/usdollar-historical-data?form=MG0AV3	The US Dollar Index indicates the strength of the US dollar relative to the basket of Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona, and Swiss Franc. The index rises when the dollar gains strength against the basket of currencies and falls when it loses strength.
Net Domestic LT-Securities	https://home.treasury.gov/archives-of-tic-monthly-data-releases	Difference between purchases and sales of long-term securities held by domestic (U.S.) investors.

Appendix B - Names of Variables & Descriptions

For all data, the "trading period," or measured periods of time are in monthly splits.

Bitcoin: Numeric (USD$),

- btc_montly_price: averaged monthly price of daily averaged OHLC (open + high + low + close) / 4) bitcoin price for each month.
- btc_open: the opening trading price of BTC at the start of a trading period, continuous
- btc_high: the highest trading price of BTC during a trading period, continuous
- btc_low: the lowest trading price of BTC during a trading period, continuous
- btc_close: the closing trading price of BTC at the end of a trading period, continuous
- btc_volume: the trading volume of BTC over the trading period, integer

Gold: Numeric (USD$)

- gold_price: market price of gold during a trading period

Consumer Price Index: Numeric,

- cpi_u: consumer price index for all urban consumers

S&P500: Numeric,

- sp500_open: opening index for the S&P 500 at the start of a trading period
- sp500_high: highest recorded index for the S&P 500 during the trading period
- sp500_low: lowest recorded index for the for the S&P 500 during a trading period
- sp500_close: closing index for the S&P 500 at the end of a trading period
- sp500_volume: total trading volume of the S&P 500 index during a trading period

10-Year Bond Yields: Numeric (USD$),

- 10yr_bond_open: 10-Year Bond opening price at the start of a trading period
- 10yr_bond_close: 10-Year Bond closing price at the end of a trading period
- 10yr_bond_high: Highest 10-Year Bond price during the trading period
- 10yr_bond_low: Lowest 10-Year Bond price during the trading period
- 10yr_bond_pct_change: percentage change in the yield of the 10-Year Bond yield over a trading period (between 0 and 1)

US Dollar Index: Numeric,

- usdx_open: the opening US Dollar Index at the beginning of a trading period
- usdx_close: the closing US Dollar Index at the end of a trading period
- usdx_high: the highest US Dollar Index value during a trading period
- usdx_low: the lowest US Dollar Index value during a trading period

Foreign and Domestic Investments: Numeric,

- tot_for_purch_us_sec: total value of long-term U.S. securities (maturity of more than one year, i.e., bonds, notes, equities) purchased by foreign investors

- tot_for_sale_us_sec: total value of long-term U.S. securities (maturity of more than one year, i.e., bonds, notes, equities) sold by U.S. investors to foreign buyers
- net_tot_for_purch_us_sec: net total value of long-term U.S. securities (maturity of more than one year, i.e., bonds, notes, equities) purchased by foreign investors, adjusted for sales by U.S. investors
- net_tot_priv_for_purch_us_sec: net total value of long-term U.S. securities (maturity of more than one year) purchased by private foreign investors
- net_priv_for_purch_us_treas_bond_note: net value of U.S. Treasury bonds and notes (maturity of more than one year) purchased by private foreign investors
- net_priv_for_purch_us_gov_agcy_bond: net value of U.S. government agency bonds (maturity of more than one year) purchased by private foreign investors
- net_priv_for_purch_us_corp_bond: net value of U.S. corporate bonds (maturity of more than one year) purchased by private foreign investors
- net_priv_for_purch_us_equity: net value of U.S. equity securities (such as stocks) purchased by private foreign investors
- net_tot_gov_for_purch_us_sec: net total value of long-term U.S. securities (maturity of more than one year) purchased by official (government) foreign institutions
- net_gov_for_purch_us_treas_bond_note: net value of U.S. Treasury bonds and notes (maturity of more than one year) purchased by official (government) foreign institutions
- net_gov_for_purch_us_gov_agcy_bond: net value of U.S. government agency bonds (maturity of more than one year) purchased by official (government) foreign institutions
- net_gov_for_purch_us_corp_bond: net value of U.S. corporate bonds (maturity of more than one year) purchased by official (government) foreign institutions.
- net_gov_for_purch_us_equity: net value of U.S. equity securities (such as stocks) purchased by official (government) foreign institutions
- tot_dom_sale_for_sec: total value of long-term foreign securities (maturity of more than one year) sold by U.S. investors
- tot_dom_purch_for_sec: total value of long-term foreign securities (maturity of more than one year) purchased by U.S. investors
- net_dom_purch_for_sec: net total value of long-term foreign securities (maturity of more than one year) purchased by U.S. investors, adjusted for sales and purchases
- net_dom_purch_for_bond: net value of foreign bonds (maturity of more than one year) purchased by U.S. investors
- net_dom_purch_for_equity: net value of foreign equity securities (such as stocks) purchased by U.S. investors
- net_for_purch_dom_longterm_sec: net value of long-term domestic securities acquired by foreign investors
- net_for_purch_us_t_bills_custodial: net value of U.S. Treasury bills and other short-term custodial items purchased by foreign investors
- tot_for_hold_us_t_bills: total value of U.S. Treasury bills held by foreign investors.
- tot_priv_for_hold_us_t_bills: total value of U.S. Treasury bills held by private foreign investors
- tot_gov_for_hold_us_t_bills: total value of U.S. Treasury bills held by official (government) foreign institutions
- tot_month_change_dom_bank_liab_for_inflow: total monthly change in domestic bank liabilities for inflows of foreign-owned, dollar-denominated assets i.e. it's looking at how much domestic banks owe due to foreign money flowing into the U.S. each month
- month_change_bank_liab_priv_for_inflow: monthly change in domestic bank liabilities held by private foreign investors for inflows of foreign-owned, dollar-denominated assets
- month_change_bank_liab_gov_for_inflow: monthly change in domestic bank liabilities held by official (government) foreign institutions for inflows of foreign-owned, dollar-denominated

assets

- month_change_bank_liab_all_for_inflow: total monthly change in liabilities across all U.S. financial institutions (not just domestic banks) from foreign money coming in i.e. includes both private and government foreign holdings, covering a wider range of liabilities from foreign inflows

Appendix C - Descriptive Statistics of Each Variables

variable	n	missing	missing_pct	unique	unique_pct	mean	min	Q1	median	Q3	max	sd
btc_monthly_price	118	0	0	118	100.0	17325.258	233.739	1148.874	9164.376	27842.550	67470.050	19126.746
btc_open	118	0	0	118	100.0	17011.822	216.867	1098.792	9169.989	28863.840	71333.485	18918.117
btc_high	118	0	0	118	100.0	20006.411	247.804	1297.210	10328.596	31293.556	73750.074	21799.625
btc_low	118	0	0	118	100.0	14742.314	171.510	975.291	7268.834	25761.100	59323.909	16384.228
btc_close	118	0	0	118	100.0	17559.416	217.464	1221.950	9220.067	29173.013	71333.648	19360.848
btc_volume	118	0	0	115	97.5	418033121107.627	13942900.000	860348512.000	22164207939.000	877000000000.000	2270000000000.000	553938692925.626
tot_for_purch_us_sec	118	0	0	118	100.0	3710085.102	2076252.000	2706366.000	3533880.500	4590264.000	6718867.000	1160308.704
tot_for_sale_us_sec	118	0	0	118	100.0	3671321.449	2016889.000	2680625.000	3488092.000	4449601.250	6698526.000	1138876.316
net_tot_for_purch_us_sec	118	0	0	118	100.0	38763.653	-241924.000	-1044.250	33936.000	76139.500	239688.000	67202.397
net_tot_priv_for_purch_us_sec	118	0	0	118	100.0	43160.449	-212471.000	13175.750	38097.500	79033.250	185579.000	58314.911
net_priv_for_purch_us_treas_bond_note	118	0	0	118	100.0	19019.119	-249590.000	-723.000	18676.500	45650.750	182851.000	50945.571
net_priv_for_purch_us_gov_agcy_bond	118	0	0	118	100.0	12788.525	-12093.000	6735.000	12352.000	17932.000	38982.000	8643.181
net_priv_for_purch_us_corp_bond	118	0	0	118	100.0	9212.449	-55754.000	3041.250	9122.500	17426.250	47230.000	15252.297
net_priv_for_purch_us_equity	118	0	0	118	100.0	2140.356	-90645.000	-14578.750	-794.000	18942.500	106297.000	30389.016
net_tot_gov_for_purch_us_sec	118	0	0	118	100.0	-4396.797	-56305.000	-19559.000	-6920.000	7806.000	65930.000	24585.964
net_gov_for_purch_us_treas_bond_note	118	0	0	118	100.0	-13017.754	-61203.000	-24260.000	-12734.000	-2232.750	47811.000	21922.435
net_gov_for_purch_us_gov_agcy_bond	118	0	0	117	99.2	7405.644	-10186.000	1604.250	5705.000	11973.750	30103.000	7971.121
net_gov_for_purch_us_corp_bond	118	0	0	116	98.3	671.653	-2704.000	-671.750	415.000	1545.000	7394.000	1912.417
net_gov_for_purch_us_equity	118	0	0	115	97.5	543.661	-15226.000	-1142.500	511.000	2235.000	20394.000	4696.065
tot_dom_sale_for_sec	118	0	0	118	100.0	1468716.907	680118.000	966759.000	1415085.000	1938914.250	2721912.000	537289.178
tot_dom_purch_for_sec	118	0	0	118	100.0	1454130.754	705803.000	970363.500	1396364.000	1918559.500	2718602.000	529604.439
net_dom_purch_for_sec	118	0	0	118	100.0	14586.153	-80997.000	2281.500	16098.000	31813.000	113822.000	27202.343
net_dom_purch_for_bond	118	0	0	118	100.0	16459.627	-42299.000	7382.500	19681.000	29076.500	113019.000	21063.166
net_dom_purch_for_equity	118	0	0	118	100.0	-1873.475	-42739.000	-9650.500	-1662.000	6050.500	39022.000	13928.589

net_for_purch_dom_longterm_sec	118	0	0	118	100.0	35055.678	-167118.000	-5202.000	23153.500	76920.750	220153.000	68761.881
net_for_purch_us_t_bills_custodial	118	0	0	118	100.0	10969.771	-69799.000	-12106.000	4395.000	26961.250	266896.000	44030.614
tot_for_hold_us_t_bills	118	0	0	118	100.0	4037.669	-74720.000	-10957.500	2276.000	17726.750	151692.000	29056.395
tot_priv_for_hold_us_t_bills	118	0	0	118	100.0	4494.059	-66709.000	-8713.250	2656.000	16284.000	103900.000	22938.476
tot_gov_for_hold_us_t_bills	118	0	0	118	100.0	-456.390	-45636.000	-9103.000	394.500	8532.500	47792.000	13993.799
tot_month_change_dom_bank_liab_for_inflow	118	0	0	118	100.0	3264.153	-209978.000	-55292.000	-9492.000	64576.000	473842.000	100092.757
month_change_bank_liab_priv_for_inflow	118	0	0	118	100.0	49289.593	-194622.000	-11822.250	49898.000	117355.500	314897.000	102695.900
month_change_bank_liab_gov_for_inflow	118	0	0	118	100.0	51459.508	-165142.000	-8224.500	47292.500	118046.250	306510.000	97804.208
month_change_bank_liab_all_for_inflow	118	0	0	117	99.2	-2170.008	-60961.000	-19731.500	-4523.000	14903.500	79380.000	27392.209
cpi_u	118	0	0	118	100.0	264.139	233.707	243.982	256.476	283.074	314.540	25.016
gold_price	118	0	0	118	100.0	1550.220	1075.740	1247.130	1474.960	1848.003	2398.200	339.325
sp500_open	118	0	0	118	100.0	3201.999	1919.650	2366.788	2939.310	4109.835	5471.080	980.045
sp500_high	118	0	0	118	100.0	3313.964	1962.960	2398.865	3017.790	4212.945	5669.670	1021.779
sp500_low	118	0	0	118	100.0	3094.252	1810.100	2284.300	2835.375	3951.668	5390.950	950.915
sp500_close	118	0	0	118	100.0	3228.651	1920.030	2368.780	2943.795	4131.520	5522.300	994.029
sp500_volume	118	0	0	116	98.3	83951065084.746	63031510000.000	75133537500.000	80915220000.000	89686535000.000	162000000000.000	14907205994.621
usdx_close	118	0	0	118	100.0	97.665	88.413	94.294	96.944	101.335	112.084	4.871
usdx_open	118	0	0	118	100.0	97.561	87.130	94.305	96.850	101.320	112.150	4.969
usdx_high	118	0	0	116	98.3	99.146	88.515	95.440	98.172	103.537	114.745	5.188
usdx_low	118	0	0	114	96.6	96.030	86.975	92.601	95.350	99.214	109.365	4.667
X10yr_bond_close	118	0	0	114	96.6	2.392	0.533	1.673	2.279	2.951	4.926	1.024
X10yr_bond_open	118	0	0	116	98.3	2.384	0.535	1.675	2.288	2.915	4.926	1.014
X10yr_bond_high	118	0	0	117	99.2	2.583	0.724	1.893	2.406	3.110	5.021	1.042
X10yr_bond_low	118	0	0	116	98.3	2.215	0.318	1.521	2.113	2.795	4.530	0.980
X10yr_bond_pct_change	118	0	0	116	98.3	0.012	-0.426	-0.048	0.012	0.065	0.325	0.121

Appendix D – Output of OLS Model

$$\begin{aligned}
\ln(\text{BTC Price}) = 8.6581 &+ 0.1469 \cdot \text{net_priv_for_purch_us_gov_agcy_bond} \\
&+ 0.4472 \cdot \text{net_gov_for_purch_us_treas_bond_note} \\
&+ 0.9299 \cdot \text{net_gov_for_purch_us_gov_agcy_bond} \\
&+ 0.4126 \cdot \text{net_gov_for_purch_us_corp_bond} \\
&+ 0.1455 \cdot \text{tot_for_hold_us_t_bills} \\
&+ 0.2295 \cdot \text{sp500_volume} \\
&+ 0.2067 \cdot \text{x10yr_bond_pct_change} \\
&+ 0.8112 \cdot \text{x10yr_bond}
\end{aligned}$$

Appendix E – Output of ElasticNet Model

$$
\begin{aligned}
\ln(\text{BTC Price}) = 8.7589 &- 0.1103 \cdot \text{net\_priv\_for\_purch\_us\_treas\_bond\_note} \\
&+ 0.0142 \cdot \text{net\_priv\_for\_purch\_us\_gov\_agcy\_bond} \\
&- 0.0421 \cdot \text{net\_priv\_for\_purch\_us\_corp\_bond} \\
&+ 0.0548 \cdot \text{net\_tot\_gov\_for\_purch\_us\_sec\_treas\_bond\_note} \\
&+ 0.0178 \cdot \text{net\_tot\_gov\_for\_purch\_us\_sec} \\
&+ 0.0747 \cdot \text{net\_gov\_for\_purch\_us\_gov\_agcy\_bond} \\
&+ 0.0740 \cdot \text{net\_gov\_for\_purch\_us\_equity} \\
&+ 0.2173 \cdot \text{tot\_for\_hold\_us\_t\_bills} \\
&+ 0.3453 \cdot \text{net\_gov\_for\_purch\_dom\_equity} \\
&- 0.0290 \cdot \text{net\_dom\_purch\_for\_bond} \\
&+ 0.1753 \cdot \text{net\_for\_purch\_us\_t\_bills\_custodial} \\
&- 0.0183 \cdot \text{net\_for\_hold\_us\_t\_bills} \\
&- 0.0183 \cdot \text{tot\_month\_change\_dom\_bank\_liab\_for\_inflow} \\
&+ 0.2516 \cdot \text{cpi\_u} \\
&- 0.0991 \cdot \text{sp500\_volume} \\
&+ 1.1576 \cdot \text{sp500} \\
&- 0.3253 \cdot \text{usdx} \\
&+ 0.2888 \cdot \text{x10yr\_bond}
\end{aligned}
$$

Appendix F – Output of MARS Model

$$
\begin{aligned}
\ln(\text{BTC Price}) = &\ 9.056 + 0.941 \cdot h(\text{sp500} + 0.532) \\
&- 5.249 \cdot h(-0.532 - \text{sp500}) \\
&+ 0.273 \cdot (-0.347 - \text{usdx}) \\
&- 0.147 \cdot h(\text{x10yearBond} + 0.812) \\
&- 0.444 \cdot h(-0.812 - \text{x10yearBond}) \\
&+ 0.777 \cdot h(\text{sp500volume} \cdot h(-0.532 - \text{sp500})) \\
&+ 0.520 \cdot h(-0.374 - \text{totForSaleUSSec}) \\
&+ 0.165 \cdot (\text{x10yearBond\%Change} \cdot h(-0.347 - \text{usdx})) \\
&- 1.835 \cdot h(0.337 - \text{goldPrice}) \cdot h(\text{sp500} + 0.532)
\end{aligned}
$$