

Article

Predictive Analytics Approaches to Modeling Bitcoin Prices During Periods of Financial Uncertainty

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Abstract

The decentralized nature of cryptocurrencies makes them an appealing choice for investors around the world in times of uncertainty. Recent global health concerns, political conflicts, and subsequent economic issues have contributed to uncertainty in financial markets worldwide. In the first part of this study, we examine the recent changes in the price of Bitcoin and explore the relationship between various financial factors and the price of Bitcoin. Previous studies have been inconclusive in establishing a linear relationship between Bitcoin and various market indexes, including the S&P 500, Dow Jones Industrial Average, Nasdaq 100, Russell 2000, and Nikkei 225, as well as the prices of commodities such as Gold and Oil. In this study, to address the issue of uncertainty due to the volatility of the stock market and its effect on the Bitcoin price, we examine the relationship between the popular measure of the stock market's expectation of volatility based on the S&P 500 index (VIX) and Bitcoin. Some non-linear analytical methods are employed to examine the impact of the aforementioned indices, commodities, and financial uncertainty measures on Bitcoin prices. This study utilizes different time frames, including weekly and monthly data from 1 January 2016 to 1 March 2026. In the second part of this study, Principal Component Analysis is utilized. Since the suggested analytical models are based on correlated financial factors, Principal Component Analysis will be used to address this issue while maintaining the high explanatory power of our suggested models.

Keywords: cryptocurrency; non-linear models; market volatility; financial indexes; commodities

JEL Classification: C53



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1. Introduction

A recent price change in Bitcoin has renewed interest in the study of cryptocurrencies, in general, and Bitcoin in particular. Bitcoin was initially introduced to the world of finance by Satoshi Nakamoto in 2009. Currently, Bitcoin is the most famous cryptocurrency in the world. Cryptocurrencies are virtual currencies that can operate independently without relying on traditional financial institutions or governmental agencies, yet can still be used for exchange and speculation, like any physical currency. There are several characteristics of cryptocurrencies that are appealing to investors and speculators. The most significant aspect of cryptocurrencies is their inability to be used in various financial transactions without the need for a central authority to oversee and approve them. As a result, peer-to-peer transactions do not need a central player. Instead, they would be verified by peers

on the Bitcoin network, which maintains a permanent record of all transactions in the Blockchain. To understand the role of Blockchain in this process, it is useful to think of it as a distributed database that anonymously tracks all records. Anonymous peers in the network would be able to verify all the transactions and confirm their legitimacy. This process makes it almost impossible to commit an error. This anonymous peer evaluation is another appealing aspect of cryptocurrencies. While the world is still trying to figure out the role cryptocurrency plays as an asset class, several theories exist about how it should perform in different economic environments. In theory, cryptocurrencies should serve as a good alternative to gold. However, in practice, due to speculation, volatility, and the presence of other viable alternatives, this issue has not materialized during the last several years.

Bitcoin is still by far the most popular cryptocurrency, despite its rapid relative decline since 2015, due to strong competition. In 2015, Bitcoin accounted for 86% of the cryptocurrency market, while in the first quarter of 2025, its market share was 59.16%, compared to Ethereum's 7.89% [1]. In a major boost to Bitcoin's adoption, the US Securities and Exchange Commission (SEC) approved Bitcoin ETFs, giving institutional and retail investors exposure to the world's cryptocurrency without directly holding it. Several institutional investors, such as BlackRock, Fidelity, and Ark Invest, offer exposure to the world's largest cryptocurrency without directly holding it [2]. The acceptance of Bitcoin has increased lately. In 2023, two countries recognized Bitcoin as legal tender [3]. Recently, several other countries have started accepting Bitcoin. Later, PayPal announced that it would enable Bitcoin and other cryptocurrencies as funding sources for purchases [4]. The recent US government policy regarding cryptocurrencies has significantly impacted the price of many of these currencies, including Bitcoin [5]. It is worth noting that several other cryptocurrencies, including Bitcoin Cash, Ethereum, Ripple, and Litecoin, are competing with Bitcoin for market share, with varying degrees of success. However, in this study, we exclusively focus on Bitcoin's performance, as it is by far the most widely used cryptocurrency.

Since March 2020, several global health issues and political conflicts have contributed to uncertainty in financial markets worldwide.

The COVID-19 virus has been one of the most devastating healthcare threats in recent history. Although initially its presence was restricted to China, it soon became clear that the virus could spread rapidly worldwide. Indeed, just a few months after the first detection of the virus, we observed it spreading worldwide exponentially and soon becoming a global pandemic. To fully understand the magnitude and effect of this pandemic, we take a closer look at some available data. As of 10 April 2026, according to the World Health Organization (WHO), more than 779 million confirmed cases have been reported to the WHO, including over 7 million deaths [6]. In the United States alone, as of 10 April 2026, the number of infected patients is well over 103 million, with a death toll of 1.23 million [6]. Obviously, such a devastating pandemic has significant consequences for the global economy, particularly the US economy. According to the World Bank data [7], the US economy is the largest economy in the world. In 2020, the COVID-19 pandemic inflicted the worst economic freeze on the US economy since the end of World War II [8]. Furthermore, the economic decline we have seen during the COVID-19 crisis is the first since the 2009 financial crisis. In addition to the COVID-19 crisis, the global political conditions worldwide have created significant economic uncertainty.

The Russia-Ukraine war started in February 2022. This war forced countries around the world to change their business partners. Before the conflict, Ukraine's agricultural sector was a significant global player, particularly in the export of grain, which accounted for 10% of global trade, and sunflower oil, which accounted for 50% [9]. The main parts

of these commodities were exported through the Black Sea, which has been significantly impacted by the ongoing war.

The Middle Eastern war between Israel and Hamas since 7 October 2023 has caused more uncertainty in the financial market. To make the situation worse, Yemen's Houthis started attacking ships that are passing the Bab el-Mandeb Strait, which is a pathway connecting Asia to Europe. Indeed, this waterway connects the Red Sea with the Gulf of Aden and the Indian Ocean, facilitating the passage of a significant portion of global trade, including oil and liquefied natural gas. Disruptions to the strait, like those caused by attacks, can have major economic and geopolitical consequences. To better understand the magnitude of this issue, over 20,000 vessels transit the Strait annually, which accounts for approximately 10% of international naval trade [10].

The continuation of the health and political conflicts mentioned above is causing economic uncertainty worldwide, particularly in the United States, the world's largest economy. This continued uncertainty will inevitably impact economic conditions. As a result, in this environment, it is natural for investors to seek alternative ways to manage the uncertainty they face. A well-diversified portfolio in times of uncertainty can help mitigate risk.

To address uncertainty, we examine stock market volatility and its effect on Bitcoin prices. In particular, we examine the relationship between the Bitcoin price and various market indexes, including the S&P 500, Dow Jones Industrial Average, Nasdaq 100, Russell 2000, Nikkei 225, and commodity prices such as Gold. To address the issue of uncertainty due to the volatility of stock markets and its effect on the Bitcoin price, we examine the relationship between the popular measure of the stock market's expectation of volatility based on the S&P 500 index (VIX). In addition, the Euro-Dollar Exchange Rate will be used to determine its impact on Bitcoin's price.

2. Literature Review

Since the creation of Bitcoin in 2009, numerous research articles have addressed various aspects of cryptocurrency, in general, and Bitcoin in particular. Some of this research focused on Bitcoin's price formation, while others examined its price volatility. A major study [11] examined the relationship between Bitcoin's price and its demand and supply fundamentals. They examined the relationships among various global financial indicators, including oil prices, the Dow Jones Industrial Average index, and the attractiveness of Bitcoin to investors (i.e., the volume of daily Bitcoin views on Wikipedia). Furthermore, they examined the impact of each variable on Bitcoin's price individually, as well as the interaction of these factors on the cryptocurrency's price. They conclude that the fundamentals of the Bitcoin market and its attractiveness to investors significantly affect Bitcoin's price. However, the authors did not find evidence that the financial variables affect Bitcoin's price. Later, the volatility of Bitcoin prices was studied [12], which concluded that a bidirectional Granger-causality relationship exists [13] between Bitcoin's realized volatility and the VIX at the 5% significance level. To predict Bitcoin's price, various variables, including returns, volatility, trading volume, transaction volume, changes in the number of unique Bitcoin addresses, the VIX index, and Google searches for Bitcoin, were used [14]. However, it was concluded that Bitcoin trading volume can be predicted only from Google searches for Bitcoin. However, none of the other variables were useful for predicting Bitcoin returns.

Time series analyses have been used to predict Bitcoin prices. However, the results have not been successful. In particular, the popular Auto-Regressive Integrated Moving Average (ARIMA) model for time series forecasting is implemented as a comparison to the deep learning models. As expected, the non-linear deep learning methods outperform the

ARIMA forecast, which performs poorly [15]. Principal Component Analysis has been used in many predictive analytics research studies to address the issue of correlated predictor variables [16]. They utilize Principal Component Analysis to reduce dimensionality. This method allows for data reduction and simplification while retaining important information. Indeed, in practice, it can maintain the explanatory power of the predictive analytical models to a large extent with a much smaller number of predictors in our model. Principal Component Analysis is capable of developing a model that is strong, and at the same time, its coefficient (s) can be statistically significant. In a related study [17], the asymmetric, time-varying volatility of Bitcoin is estimated by using an approach that explicitly separates rising and falling market periods, providing a position-dependent measure of financial risk. The separation into positive and negative components is relevant to our study, finding that Bitcoin exhibits a non-linear pattern. Another research article [18] focused on a frequency-domain approach that simultaneously decomposes relationships across short-, medium-, and long-run time horizons. It confirms through wavelet analysis that Bitcoin exhibits increasing short-term coherence with global equities post-2020 and significant medium-term coherence during the COVID-19 crisis.

3. Data Set

For this study, data were collected weekly and monthly. Weekly and monthly data were collected from 1 January 2016 to 1 March 2026. Data were downloaded for Bitcoin prices, as well as market indexes such as the Nasdaq 100, S&P 500, Dow Jones Industrial Average, Russell 2000, Nikkei 225, and commodity prices for Gold and Oil. Additionally, VIX values were downloaded for the specified dates. Furthermore, the Euro/Dollar Exchange rate was used to account for the international impact of money transfer for buying/selling Bitcoin. The investing.com site was utilized to download our data. After the data was downloaded, it was decided that some parts of the data, such as Open, Maximum, and Minimum, were not relevant to this study. So, only the **date and closing values** were kept for each variable. It must be emphasized that all the data points are measured concurrently.

The data were first stored in Excel. The preliminary analysis, including visualization, descriptive statistics, and correlation analysis, was conducted in Excel 2021 using all the data. The data were then transferred to R for more advanced statistical analysis.

4. Methodology

To gain insight into our data, a preliminary analysis was conducted. First, various analytical measures, including measures of central tendency, variation, and shape, were calculated for the entire data set (both weekly and monthly).

Based on Tables 1 and 2, we can infer that the measures of skewness and Kurtosis of Bitcoin are consistent with the characteristics of the fat-tailed distribution (Kurtosis measures the “fatness” of the tails of a distribution; positive excess kurtosis means that the distribution has fatter tails than a normal distribution). In addition, the high coefficient of variation in Bitcoin (103.97% for weekly and 102.21% for monthly) reveals a very high level of variation (as a measure of uncertainty) compared to the rest of our data.

In order to construct our regression model, we used 5 indexes (Nasdaq 100 = X_1 , S&P 500 = X_2 , DJIA = X_3 , Russell 2000 = X_4 , Nikkei 225 = X_5) and two commodities (Gold = X_6 , Oil = X_7), the stock market’s expectation of volatility based on the S&P 500 index (VIX = X_8), and Exchange Rate (Euro/Dollar Exchange Rate = X_9). To account for global health issues and political conflicts, three dummy variables were created. Three binary dummy variables are included in the model to capture the effects of major geopolitical and public health events on Bitcoin prices.

Table 1. Measures of central tendency, variation, and shape for weekly data.

	<i>Weekly Bitcoin Price</i>	<i>Weekly Nasdaq 100</i>	<i>Weekly S&P 500</i>	<i>Weekly DJIA</i>	<i>Weekly Russell 2000</i>	<i>Weekly Nikkei 225</i>	<i>Weekly Gold</i>	<i>Weekly Oil</i>	<i>Weekly VIX</i>	<i>Weekly Euro</i>
Mean	31,140.91	12,078.72	3831.15	30,733.04	1776.70	27,587.94	1890.22	67.97	18.25	1.12
Standard Error	1405.00	258.7044	58.52	361.42	16.76	378.43	33.92	0.77	0.31	0.002
Median	18,925.20	11,692.57	3714.24	30,218.26	1741.00	26,476.50	1768.59	67.77	16.42	1.12
Standard Deviation	32,375.95	5961.439	1348.55	8328.29	386.24	8720.22	781.55	17.72	7.09	0.05
Kurtosis	0.18	−0.68364	−0.59	−0.71	−0.78	0.88	4.19	0.27	9.61	−0.36
Skewness	1.12	0.568991	0.61	0.30	0.16	1.07	1.97	0.22	2.30	−0.05
Range	122,010.40	21,838.94	5101.48	34,141.83	1705.70	43,898.25	4241.19	100.57	56.90	0.28
Minimum	376.70	4019.19	1864.80	15,973.84	972.00	14,952.02	1089.10	21.44	9.14	0.97
Maximum	122,387.10	25,858.13	6966.28	50,115.67	2677.70	58,850.27	5330.29	122.01	66.04	1.25
Count	531	531	531	531	531	531	531	531	531	531
Coeff. of Variation	103.97%	49.35%	35.20%	27.10%	21.74%	31.61%	41.35%	26.07%	38.85%	4.80%

Table 2. Measures of central tendency, variation, and shape for monthly data.

	<i>Monthly Bitcoin Price</i>	<i>Monthly Nasdaq 100</i>	<i>Monthly S&P 500</i>	<i>Monthly DJIA</i>	<i>Monthly Russell 2000</i>	<i>Monthly Nikkei 225</i>	<i>Monthly Gold</i>	<i>Monthly Oil</i>	<i>Monthly VIX</i>	<i>Monthly Euro</i>
Mean	31,397.75	12,223.9	3863.89	30,913.4	1785.65	27,905.1	1925.49	67.88	18.52	1.12
Standard Error	2893.56	548.88	124.54	766.98	35.19	833.05	76.29	1.55	0.62	0.00
Median	19,698.1	12,030.1	3756.1	30,606.5	1749.65	26,433.6	1767.70	68.12	16.72	1.12
Standard Deviation	32,091.16	6087.32	1381.24	8506.18	390.33	9238.97	846.12	17.14	6.88	0.05
Kurtosis	0.05	−0.68	−0.59	−0.72	−0.82	1.31	4.49	0.08	5.43	−0.40
Skewness	1.06	0.58	0.63	0.34	0.20	1.21	2.06	0.10	1.88	−0.07
Range	115,395.20	21,657.01	5006.80	32,511.62	1621.09	43,274.35	4219.80	89.25	44.03	0.26
Minimum	369.80	4201.12	1932.23	16,466.30	1033.90	15,575.92	1116.40	26.35	9.51	0.98
Maximum	115,765.0	25,858.1	6939.0	48,977.9	2654.99	58,850.3	5336.2	115.6	53.5	1.24
Count	123	123	123	123	123	123	123	123	123	123
Coeff. of Variation	102.21%	49.80%	35.75%	27.52%	21.86%	33.11%	43.94%	25.26%	37.13%	4.82%

X_{10} is a dummy variable representing the COVID-19 pandemic period. It takes a value of 1 during the period when COVID-19 constituted a major global health emergency—defined here as March 2020 through May 2021—and 0 otherwise.

X_{11} is a dummy variable capturing the effect of the Russia-Ukraine conflict. It takes a value of 0 prior to the outbreak of the conflict and 1 from 22 February 2022 onward, reflecting the date on which Russia launched its full-scale military invasion of Ukraine.

X_{12} is a dummy variable representing the Israel-Hamas conflict period. Given the different temporal resolutions of the two datasets, the coding of this variable differs slightly by frequency. For the monthly data, X_{12} takes a value of 1 from November 2023 through October 2025, and 0 otherwise. For the weekly data, X_{12} takes the value 1 for the week of 8 October 2023, which coincides with the outbreak of the conflict, and 0 otherwise.

To gain a deeper understanding of our weekly data and to compare our variables, we employed various visualization tools. Based on these displays, it was determined that the non-linear relationship between the response variable (Bitcoin Price) and the explanatory

variables would be more appropriate. Furthermore, analysis of Bitcoin prices reveals that they have increased substantially when plotted against our explanatory variables. Therefore, we think the Sqrt Root of Bitcoin prices could be a good candidate. Furthermore, examining the relationship between our new response variable (the Sqrt Root of Bitcoin) and the explanatory variables reveals that the transformation has increased the correlation between the response variable and the explanatory variables. Therefore, a Sqrt Root transformation would be applied to our response variable (Bitcoin Prices).

Figures 1 and 2 reveal that a non-linear relationship exists between Bitcoin prices and the DJIA. The same pattern exists for the other indices. Although other non-linear transformations seem appropriate, the Sqrt Root transformation has its own advantages. Therefore, we decided to take the Sqrt Root of Bitcoin prices while leaving our explanatory variables untouched. Overall, this transformation yielded strong correlations for our indices, as shown by comparing the graphs and correlation matrices (before and after the transformation). The correlation matrices are presented in Tables 3–6 for the weekly and monthly Bitcoin prices, both before and after the transformation.

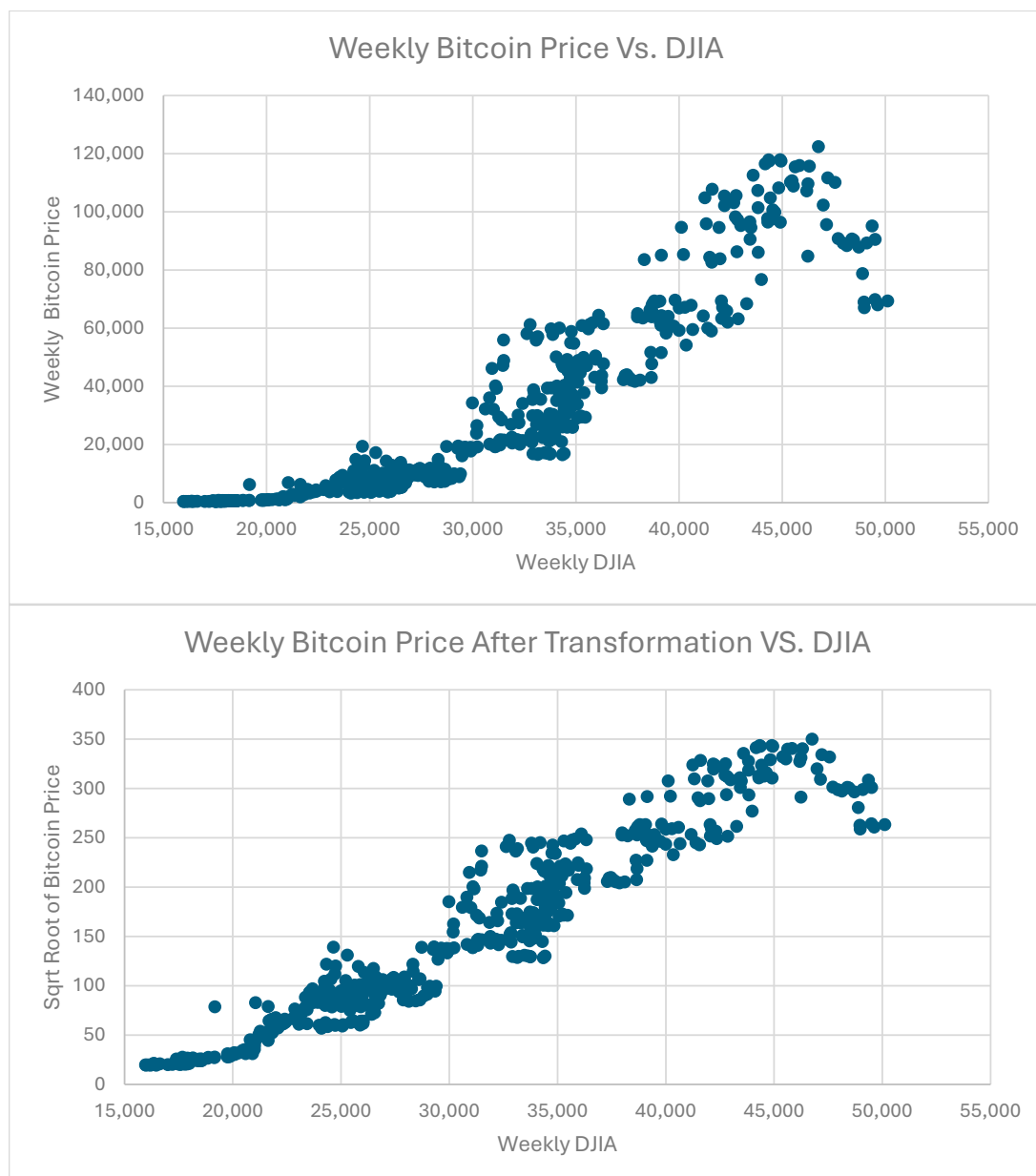


Figure 1. Plot of weekly prices of Bitcoin vs. DJIA before and after transformation.

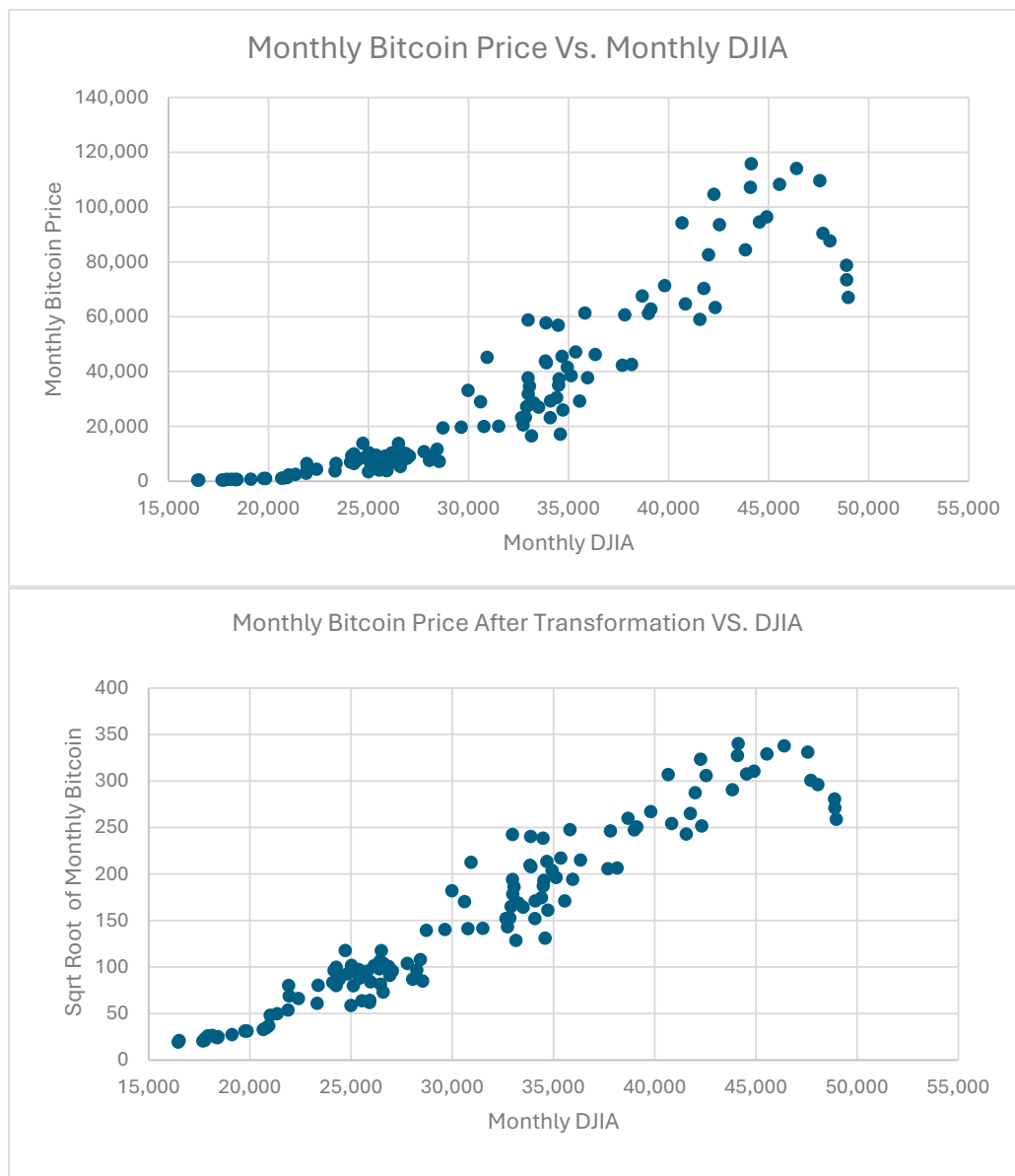


Figure 2. Plot of monthly Bitcoin prices vs. DJIA before and after transformation.

Table 3. Correlation matrix of original monthly data (original data, before transformation).

	<i>Weekly Bitcoin</i>	<i>Weekly Nasdaq 100</i>	<i>Weekly S&P 500</i>	<i>Weekly DJIA</i>	<i>Weekly Russell 2000</i>	<i>Weekly Nikkei 225</i>	<i>Weekly Gold</i>	<i>Weekly Oil</i>	<i>Weekly VIX</i>	<i>Weekly Euro</i>
Weekly Bitcoin	1.000									
Weekly Nasdaq 100	0.939	1.000								
Weekly S&P 500	0.940	0.996	1.000							
Weekly DJIA	0.911	0.981	0.990	1.000						
Weekly Russell 2000	0.847	0.903	0.911	0.933	1.000					
Weekly Nikkei 225	0.893	0.963	0.968	0.957	0.879	1.000				
Weekly Gold	0.859	0.903	0.904	0.870	0.758	0.923	1.000			
Weekly Oil	0.329	0.416	0.457	0.512	0.533	0.413	0.193	1.000		
Weekly VIX	0.023	0.075	0.044	0.037	−0.038	−0.036	0.099	−0.053	1.000	
Weekly Euro	0.013	−0.047	−0.069	−0.056	0.110	−0.027	0.046	−0.338	−0.117	1.000

Table 4. Correlation matrix of weekly data (after transformation).

	<i>Sqrt Root of Bitcoin</i>	<i>Weekly Nasdaq 100</i>	<i>Weekly S&P 500</i>	<i>Weekly DJIA</i>	<i>Weekly Russell 2000</i>	<i>Weekly Nikkei 225</i>	<i>Weekly Gold</i>	<i>Weekly Oil</i>	<i>Weekly VIX</i>	<i>Weekly Euro</i>
Sqrt Root of Bitcoin	1.000									
Weekly Nasdaq 100	0.964	1.000								
Weekly S&P 500	0.964	0.996	1.000							
Weekly DJIA	0.960	0.981	0.990	1.000						
Weekly Russell 2000	0.915	0.903	0.911	0.933	1.000					
Weekly Nikkei 225	0.909	0.963	0.968	0.957	0.879	1.000				
Weekly Gold	0.827	0.903	0.904	0.870	0.758	0.923	1.000			
Weekly Oil	0.460	0.416	0.457	0.512	0.533	0.413	0.193	1.000		
Weekly VIX	0.082	0.075	0.044	0.037	−0.038	−0.036	0.099	−0.053	1.000	
Weekly Euro	0.008	−0.047	−0.069	−0.056	0.110	−0.027	0.046	−0.338	−0.117	1.000

Table 5. Correlation matrix of original monthly data (original data, before transformation).

	<i>Monthly Bitcoin</i>	<i>Monthly Nasdaq 100</i>	<i>Monthly S&P 500</i>	<i>Monthly DJIA</i>	<i>Monthly Russell 2000</i>	<i>Monthly Nikkei 225</i>	<i>Monthly Gold</i>	<i>Monthly Oil</i>	<i>Monthly VIX</i>	<i>Monthly Euro</i>
Monthly Bitcoin	1.000									
Monthly Nasdaq 100	0.941	1.000								
Monthly S&P 500	0.942	0.996	1.000							
Monthly DJIA	0.917	0.982	0.991	1.000						
Monthly Russell 2000	0.856	0.912	0.919	0.938	1.000					
Monthly Nikkei 225	0.882	0.957	0.962	0.951	0.882	1.000				
Monthly Gold	0.836	0.897	0.900	0.867	0.767	0.931	1.000			
Monthly Oil	0.345	0.420	0.461	0.517	0.542	0.414	0.203	1.000		
Monthly VIX	0.006	0.071	0.035	0.033	−0.002	−0.039	0.072	−0.074	1.000	
Monthly Euro	0.001	−0.037	−0.061	−0.054	0.103	−0.009	0.067	−0.332	−0.093	1.000

Table 6. Correlation matrix of monthly data (after transformation).

	<i>Sqrt u of Bitcoin</i>	<i>Monthly Nasdaq 100</i>	<i>Monthly S&P 500</i>	<i>Monthly DJIA</i>	<i>Monthly Russell 2000</i>	<i>Monthly Nikkei 225</i>	<i>Monthly Gold</i>	<i>Monthly Oil</i>	<i>Monthly VIX</i>	<i>Monthly Euro</i>
Sqrt Root of Bitcoin	1.000									
Monthly Nasdaq 100	0.963	1.000								
Monthly S&P 500	0.962	0.996	1.000							
Monthly DJIA	0.960	0.982	0.991	1.000						
Monthly Russell 2000	0.919	0.912	0.919	0.938	1.000					
Monthly Nikkei 225	0.893	0.957	0.962	0.951	0.882	1.000				
Monthly Gold	0.805	0.897	0.900	0.867	0.767	0.931	1.000			
Monthly Oil	0.468	0.420	0.461	0.517	0.542	0.414	0.203	1.000		
Monthly VIX	0.081	0.071	0.035	0.033	−0.002	−0.039	0.072	−0.074	1.000	
Monthly Euro	−0.002	−0.037	−0.061	−0.054	0.103	−0.009	0.067	−0.332	−0.093	1.000

4.1. Partitioning of Monthly Data and Analytical Method

At this stage, our monthly data were imported into R to facilitate more advanced statistical analysis. The monthly data set consists of 123 observations spanning January

2016 through March 2026. To identify the best explanatory variables of Bitcoin price, we systematically evaluated multiple regression models that incorporated all available equity indices, commodities, and dummy variables as candidate explanatory variables (X_1 – X_{12}). Backward elimination was based on statistical significance (the p -value cutoff used for elimination). All explanatory variables with a p -value > 0.05 were removed. Based on this criterion, we arrived at a model using four explanatory variables: Nasdaq 100, Russell 2000, Nikkei 225, and an indicator dummy for the Israel-Hamas conflict, which yielded the highest Adjusted R^2 of 0.9603, with the Sqrt Root of the Bitcoin price as the response variable. The result is listed in Table 7. We also examined two alternative non-linear transformations of the response variable. The double-log transformation, in which both the response and all continuous explanatory variables are log-transformed (double-log), produced an Adjusted R^2 of 0.9595, while the Cube-Root transformation yielded an Adjusted R^2 of 0.9499. Both are marginally lower than the Sqrt Root model. In addition, as we proceed with further analyses, we found that the Sqrt Root transformation has its own advantages. Indeed, we should be cautious when using RMSE to compare models since different transformations can result in different units; even if we can align them in the same unit, applying RMSE to the re-transformed values often produces misleading results because the average of the transformed data does not map directly to the average of the original data.

Table 7. Coefficient and important statistics table for monthly data.

	Estimate	St. Error	T-Value	p -Value
Intercept	−74.1339	13.3306	−5.561	0.0000 ****
Monthly Nasdaq 100	0.0130	0.0012	10.633	0.0000 ****
Monthly Nikkei 225	−0.0033	0.0006	−5.270	0.0000 ****
Monthly Russell 2000	0.0853	0.0111	7.661	0.0000 ****
IH_M	35.7845	5.7918	6.179	0.0000 ****
ProofreadingMetric	Value			
RMSE	17.9754			
Standard Error of the Estimate	18.352			
R^2	0.9616			
Adjusted R-Squared	0.9603			
F-statistic	739.50			
F-statistic p -value	<0.0000 ***			

Signif. codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '.'.

All four explanatory variables were statistically significant at the $\alpha = 0.01$ level, and the Adjusted R^2 of 0.9603 confirms the model's strong explanatory power. At the same time, RMSE is 17.9754.

To examine out-of-sample predictive performance, we employed Walk-Forward Validation, which is a sequential evaluation method specifically designed for time-series data. Rather than relying on a single static train-test split, this approach iteratively trains the model on all available past observations and tests it on the immediately following period, strictly preserving the chronological ordering of the data and preventing any future information from leaking into the training set. The initial training window spanned January 2016 through December 2017, with the first forecast generated for January 2018. This process was then repeated sequentially, expanding the training window by one month at each step, until the final training set covered January 2016 through February 2026 and the final

forecast was generated for March 2026, yielding 99 validation windows in total. The model was re-estimated (refit) with the same variable set at every step to ensure reproducibility. It must be noted that the model is explanatory in nature, and that the walk-forward exercise assesses out-of-sample generalization of the fitted relationship rather than forecasting, since it uses actual (not lagged) explanatory values in each test window. Furthermore, the actual (observed) values of the explanatory variables (not forecasted ones) were used in each test window.

Three distinct R^2 measures are reported to provide a complete picture of model performance. The full-data R^2 of 0.9616 indicates how well the model fits all 123 monthly observations. The mean walk-forward training R^2 of 0.9073 represents the average in-sample fit across the 99 rolling training windows. It is lower than the full-data R^2 because early windows contain as few as 24 months of observations, providing the model with less information. Most importantly, the pooled out-of-sample R^2 of 0.9325 measures explanatory accuracy on completely unseen future data, computed by pooling the actual and predicted values across all 99 test months and applying the standard R^2 formula. The difference between the R^2 based on all the data (0.9616) and the R^2 based on completely unseen data (0.932) is very small (0.0291), indicating the strong explanatory power of our suggested model for monthly Bitcoin prices.

For the monthly data, our regression method indicates that the Monthly Nasdaq 100 (X_1), Monthly Russell 2000 (X_4), Monthly Nikkei 225 (X_5), and Monthly Israel-Hamas Conflict (X_{12}) are significant explanatory variables for the monthly model (P_M) at $\alpha = 0.01$.

Based on the above information, the regression equation for modeling the monthly Sqrt Root of the price of Bitcoin (P_M) is provided below:

$$P_M = -74.1339 + 0.0130 * X_1 + 0.08531 * X_4 - 0.00333 * X_5 + 35.7845 * X_{12}$$

The coefficients of our model indicate the impact of each explanatory variable. A unit increase in the Monthly Nasdaq 100 (X_1) will result in the Sqrt Root of Bitcoin increasing by 0.0130 units, as long as the other variables in our model remain constant. Also, a unit increase in the Monthly Russell 2000 (X_4) will result in the Sqrt Root of Bitcoin increasing by 0.08531 units, as long as the other variables in our model remain constant. On the other hand, a unit increase in the Monthly Nikkei 225 (X_5) will result in the Sqrt Root of Bitcoin decreasing by 0.00333 units, as long as the other variables in our model remain constant. This obviously is not consistent with the economic expectation. That said, this indicates multicollinearity. The Variance Inflation Factor (VIF) for our model indicates severe multicollinearity (Figure 3).

It is important to note that the high VIFs observed for several explanatory variables (particularly Nasdaq 100, Russell 2000, and Nikkei 225) indicate strong multicollinearity among our index explanatory variables. This multicollinearity inflates the standard errors of the individual coefficients, making them unstable and potentially unreliable for inference. The negative coefficient on the Monthly Nikkei 225 indicates this collinearity, as the equity indices share a strong common trend and their individual effects cannot be captured within the regression framework.

Two perspectives on this issue are worth considering. From a purely predictive standpoint, multicollinearity does not bias the model's explanatory power. Therefore, the fitted values and out-of-sample predictions remain valid as long as the correlational structure among the explanatory variables is stable over time. Under this view, the high Adjusted R^2 of 0.9603 and the out-of-sample R^2 of 0.9325 provide sufficient explanatory power, and multicollinearity is not a serious concern. From an inferential standpoint, however, the instability of individual coefficients is a serious issue and needs to be addressed.

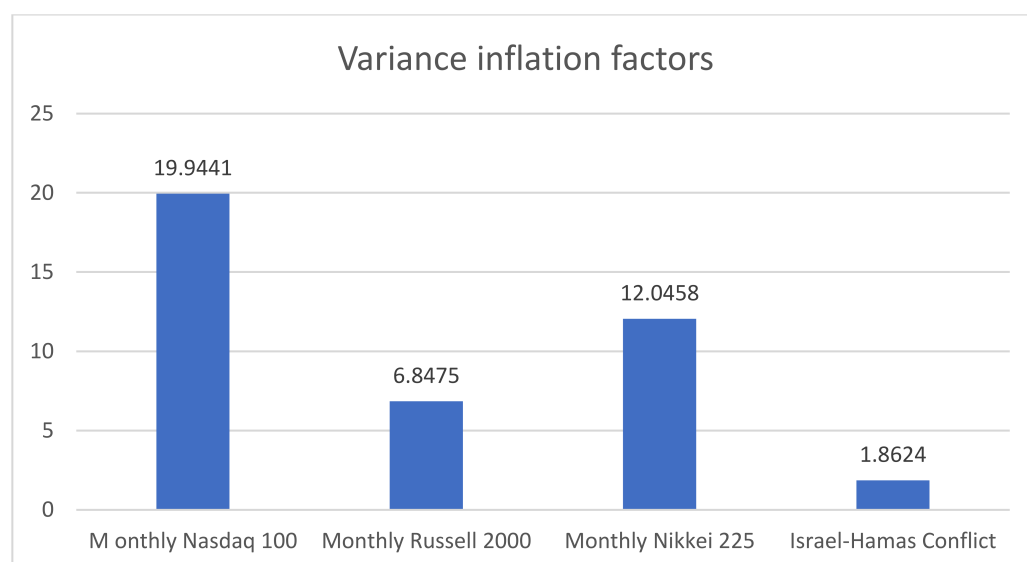


Figure 3. Variance inflation factors for our monthly data.

To address multicollinearity directly, we apply Principal Component Regression (PCR), which transforms correlated explanatory variables into a set of unrelated explanatory variables. Therefore, it could eliminate multicollinearity. Applying Principal Component Analysis to the three continuous explanatory variables (Nasdaq 100, Russell 2000, and Nikkei 225) reveals that the first principal component captures 94.47% of the total variation across all three indices, with the second component accounting for only an additional 4.22%. The loading factors for the Nasdaq 100, Russell 2000, and Nikkei 225 are 0.5847, 0.5688, and 0.5785, respectively. The relatively large loading factors for these indices confirm that this component represents global equity. Given that the first principal component alone exceeds the conventional 90% threshold, a PCR model is developed to model Bitcoin prices using the first principal component and an Israel-Hamas conflict dummy. The results of this model are presented in Table 8.

Table 8. Principal Component for monthly data (used standardized data).

	PC1 = Component 1	PC2 = Component 2	PC3 = Component 3
Variance	2.857220	0.127714	0.039656
Portion of Variance	0.9447	0.04220	0.0131
Cumulative Proportion	0.9447	0.9869	1.00

Developing a Principal Component Regression can achieve two objectives simultaneously: it resolves the structural weakness of the original regression while preserving a high level of explanatory accuracy. In our case, using only the first principal components and IH_M in a new regression model yields an Adjusted R-Squared of 0.9275, and collinearity is no longer an issue since only the first principal component is used. As a result, using Principal Components allows us to address multicollinearity while maintaining a regression model with very high explanatory power (Adjusted R-Squared of 0.9275). It must be noted that our new model, based on the first principal component, with an Adjusted R-Squared of 0.9275, compared to our original regression model with an Adjusted R-Squared of 0.9603 and a high degree of multicollinearity, represents a significant improvement. Indeed, the small reduction in the Adjusted R-Squared is the price to be paid to eliminate the multicollinearity (please see Table 9).

Table 9. Regression model based on the first Principal Component and IH_M:

	Estimate	St. Error	T Value	p-Value
Intercept	143.6040	2.5825	55.607	0.0000 ****
Principal Component 1	+46.4254	1.5961	29.067	0.0000 ****
IH_M	+42.6249	6.8912	6.186	0.0000 ****
Metric	Value			
Residual Std. Error	24.821			
RMSE	24.5165			
R ²	0.9286			
Adjusted R-Squared	0.9275			
F-statistic	780.8101			
F-statistic p-value	0.00000			

Signif. codes: 0 '****' 0.001 '**' 0.01 '*' 0.05 '.'.

In addition, the statistical tests show that the first principal component and IH_M are significant at the $\alpha = 0.01$ level. So, the following model retains a strong explanatory power compared to the original model.

$$\text{Sqrt Root of Bitcoin Model} = 143.6040 + 46.4254 * \text{PC1} + 42.6249 * \text{IH_M}$$

It must be noted that the original model based on the Sqrt Root of Bitcoin fits the data better (higher Adjusted R-Squared, lower RMSE) while Principal Components Regression is statistically cleaner (higher F-statistics, no multicollinearity). For **explanatory accuracy**, the Original Sqrt Root Bitcoin is preferred. For **inferential reliability and interpretability**, Principal Components Regression is the stronger choice (please see Table 10).

Table 10. Comparing our original regression model with the PCR model for monthly data.

Explanatory Variables	Sqrt Root of Bitcoin (Nasdaq 100, Russell 2000, Nikkei 225, IH_M)	PCR (PC1 + IH_M)
Number of Observations	123	123
Number of Explanatory variables	4	2
R ²	0.9616	0.9286
Adjusted R-Squared	0.9603	0.9275
RMSE	17.9754	24.5165
Standard Error of the Estimate	18.3522	24.8210
F-Values	739.50	780.81

4.2. Partitioning of Weekly Data and Analytical Method

Now, we are focusing on our weekly data ($n = 531$ observations). Again, we use the same procedure we used for the monthly data. After examining several multiple regression models to explain weekly bitcoin prices, the Sqrt Root transformation yielded the highest Adjusted R-Squared (0.9652) when S&P 500, Russell 2000, Nikkei 225, VIX, Oil, Euro, and the Israel–Hamas conflict indicator were used as explanatory variables (Table 11).

Table 11. Coefficient and important statistics table for weekly data.

	Estimate	St. Error	T Value	p-Value
Constant	−315.8689	20.5541	−15.368	0.00000 ****
Weekly S&P 500	+0.0564	0.0035	+16.164	0.00000 ****
Weekly Russell 2000	+0.0713	0.0069	+10.307	0.00000 ****
Weekly Nikkei 225	−0.0029	0.0004	−7.627	0.00000 ****
Weekly Oil	+0.1422	0.0604	+2.354	0.01894 *
Weekly VIX	+1.0002	0.1210	+8.267	0.00000 ****
Weekly Euro	+148.057	18.6878	+7.923	0.00000 ****
IH_W	+43.842	2.9392	+14.916	0.00000 ****
Metric	Value			
Standard Error of the Estimate	17.2303			
RMSE	17.1001			
R ²	0.9656			
Adjusted R-Squared	0.9652			
F-statistic	2099.70			
F-statistic p-value	0.00000			

Signif. codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '*'.

For the weekly data, the regression results indicate that the S&P 500 (X_2), Russell 2000 (X_4), Nikkei 225 (X_5), VIX (X_8), and the Israel-Hamas conflict (X_{12}) are statistically significant variables of Bitcoin prices at the 0.01 level, while oil prices (X_7) are significant at the 0.05 level.

$$P_W = -315.8689 + 0.0564 * X_2 + 0.0713 * X_4 - 0.0029 * X_5 + 0.1422 * X_7 + 1.0002 * X_8 + 148.057 * X_9 + 43.842 * X_{12}$$

The Adjusted R-Squared of 0.9652, together with the statistical significance of all variables at the $\alpha = 0.001$ level, confirms that the weekly regression model possesses strong explanatory power.

It must be noted that, in addition to the existing explanatory variables, trend lines were used for both time frames to address issues with the time-series analysis. However, the trend coefficients were not significant (p -values of 0.83 for Monthly and 0.37 for Weekly).

To examine out-of-sample performance, we applied the same Walk-Forward Validation procedure we used for the monthly analysis. The initial training window consists of 104 weeks (January 2016 through December 2017), with the model evaluated on the immediately following 4-week block. At each subsequent step, the training window expanded by four weeks. So we are incorporating the most recent observations before generating the next forecast block, continuing until the final training set spanned weeks 1 through 524 (January 2016 through approximately February 2026), and the final test set covered weeks 525 through 528. This sequential, expanding-window process yielded 106 non-overlapping validation windows and 424 out-of-sample weekly forecasts, providing a full and realistic assessment of the model's explanatory ability across a full decade of diverse market conditions.

Three distinct R^2 measures are reported to fully characterize model performance, each answering a fundamentally different question. The full-data R^2 of 0.9656 reflects the proportion of variation in weekly Bitcoin prices explained by the model when all 531 observations are simultaneously used. The mean walk-forward training R^2 of 0.9290

represents the average in-sample fit across the 106 rolling training windows; this figure is moderately lower than the full-data R^2 . As the training window expands over time and accumulates additional data, the window-level training R^2 rises steadily, approaching the full-data benchmark. Most critically, the pooled out-of-sample R^2 of 0.9385 quantifies the model's explanatory accuracy on the unseen data. The gap between the full-data R^2 (0.9656) and the pooled out-of-sample R^2 (0.9385) is only 0.0271, a negligible difference that provides strong evidence the model generalizes effectively to unseen data without meaningful overfitting. Taken together, these three measures paint a consistent and compelling picture of a model that fits the historical data well, maintains stable performance across rolling training windows, and retains strong explanatory accuracy when confronted with unseen new observations.

The coefficients of our model indicate the impact of each explanatory variable. A unit increase in the Weekly S&P 500 (X_2) will result in the Weekly Sqrt Root of Bitcoin increasing by 0.0564 units, as long as the other variables in our model remain constant. Also, a unit increase in the Weekly Russell 2000 (X_4) will result in the Weekly Sqrt Root remaining constant. On the other hand, a unit increase in the Weekly Nikkei 225 (X_5) will result in the Weekly Sqrt Root of Bitcoin decreasing by 0.0029 units, as long as the other variables in our model remain constant. This obviously is not consistent with the economic expectation. That said, this is a sign of multicollinearity. Using the Variance Inflation Factor (VIF) of our model confirms that our model is severely impacted by multicollinearity (Figure 4).

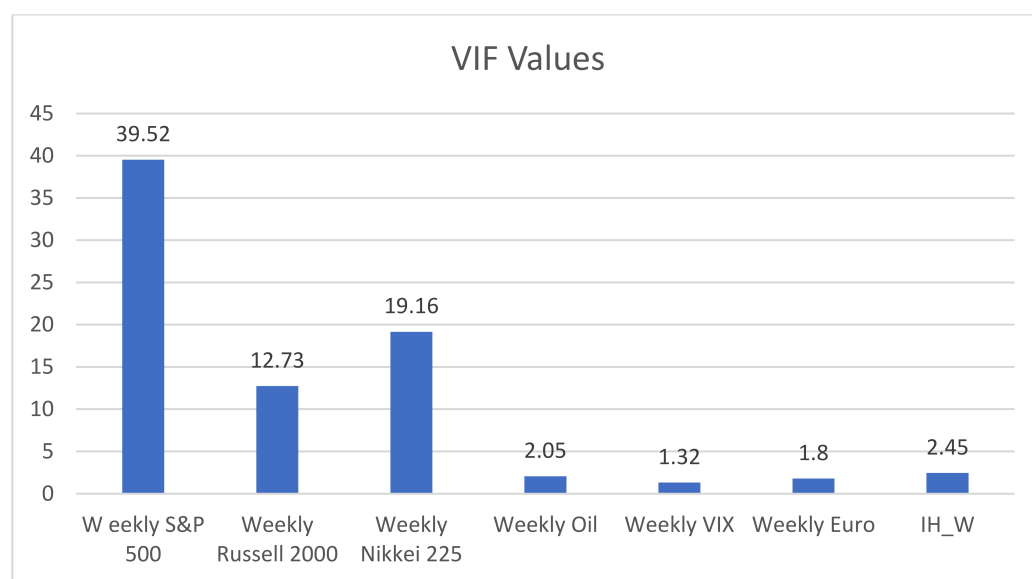


Figure 4. Variance inflation factors for our weekly data.

Examining Figure 4 reveals that some of our explanatory variables seem to have a high degree of collinearity, so we use the variance inflation factor (VIF) for our model. Based on this measure, four of our explanatory variables are correlated, indicating multicollinearity, as VIF values exceed 10 for some explanatory variables. To address this structural limitation, we apply Principal Component Regression (PCR), which transforms the six correlated continuous explanatory variables into a set of uncorrelated components prior to estimation. Using Principal Component Analysis helps address multicollinearity. Principal Component Analysis combines highly correlated original explanatory variables into a smaller set of new, uncorrelated variables (practically creating a smaller, uncorrelated set of linear combinations of the original explanatory variables), while retaining the overwhelming information of the original explanatory variables.

Given that the first four principal components exceed the conventional 90% threshold, we decided to use the first four principal components (Table 12).

Table 12. First four Principal Components for the weekly data (used standardized data).

	PC1 = Component 1	PC2 = Component 2	PC3 = Component 3	PC4 = Component 4
Variance	3.1572	1.2343	0.9961	0.5193
Portion of Variance	0.5252	0.2053	0.1657	0.0864
Cumulative Proportion	0.5252	0.7305	0.8962	0.9826

Then, we used the first four principal components and the dummy variable for the Israel-Hamas conflict to build a Principal Components Regression Model.

Further examination of the loading factors reveals that the first principal component accounts for equity markets with loadings of 0.5446, 0.5353, and 0.5337 for the S&P 500, Russell 2000, and Nikkei 225, respectively. The second principal component is dominated by the Euro and the negative Oil impact, with loadings of 0.8316 and -0.4031 , respectively. Finally, the third principal component is dominated by VIX, and the fourth principal component represents the Oil shock with the loading factor of $+0.9098$. The fourth principal component is retained by the 90% rule, but it was dropped from our regression model because it was not statistically significant at the $\alpha = 0.05$ level. So, after dropping the fourth principal component, we rerun our Principal Component Regression using the first three principal components and the Israel-Hamas conflict. Our adjusted R-Squared for the new model is 0.9489, indicating a strong explanatory power. Indeed, the statistical test shows that the first three principal components were significant at the $\alpha = 0.001$ level (Table 13).

Table 13. Regression model based on the first three Principal Components:

	Estimate	St. Error	T Value	p-Value
Constant	140.3289	1.0583	132.593	0.0000 ****
Principal Component 1	+42.2512	0.6186	+68.305	0.0000 ****
Principal Component 2	+9.0613	0.8185	+11.071	0.0000 ****
Principal Component 3	+16.8009	0.9107	+18.447	0.0000 ****
IH_W	+51.1100	2.7663	+18.476	0.0000 ****
Metric	Value			
Residual Std. Error	20.8778			
RMSE	20.7793			
R ²	0.9493			
Adjusted R-Squared	0.9489			
F-statistic	2460.29			
F-statistic p-value	0.00000			

Signif. codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '.'.

Now we compared the two models. In particular, we compare the Sqrt Root of the Bitcoin Weekly Model with the Russell 2000, Nikkei 225, Oil, VIX, Euro, and IH_W as explanatory variables against models that include the first three principal components and IH_W in Table 14.

Again, it must be noted that the original model based on the Sqrt Root of Bitcoin fits the data better (higher Adjusted R-Squared, lower RMSE) while Principal Components

Regression is statistically cleaner (higher F-statistic, no multicollinearity). For **explanatory accuracy**, the Original Sqrt Root of Bitcoin is preferred. For **inferential reliability and interpretability**, Principal Components Regression is the stronger choice (please see Table 14).

Table 14. Comparing our original regression model with the PCR model for weekly data.

Explanatory Variables	Sqrt Root of Bitcoin (S&P 500, Russell 2000, Nikkei 225, Oil, VIX, Euro, and IH_W)	PCR (PC1, PC2, PC3, and IH_W)
Number of Observations	531	531
Number of Explanatory variables	7	4
R ²	0.9656	0.9493
Adjusted R-Squared	0.9652	0.9489
RMSE	17.1001	20.7793
Standard Error of the Estimate	17.2303	20.8778
F-Values	2099.70	2460.29

5. Summary

Across both the monthly and weekly analyses, the results show a consistent pattern of variable significance. The Dow Jones Industrial Average (DJIA) was not statistically significant at any conventional level in either time frame, and was therefore excluded from any final models. In contrast, the Russell 2000 and Nikkei 225 were both significant at the $\alpha = 0.01$ level across both frequencies, as was the Israel-Hamas conflict indicator, which was significant at the 1% level in both the weekly and monthly specifications.

The consistent significance of the Russell 2000, Nikkei 225, and the Israel-Hamas conflict indicator across both time frames is particularly noteworthy. The Russell 2000 is a broad measure of U.S. small-capitalization equity performance. Obviously, the Russell 2000 represents a much broader market than the DJIA, which was not present in any of our models. On the other hand, the Nikkei 225, as a leading indicator of Asian market sentiment, together suggests that Bitcoin pricing is sensitive to equity market conditions across multiple geographies and market segments, rather than to the large-cap U.S. indices that dominate conventional financial analysis. The persistent significance of the Israel-Hamas conflict indicator, meanwhile, underscores the role of geopolitical risk as a systematic driver of Bitcoin price movements, consistent with the growing body of literature positioning Bitcoin as a relatively safe-haven asset. That these relationships hold across both weekly and monthly data provides additional credibility to their interpretation as an economic signal that can be used in decision-making.

The high degree of multicollinearity observed among our explanatory variables is clearly a sign of strong co-movement among the major equity indices and commodity prices we selected. Multicollinearity of this magnitude inflates the standard errors of the individual regression coefficients, making them unstable and potentially misleading for inferential purposes. It must be emphasized, however, that multicollinearity does not bias the model's explanatory power: as long as the correlational structure among the explanatory variables remains stable over time, the predicted values and out-of-sample performance metrics reported here remain valid. The high Adjusted R-Squared values and strong Walk-Forward Validation results suggest that multicollinearity might be a secondary concern for our prediction. In any case, for researchers and practitioners who require reliable coefficient-level inference, Principal Component Regression (PCR) provides a rigorous, well-established remedy. By transforming the correlated explanatory variables into a

set of independent components prior to estimation, PCR eliminates multicollinearity by construction, reducing all variance inflation factors to approximately 1.0 while preserving the majority of the information contained in the original explanatory variables. In our case, a single principal component captured 94.47% of the shared variation among the monthly equity indices, and four components accounted for 98.26% of the shared variation in the weekly explanatory variable set (both well above the conventional 90% retention threshold). The resulting PCR models maintained high Adjusted R-squared values of 0.9275 (monthly) and 0.9489 (weekly), confirming that the modest reduction in Adjusted R-Squared and RMSE is not significant and the PCR models have a reasonably good explanatory power relative to the original regression models, while the multicollinearity is not present in the PCR models. This represents a worthwhile trade-off for eliminating multicollinearity and recovering interpretable, stable coefficient estimates.

Building on these findings, future research could proceed along two paths. The first would incorporate lagged predictor variables (time $t - 1$) alongside the response variable's current performance (Bitcoin prices at time t). With a well-specified model, this approach could offer strong explanatory power using weekly or monthly data. The second path would apply the same approach mentioned above to shorter time horizons, such as daily or intraday data. This approach could be particularly useful for short-term investors or day traders.

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