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Article

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Forecasting Ethereum's volatility: an expansive approach using HAR models and structural breaks

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ABSTRACT

Cryptocurrencies have become a popular investment option and the Ethereum has become a mainstream cryptocurrency because of the additional functionality that can be accomplished with the backing of the powerful Ethereum network compared to Bitcoin. The high volatility of Ethereum offers both profits and risks, making it crucial to improve the forecasting ability for its price volatility. The results of this study could be useful for investors and policymakers who are interested in understanding and managing the risks associated with investing in Ethereum. Several studies have explored similar topics using heterogeneous autoregressive (HAR) models for cryptocurrencies, but this paper offers a more expansive approach. This paper employs five-minute high-frequency data to construct 4 HAR models to predict the volatility of Ethereum, taking into account the impact of structural breaks, Bitcoin, SP500 and VIX. The model that considers all factors outperforms other models for out-of-sample predictions for the 1-week forecasting. Due to the nature of the Ethereum price, the HAR-RV model has achieved a perfect fit in 1-day and 1-month forecasting. Therefore, other models have a very small improvement in fitness and prediction accuracy. This paper contributes to the understanding of Ethereum's volatility and its impact on the cryptocurrency market.

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1. Introduction

With the maturity of blockchain technology, cryptocurrencies have become an attractive investment option for numerous investors. Ethereum is in the spotlight as a mainstream currency. Ethereum, unlike its competitor Bitcoin, can not only perform the same functions as Bitcoin which are tradability and storage values of cryptocurrency, but also carry out extra tasks including developing and running applications, signing smart contracts, and carrying out different kinds of transactions that bitcoin lacks relying on Ethereum network. From November 28, 2019 to January 5, 2023, the price of Ethereum experienced a trough of \$122.17 and climbed to a peak of \$4,644.43. Such high volatility offers both profits and risks. There is growing evidence that Ethereum offers substantial diversification to investors when included in portfolios (Bhosale & Mavale, 2018). However, the high volatility of Ethereum, partly due to the immaturity of the cryptocurrency market and the lack of regulation, presents both profits and risks for investors. To effectively manage these risks, it is crucial to improve the forecasting ability for the price volatility of Ethereum.

The study (Ftiti et al., 2021) found that the heterogeneous autoregressive (HAR) model is appropriate for predicting future volatility. Furthermore, a seminal study in this area is the work of Shen et al. (2020) showing that structural breaks should also be considered when predicting the volatility of cryptocurrency. Besides, a qualitative study by Imran et al. described how the major cryptocurrencies affected each other by using high-frequency data. Mensi et al. (2019) show evidence of co-movements in time

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frequency space with leading relationships of Ethereum with Bitcoin. Moreover, Assaf et al. (2022) quantify information flows between Bitcoin and Ethereum. This indicates that analyzing Ethereum's volatility is crucial for the cryptocurrency market. The paper (Akyildirim et al., 2020) claims the existence of time-varying positive interrelationships between the conditional correlations of cryptocurrencies and financial market stress (VIX). The inclusion of VIX in the analysis allows for a better understanding of how financial market stress affects the volatility of Ethereum. Ghorbel et al. (2022) shed light on the relationship between the stock market and cryptocurrencies. To build upon their research, we extend our analysis by incorporating the SP500 index, thereby considering the potential impact of traditional stock market dynamics on the cryptocurrency market.

Forecasting the volatility of Ethereum is an extremely complicated topic that necessitates consideration of a multitude of variables and the underlying economic logic. Previous studies have explored similar topics using heterogeneous autoregressive (HAR) models for cryptocurrencies (Ftiti et al., 2021) and have considered structural breaks (Mensi et al., 2019). Opposed to just one or two factors examined in previous studies, such as Omura et al. (2023) and Shen et al. (2020), this paper considers multiple factors.

In particular, Shen et al. (2020) have studied Bitcoin by using HAR model and considering structural breaks and jumps. Based on the similarity of the research hypothesis, we replicated the logical framework of their study, for instance, the structure of the paper and some of the methods. But we took into account other factors. Therefore, more complex comparison methods are needed, making our study more comprehensive than theirs.

This study employs 5-minute high-frequency data to construct 4 Heterogeneous Autoregressive models (HAR) to predict Ethereum's volatility, incorporating the influence of structural breaks, Bitcoin, and the Volatility Index (VIX). Our results indicate that the model incorporating structural breaks outperforms other models in both in-sample analysis and out-of-sample forecasts, in the 1-week horizon. Given the peculiar price dynamics of Ethereum, the HAR-RV model exhibits an excellent fit in both 1-week and 1-month forecasts, rendering any further enhancement of the all-inclusive model's fitness and prediction accuracy trivial. However, considering the influence of structural breaks, the VIX, S&P 500 volatility, and Bitcoin price volatility marginally improves the 1-month forecast accuracy, as indicated by the out-of-sample results.

The subsequent sections of this paper are organized as follows. Section 2 presents a detailed overview of the database employed in this study. Section 3 discusses the detection and interpretation of structural breaks. We introduce the HAR-RV model as the benchmark model alongside three novel models, in Section 4. The analysis of in-sample and out-of-sample performance is evaluated in Section 5, and the robustness of the models is examined in Section 6. Finally, Section 7 concludes with a concise summary of the primary findings and recommendations for future research.

2. Data description

Considering the accuracy of volatility prediction, this paper chose 5-min as the sampling frequency. The transaction data is the price of Ethereum in USD from Bloomberg. The full sample period is from November 28, 2019 to January 5, 2023. After computing the Realized Volatility and subtracting the vacant value, 1119 trading days from December 12, 2019 to January 5, 2023 are obtained. Ethereum trades 24 hours a day, seven days a week, and therefore we have a continuous time series throughout our sample period.

To calculate the realized volatility from the 5-minute data, Andersen and Bollerslev (1997) defined the daily realized volatility as the sum of the squared intraday returns $r_{t,i}$ at a given sampling frequency $1/N$:

$$RV_t = \sum_{i=1}^N r_{t,i}^2,$$

where $r_{t,i} = 100 * (\ln P_{t,i} - \ln P_{t,i-1})$ and $P_{t,i}$ is the i^{th} intraday closing price at day t .

Figure 1 illustrates that the price of ETH exhibited a steep ascent beginning in January 2021 and reached its peak on July 10, 2021. Throughout this period, the volatility remained high and exhibited some anomalous fluctuations. Notably, between mid-April and mid-May 2021, the price experienced a



Figure 1. The price of ETH.

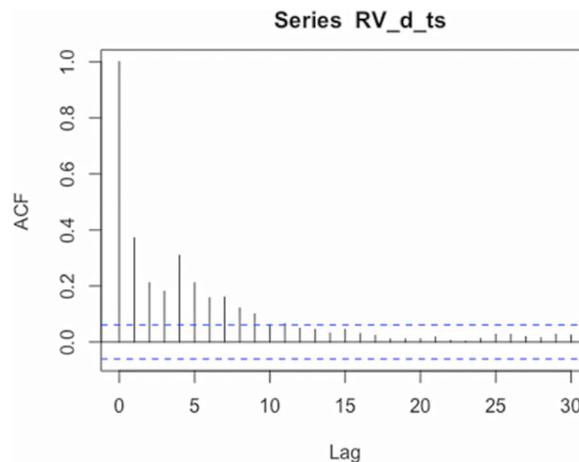


Figure 2. Autocorrelation function (ACF) of RV.

rapid increase followed by a sharp decline, indicating uncommon and dramatic fluctuations. From May 2022, the volatility stabilized gradually. Nevertheless, certain points of uncharacteristic volatility persisted.

Figure 2 depicts the Autocorrelation Function (ACF) of daily realized volatility. The ACF is a common technique used to determine the parameters of common time series models, such as p in an autoregressive model (AR) and expresses the average relationship between data points in a time series and their preceding data points. Based on Figure 2, we conjecture that standard time series models are inadequate for predicting ETH prices.

Figure 3 reveals the existence of volatility aggregation and asymmetry, as well as volatility structural breaks, which refer to critical events that led to significant changes in economic conditions, such as policy transitions and natural disasters. In the following section, we will introduce the ICSS test, which aims to identify structural breaks. Large economic events, such as a new wave of regulations implemented by the Chinese government, can trigger substantial price volatility. Additional events are summarized in the subsequent section. In other words, when modelling volatility, it is crucial to consider the impact of structural breaks to improve forecasting accuracy.

Table 1 displays the mean, extreme values, and standard deviation of ETH price volatility, S&P500 volatility, the VIX index, and Bitcoin volatility. As shown, the volatility of ETH price ranges from 2.709 to 1330.177, with a wide range and intense volatility. These findings reinforce the argument that the volatility of the ETH market fluctuates more dramatically than the SP500 volatility and the VIX index.

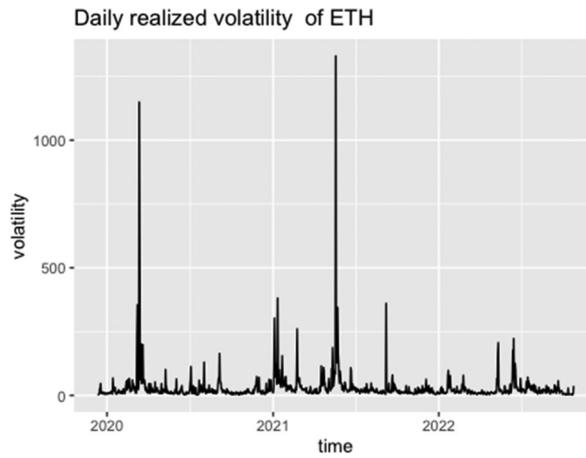


Figure 3. Daily realized volatility.

Table 1. Descriptive statistics of variables.

	Mean	Standard deviation	Minimum	Maximum
ETH vol	32.208	76.6784	2.709	1330.177
S&P500 vol	2.60458	9.442623	7.296309e-07	162.95069
VIX index	24.95	8.95617	12.10	82.69
BTC vol	18.9591	86.32096	3.747882e-06	2159.7414

Additionally, the variance of Bitcoin price volatility is larger than that of Ethereum price volatility. In summary, the mean and variance of Bitcoin, which is also a cryptocurrency, are relatively similar to those of Ethereum, while the other two index funds exhibit relatively more consistent performance.

3. Structural breaks

Liu and Maheu (2008) and Choi et al. (2010) provide strong evidence of the presence of structural breaks in high-frequency realized volatility. Furthermore, Shen et al. (2020) present a significant analysis and discussion on the structural breaks in the volatility of cryptocurrencies. While the focus of their study is on Bitcoin, their findings are still illustrative of the importance of considering structural breakpoints in similar problems. These structural breakpoints indicate the response of the volatility to unexpected information. This specific information may continue to affect Ethereum in the future. Therefore, considering structural breaks may improve the in-sample and, more importantly, the out-of-sample performance of HAR-RV models.

3.1. ICSS algorithm

To identify the breakpoints, we apply the iterative cumulative sum of squares (ICSS) approach which is developed by Inclan and Tiao (1994). This algorithm calculates the standard deviations between the change points to determine the number of structural breaks. Firstly, the cumulative sum of squares C_k for all potential breakpoints observations 1 through k were found by using the model error terms.

$$C_k = \sum_{t=1}^k e_t^2, \quad k = 1, 2, T.$$

The cumulative sum of squares should be normalized and centralized, using the partial series CSS, C_k , and the full series CSS.

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}.$$

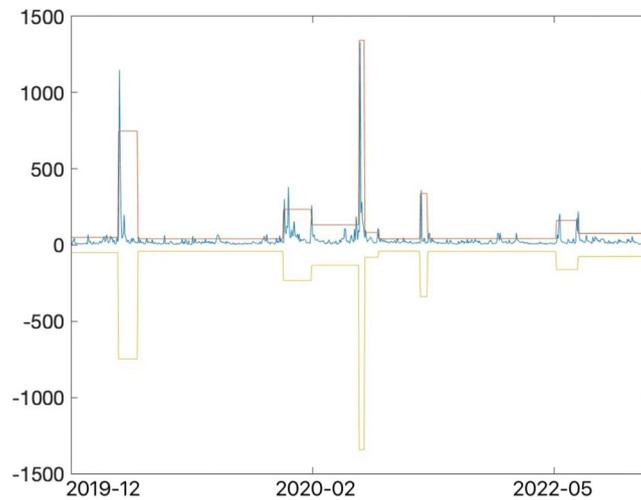


Figure 4. The daily realized volatility of ETH with breakpoints and ± 3 standard deviation bands.

Table 2. Structural breaks of the price volatility of ETH.

The number of structural breaks	The start date	The corresponding RV	The standard deviation
1	2019/12/13	2.68305724	295.651204779579
51	2020/3/12	1149.39232	62177.3108302296
75	2020/4/16	52.6640161	188.543492847102
256	2021/1/4	303.189407	6090.06181303180
291	2021/2/24	67.755719	1934.32046950623
350	2021/5/19	1330.17719	200512.850868375
357	2021/5/28	96.4865332	739.206107114457
374	2021/6/23	31.2711186	184.801051255078
426	2021/9/7	360.55141	12712.3531384881
435	2021/9/20	62.5920544	200.527839435528
595	2022/5/9	66.5191775	2890.35130621410
622	2022/6/16	75.8704794	640.129340713273
722	2022/10/25	37.2680671	0

Furthermore, the potential breakpoint should be found, k^* , which is the location in the series of the maximum absolute value of the centralized cumulative sum of squares D_k . Finally, the IT with the following formula must be checked, if IT exceeds the critical value of the limiting distribution, then k^* represents a statistically significant breakpoint. In this paper, 1.628 (Gong & Lin, 2021) was selected as the approximate threshold at the 99th percentile of the asymptotic distribution of IT.

$$IT = \sqrt{\frac{T}{2}} D_{k^*}.$$

Figure 4 plots the daily realized volatility of ETH with breakpoints and ± 3 standard deviation bands. Table 2 reports the number and start time of structural breaks in volatility that are identified by the ICSS algorithm. The price volatility differs significantly at different stages.

3.2. Identification

The consistency of the ICSS algorithm is demonstrated through its ability to identify specific events that correspond to structural breaks. For example, on April 16, 2020, the scaling down of Facebook-backed Libra caused panic in the cryptocurrency market, leading to the occurrence of a structural breakpoint. Surprisingly, volatility remained stable within an acceptable range until January 4th, 2021, when the interest from investors seeking fast gains and protection against inflation caused a rapid surge in the prices of various digital currencies, including Ethereum, leading to another structural breakpoint.

Subsequently, the price of Ethereum experienced a rapid rise, culminating in a structural breakpoint on February 24th, since traditional financial institutions began accepting it as a routine payment vehicle and asset. However, on May 19th, Ethereum experienced a sudden drop, with a volatility break point attributed to institutional investors shifting their focus from cryptocurrencies to gold, amidst growing regulatory concerns. Notably, regulatory concerns from authorities in China and the United States contributed to the weakness observed. On 28th May and 23rd June, two new breakpoints emerged respectively, revealing the significant fluctuation in the price of Ethereum. On September 7th, Saldo established cryptocurrencies as legal tender, leading to heightened volatility and a significant break point in the cryptocurrency market. On September 20th of the same year, signs of stress in China's credit markets led to bearish sentiment in global markets, triggering a massive sell-off in cryptocurrencies with substantial price fluctuations and a breakpoint. Tightening monetary policy in response to inflationary pressures has dissuaded investors from speculative assets, resulting in ETH's volatility once again occurring a breaking point on May 9th, 2022. On June 16th, due to the precarious and often perilously unstable junction between emerging technologies and traditional currency, the instability of ETH's price led to a corresponding breakpoint. The period we chose happened to coincide with the COVID-19 pandemic. From a macroeconomic perspective, we cannot overlook the sudden uncertainty brought about by this unprecedented event. This helps explain the occurrence of numerous structural breaks in the short term. Additionally, the rapid development of the cryptocurrency market and its own unique characteristics further contribute to the emergence of a significant number of structural break points.

4. Method

This section presents four HAR-type models designed to forecast the volatility of ETH, consisting of original HAR-type models (HAR-RV) as benchmark models, and three improved HAR-type models (i.e., HAR-RV-VBS, HAR-RV-SB, HAR-RV-SB-VBS) that incorporate structural breaks, the VIX index, the S&P500 index, and the price volatility of Bitcoin.

The first model introduced is the classical HAR-RV model, which employs a linear form to determine whether the RV provides sufficient information. Subsequently, the HAR-RV-SB model is developed by incorporating the effects of structural breaks. Additionally, the HAR-RV-VBS model is presented, which incorporates the VIX and S&P500 indices, representing investor sentiment and market conditions, respectively, along with the price volatility of Bitcoin, to enhance forecasting accuracy. Finally, an improved HAR-RV-SB-VBS model is established by considering all the above factors simultaneously.

The subsequent sections provide detailed explanations of each of these models.

4.1. HAR-RV

We use the simple AR-type model established by Corsi (2008). In the data description section, we mentioned how to calculate daily realized volatility. Therefore, the weekly RV and the monthly RV of the trading day t , denoted as $RV_{t,w}$ and $RV_{t,m}$, respectively, are defined as follow.

$$RV_t^w = \frac{RV_t^d + RV_{t-1}^d + \dots + RV_{t-6}^d}{7};$$

$$RV_t^m = \frac{RV_t^d + RV_{t-1}^d + \dots + RV_{t-28}^d}{29}.$$

In addition, the linear form of the HAR model is expressed as

$$RV_{t+1}^d = \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m.$$

4.2. HAR-RV-VBS

In this section, we aim to investigate the impact of the S&P500 index, the VIX index, and the volatility of Bitcoin price on the volatility forecasting of ETH price through the implementation of the HAR-RV-VBS model.

Sovbetov (2018) found that S&P500 index has a positive long-run effect on Ethereum, and Yousaf and Ali also found that S&P 500 impacted the volatility of the Returns of Ethereum. Therefore, we hypothesize that the price volatility of ETH is influenced by the S&P500 index, and thus we introduce the historical volatility of S&P500 into the model.

In addition, it is well-established that the prices of cryptocurrencies are interrelated, with Bitcoin and Ethereum exhibiting co-movements (Mensi et al., 2019). Furthermore, Beneki et al. (2019) found that Bitcoin volatility has a delayed response on Ethereum returns, while Meynkhard (2020) suggested that Bitcoin plays a significant role in guiding the cryptocurrency market. Therefore, we argue that incorporating Bitcoin price volatility into the model will enhance our ability to predict the price volatility of ETH.

Moreover, the VIX index is widely regarded as one of the most crucial market uncertainty indices (Adrian et al., 2019). Leirvik (2022) found that the VIX index has a negative impact on the returns of Ethereum. Thus, we theorize that including the VIX index into the model could improve the volatility forecasting model for ETH.

In conclusion, building upon the HAR-RV model, we further introduce the S&P500 index, VIX index, and Bitcoin price volatility into our model. As a result, we present the HAR-RV-VBS model, which can be expressed as follows.

$$RV_{t+1}^d = \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \beta_v VIX_t + \beta_{bic} R_t^2 + \beta_{sp} R_t^2.$$

4.3. HAR-RV-SB

Structural breaks are a ubiquitous feature in the high-frequency volatility of financial markets. Ignoring structural breaks tends to overestimate the long memory of volatility and consequently results in unreliable forecasting outcomes. Therefore, when modeling volatility, it is imperative to account for the effects of structural breaks. To this end, we identify 11 structural break points through a test conducted in Section 3 and incorporate them into the HAR-RV model in the form of dummy variables.

Building upon the HAR-RV model, we establish a linear form of the HAR-RV-SB model by incorporating the effects of structural breaks, as follows:

$$RV_{t+1}^d = \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \sum_{i=1}^n \beta_i D_i.$$

The variable n represents the number of structural break points, while D_i ($i = 1, 2, \dots, n$) denotes the dummy variable for the i th structural break point in the price volatility of ETH, which is obtained through the ICSS algorithm. We assign the value of 1 to D_i after the i th structural break point to reflect the notion that the corresponding event at that break point affects price volatility from that day forward. Otherwise, the D_i value should be assigned as 0. Comparing the coefficients of the dummy variables allows for a comparison of the influence of each event. As outlined in Section 3, the volatility sequence contains 12 break points, thus $n = 12$.

4.4. HAR-RV-SB-VBS

In order to comprehensively examine the factors that influence the volatility forecasting of the Ethereum market, we develop a HAR-RV-SB-VBS model class that incorporates structural breaks, the VIX index, the volatility of the S&P500, and the volatility of Bitcoin prices into the corresponding original HAR-type models. By doing so, we aim to better capture the complexities and nuances of the Ethereum market and enhance our ability to forecast its volatility. As a result, we present the HAR-RV-SB-VBS model, which can be expressed as follows.

$$RV_{t+1}^d = \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \beta_v VIX_t + \beta_{bic} R_t^2 + \beta_{sp} R_t^2 + \sum_{i=1}^n \beta_i D_i.$$

5. Result analysis

5.1. In-sample analysis

In this section, we employ the ordinary least squares (OLS) method to estimate the parameters of four heterogeneous autoregressive models of realized volatility (HAR-RV) type, following Corsi (2008). Furthermore, we compare the predictive performance of four HAR models, namely, HAR-RV, HAR-RV-SB, HAR-RV-VBS, and HAR-RV-SB-VBS, with the aim of testing the impact of structural breaks, the VIX index, and the volatility of both SP500 and Bitcoin prices. Table 3 summarizes the parameter estimates for the four models when forecasting the volatility of ETH at three different horizons, i.e., daily, weekly, and monthly.

The estimation results from the HAR-RV model indicate that only weekly volatility is statistically significant in predicting one-day volatility. However, for the 1-week forecast, the realized volatility (RV) at all three time periods is significantly positive. The adjusted R-squared value of 0.2549 suggests that the HAR-RV model is not adequately informative for 1-day volatility prediction. Moreover, the findings reveal that the monthly volatility of the ETH market contains a substantial amount of information for predicting long-term RV. This result implies the existence of long memory in the RV of ETH. In other words, the ETH market is heterogeneous.

The findings from the estimation results of the HAR-RV-VBS model suggest that the coefficients associated with the daily, weekly, and monthly lags are statistically significant associated with the 1-day and 1-week volatilities of ETH price. The parameter estimation results further reveal that the VIX index exerts a positive and significant influence on the short-term and mid-term forecasting results. Additionally, our analysis shows that the S&P500 volatility contains relevant information for short-term forecasting. Furthermore, the volatility of Bitcoin price appears to have a statistically significant effect on ETH volatility at all three forecasting horizons, indicating that it is important to take into account when predicting ETH volatility. Therefore, we conclude that the inclusion of the VIX index, Bitcoin price volatility, and S&P500 volatility in the forecasting model can improve the accuracy of the ETH volatility forecasts.

The estimation results of the HAR-RV-SB model indicate that most of the coefficients of daily, weekly, and monthly volatility are statistically significant, which is consistent with the results of the HAR-RV model. Additionally, we conduct an analysis of the coefficients associated with the structural breaks (D_i). This analysis reveals that only half of the coefficients of D_i are statistically significant, indicating that financial events have limited impacts on ETH volatility. Through a thorough examination of coefficients, we discover that the structural breaks which are statistically significant provide crucial information. It is noteworthy that the majority of the events that affect long-term volatility are also present in short-term forecasting. Therefore, we can infer that the detection of structural breaks may not be entirely precise, as Ethereum's volatility experiences drastic fluctuations. Consequently, it is still essential to consider the impact of structural breaks on volatility.

The estimation results of the HAR-RV-SB-VBS model demonstrate that structural breaks, the VIX index, and the volatility of BTC and SP500 exhibit analogous effects as in our analyses using the HAR-RV-SB and HAR-RV-VBS models. This finding strengthens the argument that these factors should not be disregarded when predicting the volatility of ETH. The impact of some structural breaks, however, does not remain statistically significant according to the HAR-RV-SB-VBS model, contrary to the HAR-RV-SB model. We can speculate that the Bitcoin volatility, the VIX index and SP500 volatility may have the same information with the structural breaks. Additionally, Figure 5 illustrates the in-sample adjusted R-squared values of the four models for varying time horizons, further highlighting the necessity of considering these factors.

5.2. Out-of-sample analysis

This paper evaluates the forecasting power of four models for the volatility of ETH through the use of different loss functions, referencing Witt and Witt (1992). It is important to note that when conducting out-of-sample forecasting, we do not consider structural breakpoints that were not present at the time of the forecast. Specifically, we employ the mean square error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and quasi-likelihood (QLIKE) loss

Table 3. Parameter estimation results of models.

	1-Day	1-Week	1-month	1-Day	1-Week	1-Month	1-Day	1-Week	1-Month	1-Day	1-Week	1-Month	1-Day	1-Week	1-Month
RV_t^d	0.22033*** (1.58e-07)	0.074296*** (<2e-16)	0.006579*** (0.00117)	0.10636** (0.038195)	0.059789*** (1.71e-09)	0.003913 (0.1214)	0.23983*** (1.53e-08)	0.077084*** (<2e-16)	0.008459*** (3.19e-05)	0.12435** (0.016176)	0.05979*** (2.40e-09)	0.0058** (0.0223358)	0.12435** (0.016176)	0.05979*** (2.40e-09)	0.0058** (0.0223358)
RV_t^w	0.22728** (0.0209)	0.865842*** (<2e-16)	0.026992*** (1.92e-09)	0.42754*** (6.24e-06)	0.859041*** (<2e-16)	0.027522*** (4.24e-09)	0.44763*** (2.40e-05)	0.885248*** (<2e-16)	0.026764*** (1.80e-07)	0.41861*** (0.002036)	0.8487*** (<2e-16)	0.02589*** (3.90e-06)	0.41861*** (0.002036)	0.8487*** (<2e-16)	0.02589*** (3.90e-06)
RV_t^m	0.37413*** (4.76e-05)	0.021583 (0.248)	0.963007*** (<2e-16)	-0.03175 (0.790833)	-0.01342 (0.5578)	0.957666*** (<2e-16)	0.56403*** (0.009138)	0.059512 (0.147725)	1.008795*** (<2e-16)	0.20244 (0.370151)	0.013407 (0.756804)	0.998669*** (<2e-16)	0.20244 (0.370151)	0.013407 (0.756804)	0.998669*** (<2e-16)
VIX				0.56285*** (0.000343)	0.073994** (0.0136)	0.011456 (0.1376)				1.87959*** (1.64e-06)	0.233183*** (0.001827)	0.051973*** (0.006652)	1.87959*** (1.64e-06)	0.233183*** (0.001827)	0.051973*** (0.006652)
S&P500				-0.62313* (0.052164)	0.095731 (0.1187)	-0.00402 (0.7990)				-0.89979** (0.018768)	0.154713** (0.034968)	-0.02417 (0.198081)	-0.89979** (0.018768)	0.154713** (0.034968)	-0.02417 (0.198081)
BTC				0.14984*** (0.000209)	0.014883* (0.0533)	0.003279* (0.0982)				0.1504*** (0.000178)	0.015387** (0.044643)	0.003472* (0.076947)	0.1504*** (0.000178)	0.015387** (0.044643)	0.003472* (0.076947)
D_1							-70.3257*** (0.006896)	-11.7613** (0.017522)	-5.490759*** (1.33e-05)	-116.43218*** (2.39e-05)	-20.8413*** (7.88e-05)	-6.743058*** (6.72e-07)	-116.43218*** (2.39e-05)	-20.8413*** (7.88e-05)	-6.743058*** (6.72e-07)
D_2				65.53691*** (0.005250)	11.258717** (0.011709)	4.616738*** (4.82e-05)				68.89073*** (0.003416)	15.31082*** (0.000697)	4.686718*** (5.26e-05)	68.89073*** (0.003416)	15.31082*** (0.000697)	4.686718*** (5.26e-05)
D_3				-19.6257 (0.209605)	-0.296722 (0.920563)	-2.269241*** (0.0027)				6.65367 (0.687971)	5.071113 (0.110629)	-1.544019* (0.058078)	6.65367 (0.687971)	5.071113 (0.110629)	-1.544019* (0.058078)
D_4				37.70308** (0.017972)	3.080504 (0.308946)	2.429282*** (0.0016)				31.60437** (0.044372)	1.083975 (0.718678)	2.260567*** (0.003464)	31.60437** (0.044372)	1.083975 (0.718678)	2.260567*** (0.003464)
D_5				-140.148*** (0.000125)	-25.44124*** (0.000251)	-7.300272*** (3.47e-05)				-76.80663* (0.052788)	-8.3918 (0.269249)	-5.634019*** (0.003882)	-76.80663* (0.052788)	-8.3918 (0.269249)	-5.634019*** (0.003882)
D_6				67.96268* (0.071689)	16.160205** (0.024527)	0.775770 (0.6696)				38.12799 (0.332645)	3.800119 (0.614388)	0.053539 (0.977897)	38.12799 (0.332645)	3.800119 (0.614388)	0.053539 (0.977897)
D_7				50.12002* (0.064090)	6.071954 (0.238222)	5.867622*** (7.89e-06)				16.68813 (0.544634)	0.984468 (0.852089)	4.92941*** (0.00287)	16.68813 (0.544634)	0.984468 (0.852089)	4.92941*** (0.00287)
D_8				-22.697 (0.360427)	-5.47737 (0.246281)	-0.551768 (0.6447)				-20.81154 (0.391741)	-4.22804 (0.364069)	-0.514302 (0.666470)	-20.81154 (0.391741)	-4.22804 (0.364069)	-0.514302 (0.666470)
D_9				26.43074 (0.263123)	5.797396 (0.197228)	1.020472 (0.3703)				12.73843 (0.584568)	2.624222 (0.556849)	0.657056 (0.565873)	12.73843 (0.584568)	2.624222 (0.556849)	0.657056 (0.565873)
D_{10}				8.4157 (0.558738)	0.99488 (0.716423)	-0.080568 (0.9076)				4.98957 (0.723573)	0.71721 (0.790846)	-0.183781 (0.790828)	4.98957 (0.723573)	0.71721 (0.790846)	-0.183781 (0.790828)
D_{11}				-9.14025 (0.538867)	-1.133786 (0.688750)	-0.174255 (0.8081)				-8.4909 (0.559142)	-1.1862 (0.670323)	-0.151674 (0.831751)	-8.4909 (0.559142)	-1.1862 (0.670323)	-0.151674 (0.831751)
Adj-R ²	0.2549	0.9352	0.9929	0.2791	0.9338	0.9929	0.2717	0.9338	0.9932	0.3050	0.9359	0.9932	0.3050	0.9359	0.9932

Significant code: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

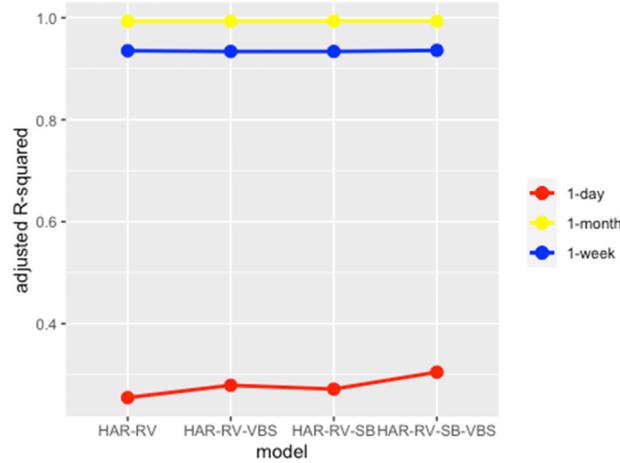


Figure 5. The in-sample adjusted R-squared values.

function to evaluate the performance of the models. A smaller value for these loss functions indicates better forecasting performance. Furthermore, we use R-squared (R^2) as a metric to reflect the goodness of fit of the model. The numerical value of R^2 indicates the extent to which an independent variable in a regression model explains the variation of a dependent variable. A value closer to 1 implies better predictive power of the model. The definitions of R-squared, MSE, RMSE, MAE, MAPE and QLIKE are provided below,

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\bar{y} - y_i)^2},$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2;$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2};$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|;$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right|;$$

$$QLIKE = \frac{1}{n} \sum_{i=1}^n \left(\frac{y_i}{\hat{y}_i} - \log \frac{y_i}{\hat{y}_i} - 1 \right);$$

where \hat{y}_i is the predicted value and y_i is the real value.

To ensure the accuracy of our findings, we conduct out-of-sample predictions and calculate loss functions for both 15-day and 30-day horizons. Tables 4 and 5 summarize the results obtained. As shown in Table 4, the ability to forecast daily volatility remains inadequate, regardless of the model utilized. This outcome is in line with the findings of Table 5. Except for the HAR-RV-SB model, which exhibits a higher out-of-sample forecast R-squared value than the benchmark model HAR-RV, all the loss function values are larger than those of the benchmark model, indicating greater forecast bias. Nonetheless, our analysis surprisingly reveals that the HAR-RV-SB-VBS model has a lower loss function value for 1-week forecasting, both in-sample and out-of-sample testing. In other words, for 1-week forecasts, the HAR-RV-SB-VBS model provides the most accurate predictions of ETH prices.

Figure 6 provides a visual comparison of the predicted and actual values of the four models, which yields further insights into the prediction outcomes. The comparison reveals that the HAR-RV model has a high level of forecasting accuracy for both the 1-day and 1-month forecasts. Conversely, the

Table 4. Loss function values of different models (15 days).

	Models	R2	MAE	MSE	RMSE	MAPE	QLIKE
1-DAY	HAR-RV	0.2556232	5.030887	43.723431	6.612370	1.156446	7.864924
	HAR-RV-VBS	0.2726917	10.696708	134.871020	11.613398	4.136963	5.882498
	HAR-RV-SB	0.3768803	4.6361775	57.4482277	7.5794609	0.6233423	85.03268
1-WEEK	HAR-RV-SB-VBS	0.09637671	4.5716742	53.3189320	7.3019814	0.8183098	49.26835
	HAR-RV	0.4814256	0.8004395	1.2116307	1.100741	0.1387946	4.489524
	HAR-RV-VBS	0.6505875	1.4198022	2.5287691	1.5902104	0.2700986	4.482155
1-MONTH	HAR-RV-SB	0.454408	0.6837248	1.4625435	1.2093566	0.1147395	4.557017
	HAR-RV-SB-VBS	0.7440659	0.5788957	0.4925055	0.7017874	0.1022475	4.399877
	HAR-RV	0.8955474	0.478313	0.5226664	0.7229567	0.0617387	5.031602
1-MONTH	HAR-RV-VBS	0.8959978	0.64246405	0.73216299	0.85566523	0.08411879	5.037181
	HAR-RV-SB	0.8960296	0.66351365	0.55682399	0.74620640	0.08827835	5.041423
	HAR-RV-SB-VBS	0.8918273	0.64099466	0.54794074	0.74023019	0.08496546	5.040975

Table 5. Loss function values of different models (30 days).

	Models	R2	MAE	MSE	RMSE	MAPE	QLIKE
1-DAY	HAR-RV	0.01247072	3.333826	23.996671	4.898640	1.256157	5.360493
	HAR-RV-VBS	0.005392847	10.80667	129.689750	11.388141	6.758444	5.540398
	HAR-RV-SB	0.02334532	3.893775	35.316023	5.942729	1.249304	53.31885
1-WEEK	HAR-RV-SB-VBS	0.01156551	3.580830	34.975000	5.913967	1.049793	44.07986
	HAR-RV	0.7416594	0.6758517	0.9844192	0.9921790	0.1506025	3.769224
	HAR-RV-VBS	0.7875997	1.540061	3.026488	1.739680	0.482804	3.941041
1-MONTH	HAR-RV-SB	0.7456736	0.7206301	1.1549796	1.0746998	0.1803232	3.862043
	HAR-RV-SB-VBS	0.8110957	0.6474996	0.7299848	0.8543915	0.1650774	3.740789
	HAR-RV	0.9606352	0.29405589	0.27217478	0.52170373	0.04233162	4.554424
1-MONTH	HAR-RV-VBS	0.9607979	0.47904064	0.42136446	0.64912592	0.07589582	4.560791
	HAR-RV-SB	0.9608473	0.7452121	0.6279802	0.7924520	0.1348420	4.610126
	HAR-RV-SB-VBS	0.9583689	0.7275258	0.6127803	0.7828028	0.1311025	4.60565

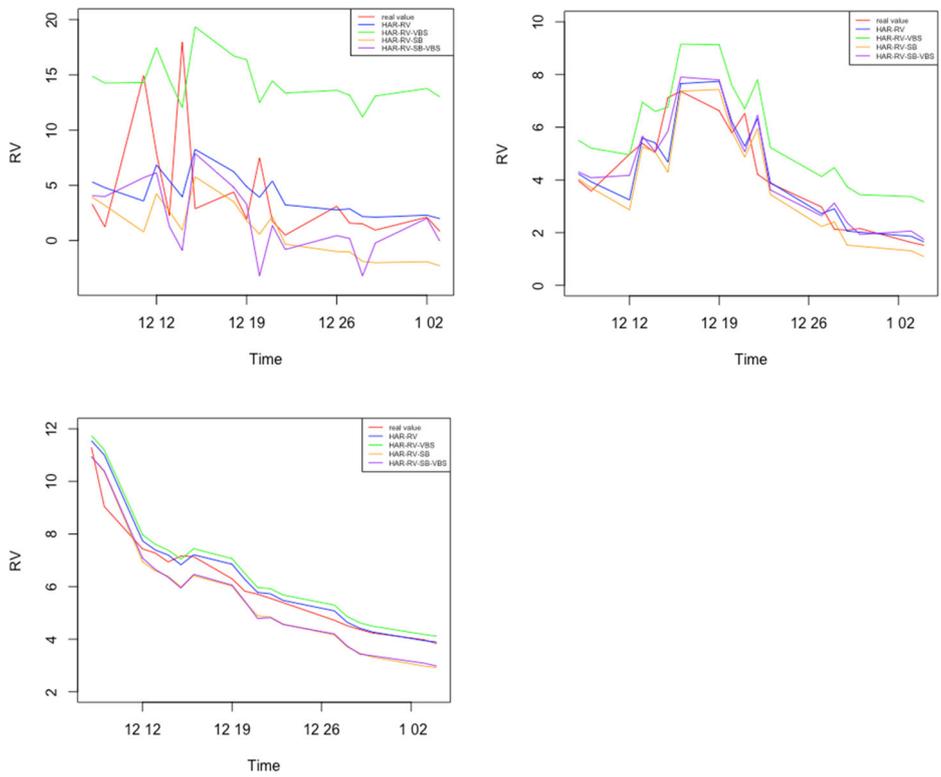


Figure 6. Predict results of 4 models.

information added to the model did not significantly improve the accuracy of daily volatility forecasts. Furthermore, the figure shows that forecasting mid-term volatility for Ethereum necessitates considering the effects of structural breakpoints, the VIX index, S&P 500 volatility, and Bitcoin price volatility.

Although the loss function approach enables us to determine which model performs better from different perspectives, it has a limitation in that it does not indicate whether the results can be considered trustworthy.

5.3. DM test

The DM test, introduced by Diebold and Mariano (1995), is a statistical method widely used to compare the forecasting performance of two models (Sadorsky, 2006). This technique is based on the loss functions which can quantify the difference between the forecasted and actual values. The null hypothesis of the DM test is that the two models have the same predictive accuracy. The DM statistic is calculated as follows:

$$DM = \frac{\bar{d}_t}{\sqrt{\frac{\widehat{\text{Var}}(d_t)}{T}}} \rightarrow N(0, 1).$$

where \bar{d}_t denotes the mean of d_t , and d_t is the difference of the loss function. In this part, we use MSE, RMSE, MAE, MAPE and QLIKE as the loss function. $\widehat{\text{Var}}(d_t)$ represents the robust estimate of the asymptotic variance for d_t , with heteroscedasticity and autocorrelation. If the DM test statistic exceeds the critical value, the predictive performance of the models is deemed significantly different. When DM-value is greater than 0, the new model is better than the previous one. Therefore, the DM test is a valuable tool for assessing the relative forecasting power of different models. Nevertheless, in this study, we have actually employed the modified test proposed by Harvey et al. (1997), which enhances robustness.

To evaluate the performance of various Ethereum forecasting models, we established the HAR-RV model as a benchmark and conducted a DM-test to investigate whether the forecasting accuracy of the HAR-RV-VBS, HAR-RV-SB, and HAR-RV-SB-VBS models was significantly improved. The results of the DM-test are presented in Table 6.

Table 6 reveals that the various HAR-type models exhibit distinct forecasting accuracy. Regardless of the loss function selected (MSE, MAE, MAPE, RMSE and QLIKE), all three models perform worse than the HAR-RV model in terms of 1-day and 1-month ETH volatility forecasting. This outcome aligns with in-sample forecasting. In addition, different loss functions do not get consistent conclusions. Based on the DM-test results of QLIKE, we can find that in 1-week forecasting, the HAR-RV-SB-VBS model outperforms the benchmark model.

In summary, we posit that considering all factors within the original HAR-type model (i.e., HAR-RV-SB-VBS) yields the most precise out-of-sample forecasting of all models we have established in 1-week forecasting. This finding indicates that the combination of the market information effectively enhances the accuracy of 1-week ETH volatility forecasting. Additionally, the HAR-RV model is the optimal model for ETH 1-month and 1-day forecasting. Incorporating other factors into the prediction may disturb the efficacy of the HAR-RV model.

5.4. Model Confidence Set (MCS) Procedure

To evaluate the performance of various Ethereum forecasting models, we employ the Model Confidence Set (MCS) Procedure. The MCS test, introduced by Hansen et al. (2011), is based on the loss function. It offers an alternative approach to assessing predictive performance compared to simple comparisons of loss functions. It addresses the issue of 'outliers leading to a significant increase in the loss function', resulting in more robust and reliable results. A large amount of research, such as Huang et al. (2021) and Liu and Lee (2021), have demonstrated the robustness of this method.

In simpler terms, the MCS test is a significance test where a set of volatility forecasting models, denoted as M_0 . The test aims to remove models with poor predictive ability from the set M_0 . In each test, the null hypothesis assumes that two volatility forecasting models within M_0 have the same

Table 6. DM test results for out-of-sample forecasting.

BENCHMARK	MAE			MSE			RMSE			MAPE			QLIKE		
	1-day	1-week	1-month	1-day	1-week	1-month	1-day	1-week	1-month	1-day	1-week	1-month	1-day	1-week	1-month
HAR-RV	-4.3767***	-2.7881**	-3.4578***	-1.5793	-1.5793	-1.115	-4.3767***	-2.7881**	-3.4578***	-2.2119**	-3.1575***	-5.5749***	0.95531	-1.6105	-5.9058***
HAR-RV-VBS	-1.6337	-0.92244	-2.0947*	-0.9881	-0.9881	0.37266	-1.6337	-0.92244	-2.0947*	0.32704*	-0.93445	-3.3368***	-1.6178	-2.3033**	-3.6395***
HAR-RV-SB	-1.0083	0.8964	-2.0206*	0.95841	0.95841	0.37025	-1.0083	0.8964	-2.0206*	0.91401	-0.32826	-3.4065***	-1.2727	1.072*	-3.8043***

Statistics in parentheses. * p < 0.1, ** p < 0.05, ***p < 0.01.

Table 7. MCS test results for out-of-sample forecasting.

MODEL	DAILY	WEEKLY	MONTHLY
HAR-RV	1.000	0.358	1.000
HAR-RV-VBS	0.000	0.000	0.028
HAR-RV-SB	0.063	0.363	0.098
HAR-RV-SB-VBS	0.257	1.000	0.054

predictive ability for future volatility, which can be expressed as follows:

$$H_{0,M} : E(d_{i,uv}) = 0.$$

The variable $d_{i,uv}$ represents the difference in loss functions (MSE) between two volatility forecasting models, u and v . The models are continuously tested using the equivalence test δM and the elimination rule eM . The testing process ends when no models are eliminated from the set. The MCS test involves multiple complex statistical measures, including the maximum deviation to the average loss (maxT), the traditional quadratic-form test (chi), the chi test with sample size correction (F), the deviation from the common average (ComAve), the range-based statistic (Range), and the semi-quadratic statistic (SemiQ). Due to the small differences in the results of these statistical measures, this study only employs the commonly used range-based statistic as the test statistic, which can be defined as:

$$Range = \max_{u,v \in M} \frac{|d_{i,uv}|}{\sqrt{\text{var}(d_{i,uv})}}$$

If the range-based statistic (Range) exceeds a given critical value, the null hypothesis is rejected. The true distribution of the Range statistic is complex as it depends on the ‘aversion parameter’. In empirical applications, the value of the range-based statistic (Range) and the corresponding test can be obtained through bootstrapping. Typically, when the p-value is greater than the commonly set threshold of 0.1, it indicates that the criterion model exhibits good predictive ability. A higher p-value suggests a greater likelihood of strong predictive ability.

Table 7 presents the results of the MCS test, conducting consistent findings with the DM test. The data provides evidence that in mid-term forecasting, the volatility of Ethereum is significantly influenced by both traditional financial market information (S&P500 and VIX), Bitcoin and structural breaks.

6. Robustness test

This section aims to assess the robustness of both the in-sample and the out-of-sample forecasting by altering the sample range. While the forecasting results are consistent with those presented in Sections 5 and 6, this section will solely focus on the robustness of the results obtained.

6.1. In-sample

To determine the reliability of forecasting outcomes across different samples, a division of the total 722 samples into two sub-samples was conducted. Subsample 1 contains samples 1 to 360, while Subsample 2 comprises samples 360 to 722. Following this, an in-sample regression analysis was performed on both subsamples, and the adjusted R-squares were calculated as an indicator of the model’s predictive accuracy. The results of this analysis are presented in Table 8.

Table 8 displays the results of the estimation of 1-day volatility by using four models on two subsamples, namely subsample 1 and subsample 2. The adjusted R-squares in subsample 1 and subsample 2 exhibit considerable disparity and lack robustness, implying that these models are sensitive to the selection of data in estimating 1-day volatility. Conversely, the adjusted R-squares in the medium-term and long-term volatility estimation demonstrate consistent and stable results for both subsamples, indicating that each model performs reliably in these horizons. Consequently, we infer that the four models are robust for the medium-term and long-term volatility estimation of Ethereum.

Table 8. Adjusted R-squares of sample 1 and sample 2.

	1-DAY		1-WEEK		1-MONTH	
	Sample1	Sample2	Sample1	Sample2	Sample1	Sample2
HAR-RV	0.2242	0.5693	0.9268	0.9671	0.9929	0.9933
HAR-RV-VBS	0.2462	0.5964	0.9281	0.9683	0.9929	0.9933
HAR-RV-SB	0.247	0.6063	0.9284	0.9684	0.9932	0.9934
HAR-RV-SB-VBS	0.2751	0.6146	0.9307	0.9695	0.9933	0.9934

Table 9. Loss function values for out-of-sample forecasting.

		MAE	MSE	RMSE	MAPE	QLIKE
1-day	HAR-RV	27.4846496	3082.3348805	55.5187795	0.4828582	12.15608
	HAR-RV-VBS	29.8249030	2825.5711936	53.1561021	0.9651824	9.452772
	HAR-RV-SB	30.1992042	3051.7679375	55.2428089	0.6754943	13.62258
	HAR-RV-SB-VBS	31.720395	2624.748218	51.232297	1.179675	8.846167
1-week	HAR-RV	4.2493449	69.3521325	8.3277928	0.1151712	6.82639
	HAR-RV-VBS	4.8032075	67.5840474	8.2209517	0.1936859	6.842171
	HAR-RV-SB	4.3065354	63.4602906	7.9661967	0.1300311	6.826794
	HAR-RV-SB-VBS	5.545689	68.264191	8.262215	0.269310	6.876887
1-month	HAR-RV	0.92266384	3.59290193	1.89549517	0.04988561	5.92362
	HAR-RV-VBS	1.01115922	3.45428263	1.85857005	0.06223437	5.922597
	HAR-RV-SB	1.3612582	4.1759564	2.0435157	0.0940295	5.935592
	HAR-RV-SB-VBS	0.98000226	3.45322453	1.85828537	0.05559051	5.922385

6.2. Out of sample

To assess the accuracy of out-of-sample forecasts within the Ethereum market, the rolling window was altered from 1046 days to 846 days, covering the period from December 12, 2019 to April 8, 2022. Consequently, a predicted sample of observations spanning the time period from April 8, 2022 to March 30, 2018 was obtained. The outcomes of this analysis are presented in Table 8, which showcases the results of four loss functions.

Analysis of Table 9 reveals that, on the whole, the loss function values exhibit a marginal decrease following the change in window size; however, the overall trend remains consistent with the previous outcomes.

7. Conclusion

This study aims to provide a novel perspective on Ethereum (ETH) price forecasting, building upon existing literature (Ftiti et al., 2021) by utilizing a HAR-type model that considers the impact of various factors on ETH prices. The improved HAR-type model in this study incorporates structural breaks to enhance the robustness and validity of predictions. Furthermore, the study expands upon the HAR-RV model by investigating the impact of the VIX and S&P500 indices, which represent investor sentiment and market direction, respectively, contributing to the existing literature. Besides, the volatility of Bitcoin which is closely connected with ETH volatility is also considered. We establish three novel models, namely HAR-RV-SB, HAR-RV-VBS, and HAR-RV-SB-VBS, which are utilized in both in-sample and out-of-sample analysis of the RV of Ethereum prices. Based on our analysis, we propose several conclusions.

Our results demonstrate that the HAR-RV model achieves a perfect fit in 1-week and 1-month forecasting due to the characteristics of Ethereum itself. The model that considers all factors has only a small improvement in fitness and prediction accuracy. However, in out-of-sample forecasting, considering the effects of structural breakpoints, VIX, S&P 500 volatility, and Bitcoin price volatility improves the accuracy of 1-week forecasts, albeit marginally.

Despite these findings, three main limitations of this study should be acknowledged. Firstly, we did not consider simple models such as HAR-RV-VIX and HAR-RV-SP, which do not sufficiently analyze the impact of individual factors but rather include all factors, resulting in increased complexity. Secondly, we need to consider the duration of the impact of different structural breakpoints. Some breakpoints occur merely due to unforeseen financial events and do not have a lasting influence. Finally, we did not decompose the volatility component further to capture the volatility of Ether more accurately, which

could lead to reduced accuracy in predictions. Future research may consider incorporating the leverage effect into a model for predicting ETH price volatility and try to use some Machine Learning models like short- and long-term memory networks.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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