International Journal of
Financial Studies

MDPI

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Predicting the Volatility of Cryptocurrencies' Returns Using High-Frequency Data: A Comparative Analysis of GARCH, EGARCH, IGARCH, GJR-GARCH, LRE, and HAR Models

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Abstract

This study provides a comprehensive evaluation of six volatility forecasting models applied to twelve dominant and less dominant cryptocurrencies across multiple time horizons using high-frequency intraday data. The exponential generalized autoregressive conditional heteroskedastic (EGARCH), integrated GARCH (IGARCH), standard GARCH, GJR-GARCH, lagged realized volatility (LRE), and heterogeneous autoregressive (HAR) models are systematically compared using 5 min computed return data from September 2018 to September 2020. Our analysis encompasses three forecast horizons (1-day, 7-day, and 30-day) to assess model performance under varying temporal constraints. Through univariate Mincer–Zarnowitz regressions, encompassing tests, and out-of-sample evaluation using root mean squared error (RMSE) and quasi-likelihood loss (QLIKE) functions, we identify significant performance heterogeneity across models and cryptocurrencies. The HAR model exhibits stronger predictive accuracy at short horizons, while EGARCH exhibits relatively stronger performance at longer horizons, although overall explanatory power declines as forecast horizon increases. Importantly, no single model consistently provides optimal forecasts across all cryptocurrencies. Consistent with prior evidence suggesting model performance varies across assets. Encompassing regressions reveal that combining HAR with EGARCH specifications significantly enhances explanatory power across all temporal frames. Out-of-sample Diebold–Mariano tests indicate that HAR generates the lowest forecast errors for most cryptocurrencies, though EGARCH performs exceptionally well for high-market-capitalization assets. These findings provide regime-conditional insights into horizon- and asset-specific volatility dynamics during the pre-institutionalization phase of cryptocurrency markets. The study contributes to emerging literature by incorporating less-dominant cryptocurrencies and offering robust empirical evidence on the asymmetric and persistent volatility characteristics unique to digital asset markets. These findings should be interpreted within the context of the 2018–2020 sample period, representing a pre-institutionalized phase of cryptocurrency markets, and may not fully generalize to structurally different market regimes characterized by increased institutional participation and regulatory development.

Keywords: cryptocurrency; volatility forecasting; high-frequency data; GARCH models; realized volatility; HAR; EGARCH

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Academic Editors: Periklis Gogas and Yosef Bonaparte

Received: 25 January 2026
Revised: 20 March 2026
Accepted: 25 March 2026
Published: 3 April 2026

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1. Introduction

Since the seminal introduction of Bitcoin by (Nakamoto, 2008), cryptocurrencies have transformed the landscape of financial innovation. Cryptocurrencies represent a novel class of non-tangible digital assets secured through cryptographic algorithms, operating independently of traditional regulatory authorities and financial intermediaries (Nakamoto, 2008). These peer-to-peer electronic cash systems enable direct online payments without intermediary institutions, fundamentally altering transaction cost structures and monetary transfer mechanisms (Cheah & Fry, 2015). The distinctive characteristics of cryptocurrencies—including algorithmic security, absence of government backing, and purely digital representation—have catalysed their rapid adoption as both alternative payment systems and innovative investment instruments (Baur et al., 2018).

The cryptocurrency market has witnessed exponential growth, with thousands of digital currencies now available for trading. Bitcoin, first traded in 2009, remains the dominant cryptocurrency, yet a multitude of alternative coins (altcoins) have emerged, including Ethereum, Ripple, Litecoin, and others with varying market capitalizations and technological architectures (Catania & Sandholdt, 2019). This diversity has attracted considerable scholarly attention, with researchers attempting to comprehend the unique behavioral patterns, pricing dynamics, and volatility characteristics that distinguish cryptocurrencies from traditional financial assets (Kristoufek, 2015).

Volatility forecasting represents a critical component of cryptocurrency market analysis, serving essential functions for portfolio optimization, risk management, derivative pricing, and regulatory oversight. Unlike conventional fiat currencies, cryptocurrencies exhibit extreme volatility levels, rendering accurate volatility prediction both challenging and economically consequential. The inherent volatility clustering, long memory properties, and asymmetric shock responses observed in cryptocurrency returns necessitate sophisticated econometric models capable of capturing these complex dynamics (Mensi et al., 2019).

Despite extensive research efforts, the academic community exhibits significant disagreement regarding the most appropriate volatility forecasting methodology for cryptocurrency markets. Traditional GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, while widely applied, demonstrate inconsistent performance. Hansen and Lunde (2005) confirmed GARCH efficiency for IBM returns, while subsequent studies (Caporale & Zekokh, 2019) identified over 1000 potential GARCH specifications, concluding that standard GARCH models often produce inaccurate Value-at-Risk (VaR) and Expected Shortfall (ES) predictions for cryptocurrencies.

This study addresses several critical gaps in existing literature. First, we systematically evaluate six prominent volatility forecasting models—GARCH, IGARCH, EGARCH, GJR-GARCH, LRE, and HAR—using uniform high-frequency data across twelve cryptocurrencies with diverse market capitalizations. This approach enables direct model comparison while accounting for cryptocurrency-specific heterogeneity. Second, we examine multiple forecast horizons (1-day, 7-day, and 30-day) to assess temporal stability in model performance. Third, we incorporate less-dominant cryptocurrencies (Monero, Stellar, Dash, Zcash, Ethereum Classic, Augur) alongside major assets (Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, EOS), providing comprehensive market coverage often neglected in the literature focused primarily on Bitcoin (Catania & Sandholdt, 2019).

Beyond traditional econometric specifications, recent studies have compared GARCH-family models with machine learning and hybrid forecasting approaches. Recent studies such as (Walther et al., 2019) report that deep learning models can outperform classical GARCH variants under certain conditions, yet performance remains strongly asset- and horizon-dependent. Similarly, Katsiampa (2017) find that EGARCH and HAR models

often dominate symmetric GARCH specifications in cryptocurrency volatility forecasting. These comparative findings reinforce the importance of structured multi-horizon model evaluation within a unified empirical framework.

Our research design employs rigorous econometric methodologies, including Mincer–Zarnowitz regressions for in-sample fit assessment, encompassing regressions to evaluate complementary model information, and out-of-sample Diebold–Mariano tests using RMSE and QLIKE loss functions. The utilization of 5 min log returns from September 2018 to September 2020 captures diverse market conditions during the pre-institutionalization phase of cryptocurrency markets, including bull and bear phases.

Beyond comparative evaluation, the study advances the literature by offering an economic interpretation of horizon- and asset-specific model performance. Rather than treating forecasting differences as purely statistical rankings, we link model dominance to underlying volatility mechanisms, including heterogeneous information arrival, asymmetric shock transmission, and persistence dynamics. The results indicate that short-horizon volatility is primarily driven by realized fluctuations and multi-scale information aggregation, whereas longer-horizon volatility reflects nonlinear persistence and asymmetric innovation effects. By integrating empirical evidence with structural interpretation, the study provides a framework for understanding volatility formation in digital asset markets and offers economically grounded guidance for model selection in risk management and portfolio applications.

Portions of the empirical analysis presented in this study build upon the first author's doctoral dissertation (University of East Anglia, 2023), which examined volatility forecasting models for cryptocurrencies over the same sample period. While certain baseline regression results are derived from the dissertation dataset, the present manuscript substantially extends the original framework through expanded asset coverage, formal multi-horizon structural interpretation, comprehensive encompassing regressions, enhanced out-of-sample forecast evaluation, and a fully restructured theoretical positioning. This dissertation has not been previously published in journal form.

Specifically, the univariate Mincer–Zarnowitz regression results reported in Tables 2–4 for ten cryptocurrencies replicate the baseline estimations presented in the doctoral dissertation, while the present manuscript extends the analysis through additional assets, expanded forecasting evaluation, and structural economic interpretation.

Beyond providing a comparative statistical evaluation, this study extends prior dissertation-based empirical work in several substantive ways. First, it expands the cross-sectional scope by incorporating additional cryptocurrencies not analyzed in the original thesis, thereby enhancing heterogeneity and external validity. Second, it formalizes a structural economic interpretation of horizon-dependent volatility dynamics, linking model dominance to heterogeneous information arrival and asymmetric persistence mechanisms. Third, it introduces a comprehensive encompassing regression architecture to examine model complementarity. Fourth, it implements a fully recursive rolling-window out-of-sample evaluation framework with HAC corrections and Diebold–Mariano testing. Collectively, these extensions reposition the analysis from a purely comparative exercise toward an economically grounded framework for conditional model selection in cryptocurrency risk management.

This study contributes to the growing literature on cryptocurrency volatility forecasting in several important ways. First, it provides a comprehensive comparative analysis of six widely used volatility forecasting models—including GARCH, IGARCH, EGARCH, GJR-GARCH, LRE, and HAR—using high-frequency intraday data. While prior studies have often focused on a limited set of models or individual cryptocurrencies, this study simultaneously evaluates multiple model classes across twelve major and emerging

cryptocurrencies. This study moves beyond comparative evaluation by linking model performance to underlying volatility mechanisms, including information aggregation and asymmetric persistence. Unlike prior studies, this paper provides an economic interpretation of horizon-dependent volatility dynamics rather than purely statistical comparison.

Second, the analysis incorporates realized volatility constructed from 5 min returns, enabling a detailed examination of short-horizon volatility dynamics that are often obscured in lower-frequency datasets. This high-frequency framework allows for a more accurate assessment of intraday information aggregation and volatility persistence.

Third, the study explicitly evaluates model performance across multiple forecast horizons (1-day, 7-day, and 30-day), providing new insights into horizon-dependent forecasting performance. The results reveal substantial heterogeneity across assets and horizons, highlighting that no single model consistently dominates across all cryptocurrencies.

Finally, by integrating encompassing regressions, out-of-sample forecasting tests, and Diebold–Mariano comparisons, the study provides robust evidence regarding the relative predictive performance of competing volatility models in digital asset markets.

It is important to emphasize that the empirical results are conditional on the structural characteristics of the sample period (2018–2020), which reflects a predominantly retail-driven and pre-institutionalized phase of cryptocurrency market development. Given the substantial structural transformations observed in digital asset markets after 2020—including increased institutional participation, expanded derivatives markets, and evolving regulatory frameworks—the generalizability of the findings to alternative market regimes may be limited. Accordingly, the results should be interpreted as regime-specific rather than universally applicable across all periods.

1.1. Research Questions and Hypotheses

To strengthen the conceptual structure of the analysis, this study is guided by the following research questions:

RQ1: Does the predictive performance of volatility models differ systematically across forecast horizons (1-day, 7-day, and 30-day)?

RQ2: Do asymmetric volatility models (EGARCH, GJR-GARCH) outperform symmetric specifications (GARCH, IGARCH) at longer forecast horizons?

RQ3: Does the incorporation of realized high-frequency information (HAR, LRE) improve short-horizon volatility forecasting performance?

RQ4: Is there evidence of model complementarity, such that combining realized volatility models with asymmetric GARCH specifications enhances explanatory power?

These research questions lead to the following testable hypotheses:

H1. *Forecast performance declines as the forecast horizon increases, reflected in decreasing explanatory power across models.*

H2. *Asymmetric volatility models (particularly EGARCH) outperform symmetric GARCH specifications at medium and longer horizons due to nonlinear shock transmission mechanisms.*

H3. *Realized volatility models (HAR, LRE) exhibit superior performance at short horizons due to high-frequency information aggregation.*

H4. *Encompassing regressions combining HAR and EGARCH generate higher explanatory power than single-model specifications.*

These hypotheses are evaluated using Mincer–Zarnowitz regressions, encompassing tests, and rolling out-of-sample forecast comparisons.

1.2. Literature Review

The academic discourse on cryptocurrency volatility modeling reflects a rapidly evolving field characterized by methodological pluralism and ongoing debate regarding optimal forecasting approaches. This literature review synthesizes existing research streams, highlighting consensus, controversies, and emerging insights that inform our empirical investigation.

1.2.1. Cryptocurrency Market Characteristics and Volatility Drivers

Early research established fundamental distinctions between cryptocurrencies and traditional financial assets. Kyriazis et al. (2019) emphasized that cryptocurrency values derive not from tangible assets or national economic fundamentals but from algorithmic security and network effects. This unique valuation mechanism contributes to extreme volatility and speculative bubble formation, as documented by (Cheah & Fry, 2015; Cheung et al., 2015). The detachment from regulatory oversight and government control, while fostering innovation, simultaneously eliminates traditional stabilizing mechanisms present in fiat currency markets.

The functional role of cryptocurrencies remains contested in academic literature. While Wu and Pandey (2014) concluded Bitcoin's limited utility as a currency, their findings supported its portfolio efficiency-enhancing properties. This perspective was reinforced by (Baur et al., 2018), who demonstrated that Bitcoin primarily functions as an investment instrument rather than transaction medium. Bitcoin exhibits hybrid properties, demonstrating characteristics of both traditional financial assets and speculative instruments. These divergent perspectives underscore the necessity for specialized volatility modeling approaches that accommodate cryptocurrency-specific features (Kristoufek, 2015).

1.2.2. GARCH-Based Volatility Models: Performance and Limitations

GARCH models represent the most extensively applied methodology for conditional variance analysis in cryptocurrency markets. However, performance evaluations yield contradictory conclusions. Hansen and Lunde (2005) demonstrated GARCH superiority for IBM returns using superior predictive ability (SPA) and reality check (RC) frameworks. In contrast, (Caporale & Zekokh, 2019) evaluated over 1000 GARCH specifications across Bitcoin, Ethereum, Ripple, and Litecoin, finding standard GARCH models inadequate for VaR and ES prediction.

The necessity of accommodating asymmetries and structural breaks emerges as a critical theme. IGARCH (1,1) and GJR-GARCH combinations were found to provide optimal fits for most cryptocurrencies, although model effectiveness varied significantly across assets. Specifically, IGARCH (1,1) best fit Bitcoin, Dash, Litecoin, Maidsafecoin, and Monero, while GJR-GARCH (1,1) optimally described Dogecoin volatility (Chu et al., 2017). AR-CGARCH was identified as Bitcoin's best-fitting model, contradicting simpler GARCH specifications (Katsiampa, 2017).

Long memory properties represent another crucial dimension. Dual long memory in Bitcoin and Ethereum was documented using ARFIMA-GARCH variants, with evidence showing that structural breaks significantly reduce persistence estimates (Mensi et al., 2019). Similar findings were reported across twelve cryptocurrencies, where squared and absolute returns exhibited long memory features that diminished when structural breaks were incorporated (Abakah et al., 2020). Collectively, these results suggest that conventional short-memory GARCH models may inadequately capture cryptocurrency volatility dynamics.

More recent research highlights that cryptocurrency volatility persistence may be regime-dependent rather than strictly integrated. Kayal and Dutta (2024) document struc-

tural shifts in volatility dynamics across pre- and post-pandemic periods, suggesting that persistence parameters may vary under evolving liquidity and market participation structures. These findings imply that imposing strict unit-root persistence, as in IGARCH models, may be overly restrictive for certain assets and forecast horizons.

1.2.3. Realized Volatility and High-Frequency Approaches

The advent of high-frequency trading data has enabled realized volatility measures that substantially improve forecast accuracy. Realized variance-based models have been shown to outperform daily return GARCH specifications for Bitcoin and Ethereum. Additionally, jump-robust realized measures enhance Bitcoin volatility estimation, with RGARCH models generating superior forecasts relative to standard GARCH approaches (Hung et al., 2020).

The Heterogeneous Autoregressive (HAR) model, originally developed for realized volatility, has shown particular promise. Its capacity to estimate long memory while maintaining strong out-of-sample performance has been well documented (Audrino & Knaus, 2016). More recently, dynamic models incorporating time-varying skewness and kurtosis have demonstrated enhanced density and quantile forecasts across 606 cryptocurrencies Catania and Grassi (2022). These advances underscore the importance of high-frequency data and realized volatility measures in cryptocurrency markets.

Recent contributions extend realized volatility modeling in cryptocurrency markets by incorporating microstructure and trading intensity features. Slim et al. (2023) show that integrating price duration into HAR-type models enhances short-horizon volatility forecasts. Similarly, Katsiampa (2017) demonstrates that model-averaging techniques within the HAR framework improve predictive stability under specification uncertainty. These findings suggest that the informational content of high-frequency data may play a crucial role in horizon-dependent forecasting performance.

1.2.4. Asymmetric Effects and Market Anomalies

Cryptocurrency markets exhibit unique asymmetric volatility patterns that diverge from those observed in equity markets. An analysis of twenty cryptocurrencies revealed that positive shocks increase volatility more than negative shocks, representing a reversal of the traditional leverage effect (Baur & Dimpfl, 2018). Similarly, Bitcoin has been found to exhibit a low leverage effect, while leading digital currencies demonstrate inverse leverage and substantial long memory characteristics (Klein et al., 2018). Furthermore, evidence indicates that movements in the S&P 500 exert negative effects on cryptocurrency long-term volatility, reflecting irregular co-movements compared to conventional financial markets (Conrad et al., 2018). These anomalous relationships challenge standard risk models and necessitate specialized asymmetric volatility specifications, such as EGARCH and GJR-GARCH.

1.2.5. Portfolio Selection and Risk Management Applications

Cryptocurrency portfolio optimization introduces distinct challenges due to non-normal return distributions and extreme tail risks. Evidence suggests that Cauchy distributions better describe cryptocurrency returns than Gaussian alternatives, enabling analytical Value-at-Risk (VaR) calculations (Petro et al., 2019). Additionally, hidden "beta-in-the-tails" risks similar to hedge fund exposures have been identified across 100 cryptocurrencies (Liew et al., 2019). It has also been shown that maximum price and previous close price variables most effectively capture cross-sectional return variations in large cryptocurrency portfolios (Yang & Zhao, 2021).

Sophisticated optimization techniques further demonstrate promise for cryptocurrency portfolio management. Black–Litterman models incorporating variance constraints

have been found to outperform naive diversification strategies (Platanakis & Urquhart, 2019). Vine copula approaches have also been applied to model dependencies among six cryptocurrencies, with findings indicating that Ethereum provides optimal risk–reward trade-offs under short-selling constraints (Boako et al., 2019). Moreover, GARCH models enhanced with multivariate normal tempered stable distributions have achieved superior risk–return balance for major cryptocurrency portfolios (Boako et al., 2019).

2. Materials and Methods

2.1. Research Design

This study employs an ex post facto research design utilizing historical high-frequency cryptocurrency price data to evaluate competing volatility forecasting models. The analytical framework integrates both in-sample and out-of-sample evaluation procedures to ensure comprehensive model assessment. We structure our investigation around three core components: (1) in-sample fit evaluation via Mincer–Zarnowitz regressions, (2) model complementarity assessment through encompassing regressions, and (3) out-of-sample predictive accuracy testing using Diebold–Mariano statistics.

The research design explicitly addresses the heterogeneous nature of cryptocurrency markets by including assets with varying market capitalizations, trading volumes, and technological architectures. This stratified sampling approach ensures findings generalize across market segments rather than reflecting dominant-cryptocurrency-specific phenomena.

The empirical framework is implemented separately for each cryptocurrency to preserve asset-specific volatility dynamics. This univariate approach allows model parameters to vary freely across assets, thereby accommodating potential structural heterogeneity in persistence, asymmetry, and realized volatility dynamics. While cross-sectional differences are documented and interpreted, the primary objective of the study is to evaluate model performance conditional on each asset's volatility process rather than to estimate pooled structural determinants of volatility across cryptocurrencies. Panel or hierarchical extensions incorporating observable asset characteristics represent a promising avenue for future research.

2.2. Data Collection and Sample Construction

Our empirical analysis utilizes 5 min log-return data for twelve cryptocurrencies spanning 1 September 2018, to 30 September 2020, comprising 761 trading days and 219,200 high-frequency observations per asset (Table 1). The sample period captures diverse market conditions, including the 2018 cryptocurrency bear market, subsequent recovery phases, and the 2020 COVID-19 pandemic volatility surge, enhancing external validity.

While the sample includes major structural shocks—most notably the COVID-19 volatility episode—it concludes prior to the accelerated institutionalization phase observed after 2020. The post-2020 period has been characterized by expanded derivatives markets, increased institutional participation, greater regulatory scrutiny, and deeper liquidity pools. These structural changes may alter volatility persistence, shock transmission mechanisms, and model performance rankings. Accordingly, the empirical findings of this study should be interpreted as reflecting volatility dynamics within a predominantly retail-driven and structurally evolving regime. Extending the analysis to include post-2020 data would require modeling regime heterogeneity explicitly rather than assuming parameter stability across structurally distinct market phases. This represents an important avenue for future research.

Table 1. List of the Cryptocurrencies: Start and End dates.

Cryptocurrency	Symbol	Start Date	End Date	Number of Observations in 5 min	Number of Observations in Days
Bitcoin	BTC	1 September 2018	30 September 2020	219,200	761
Ethereum	ETH	1 September 2018	30 September 2020	219,200	761
Ripple	XRP	1 September 2018	30 September 2020	219,200	761
Litecoin	LTC	1 September 2018	30 September 2020	219,200	761
Bitcoin Cash	BCH	1 September 2018	30 September 2020	219,200	761
EOS	EOS	1 September 2018	30 September 2020	219,200	761
Monero	XRM	1 September 2018	30 September 2020	219,200	761
Dash	DASH	1 September 2018	30 September 2020	219,200	761
Zcash	ZEX	1 September 2018	30 September 2020	219,200	761
Ethereum Classic	ETC	1 September 2018	30 September 2020	219,200	761
Augur	REP	1 September 2018	30 September 2020	219,200	761

Return data were obtained from the Kraken exchange (https://www.kraken.com) (accessed on 12 October 2020), a reputable cryptocurrency trading platform known for liquidity and reliable data feeds. We compute daily, weekly, and monthly realized volatilities from 5 min returns following standard procedures in the realized volatility literature (Kourtis et al., 2016).

It is important to note that realized volatility serves as an observable proxy for latent integrated volatility rather than a direct measure of the underlying continuous-time variance process. At high frequencies, realized measures may incorporate microstructure noise, bid–ask bounce effects, and discrete price adjustments, as well as discontinuous jump components. While these effects cannot be entirely eliminated, the use of 5 min sampling intervals is intended to mitigate microstructure contamination relative to ultra-high-frequency data. Moreover, because all forecasting models are evaluated against the same realized volatility proxy, comparative inference across models remains internally consistent.

The 5 min interval was selected as a widely adopted compromise between microstructure noise and information efficiency in the realized volatility literature (Catania & Sandholdt, 2019). Ultra-high-frequency data (e.g., tick-by-tick) may suffer from bid–ask bounce and liquidity distortions, whereas lower-frequency intervals may obscure intraday volatility clustering. While optimal sampling frequency may differ across cryptocurrencies depending on liquidity depth and trading intensity, the use of a uniform 5 min interval ensures methodological consistency across assets and facilitates direct model comparison. Asset-specific optimal frequency selection represents a potential extension for future research.

Although alternative noise-robust estimators—such as realized kernels or bipower variation—could further isolate continuous volatility from jump components, incorporating such refinements would substantially alter the empirical framework and extend beyond the comparative objective of this study. Similarly, formal intraday periodicity adjustments may improve volatility estimation for certain assets, particularly those with uneven trading intensity. These extensions represent promising directions for future research but are not central to the present model comparison framework.

For longer forecast horizons (7-day and 30-day), realized volatility is constructed through aggregation of daily realized measures rather than direct accumulation of raw 5 min returns over extended intervals. Specifically, multi-day volatility is computed as the square root of the sum of daily realized variances over the corresponding horizon. This aggregation approach is standard in the realized volatility literature and preserves

consistency with the continuous-time variance framework. Overlapping forecast horizons are addressed using (Newey & West, 1987) heteroskedasticity and autocorrelation consistent standard errors to ensure valid inference.

2.3. Volatility Forecast Models

Our study evaluates six forecasting models spanning GARCH-family specifications and realized volatility approaches. Each model addresses specific empirical features of cryptocurrency volatility. All GARCH-family models were estimated via maximum likelihood under a Student-t conditional distribution to accommodate excess kurtosis commonly observed in cryptocurrency returns. Robust (QMLE) standard errors were computed to mitigate potential distributional misspecification.

The selected models represent the most widely used families of volatility forecasting approaches in financial econometrics, capturing distinct volatility dynamics including persistence (GARCH, IGARCH), asymmetry (EGARCH, GJR-GARCH), long-memory components (HAR), and realized volatility structures (LRE). This combination enables a comprehensive comparison of traditional and realized-volatility-based forecasting frameworks.

2.3.1. Lagged Realized Volatility (LRE) Model

The LRE framework posits that future volatility depends linearly on past realized volatility, capturing persistence mechanisms inherent in cryptocurrency markets. Realized volatility measures exploit high-frequency data to provide ex-post estimates of daily return variation, calculated as follows (Kourtis et al., 2016):

$$\mathrm{RV_t} = \sqrt{\sum_{j=1}^{m} r_{tj}^2} \quad (1)$$

Therefore, the lagged realized volatility can be calculated:

$$\mathrm{LRE} = \sqrt{\sum_{j=1}^{m} r_{t-1}^2} \quad (2)$$

These variables are crucial because they are based on the assumption that volatility follows a Markov process, implying that current volatility contains predictive information about future realizations. A primary advantage of this approach lies in its direct incorporation of high-frequency information without imposing restrictive parametric assumptions (Kourtis et al., 2016). Empirical evidence further confirms that lagged realized volatility effectively captures volatility persistence in cryptocurrency markets (Kaminska & Roberts-Sklar, 2018). In addition, significant lagged realized volatility coefficients have been shown to indicate strong persistence effects, a robust characteristic of digital asset markets (Sensoy & Omole, 2018). Moreover, the inclusion of realized volatility measures has been found to generate superior forecasts, particularly during periods of elevated market turbulence (Huang et al., 2019).

2.3.2. Standard GARCH Model

Bollerslev (1986) GARCH (1,1) model remains the benchmark for conditional volatility modeling despite documented limitations for cryptocurrencies. The specification is:

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

The $\alpha_1 + \beta_1$ coefficients account for the degree of volatility clustering captured by the model. Also, when considering $\alpha_1 + \beta_1 < 1$, that means there is weak stationarity.

2.3.3. EGARCH Model

Nelson (1991) exponential GARCH specification addresses three key GARCH limitations: (1) asymmetry accommodation, (2) unconditional positivity enforcement via logarithmic transformation, and (3) exogenous variable incorporation. The EGARCH equation:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) \quad (4)$$

This specification captures asymmetric responses in which positive and negative shocks exert differential impacts on volatility. The EGARCH model has been shown to effectively capture negative return–volatility correlations, time-series clustering, and lognormality—features that are particularly relevant for cryptocurrency market (Brandt & Jones, 2006). Additionally, the exponential functional form offers advantages in modeling information asymmetries associated with news effects (Petrică & Stancu, 2017).

2.3.4. Integrated GARCH (IGARCH) Model

The IGARCH framework imposes a unit root constraint on GARCH parameters, permanent volatility shocks, and infinite unconditional variance. Mikosch and Stărică (2004) express the IGARCH equation as follows:

$$\begin{gathered} \alpha_t = \sigma_t Z_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\ t \in \mathbb{Z}, \end{gathered} \quad (5)$$

IGARCH has been shown to be particularly useful for capturing the persistent influence of past squared shocks, making it well suited for cryptocurrency markets that exhibit long-memory characteristics (Bentes, 2015). Furthermore, the applicability of IGARCH is supported by evidence indicating that policy changes and structural shifts are inadequately captured by stationary GARCH specifications (Chu et al., 2017).

2.3.5. GJR-GARCH Model

The GJR-GARCH specification introduces asymmetry through an indicator function distinguishing positive and negative return impacts:

$$h_t = \omega + \alpha e_{t-1}^2 + \gamma I_{\{e_{t-1}<0\}} e_{t-1}^2 + \beta h_{t-1} \quad (6)$$

where $(\gamma I_{\{e_{t-1}<0\}} e_{t-1}^2)$ equals one for negative returns. This structure allows differential volatility responses to bad news versus good news. GJR-GARCH offers particular advantages in analyzing asymmetric behaviors that are prevalent in highly volatile markets (Nugroho et al., 2019). Empirical evidence has further documented cryptocurrency-specific asymmetries, including inverse leverage effects and substantial long-memory characteristics, thereby validating the relevance of the GJR-GARCH specification for digital asset markets (Klein et al., 2018).

2.3.6. Heterogeneous Autoregressive (HAR) Model

The HAR framework, developed by (Corsi, 2009) captures long memory through hierarchical volatility components. The daily HAR-RV model specification is expressed as the following equation:

$$RV_{t:t+k} = \omega + \beta_d RV_t + \beta_w RV_{t-7:t} + \beta_m RV_{t-30:t} + e_{t+k} \quad (7)$$

where ($\beta_d RV_t$) denotes daily realized volatility, ($\beta_w RV_{t-7:t}$) represents weekly volatility, and ($\beta_m RV_{t-30:t}$) captures monthly volatility components. This additive structure parsimoniously approximates long-memory processes while maintaining model simplicity. The HAR model has been shown to deliver strong out-of-sample performance while effectively capturing long-memory dynamics in volatility processes (Audrino & Knaus, 2016). In addition, its structure enables the modeling of both sign and size asymmetries in return behavior (McAleer & Medeiros, 2008).

2.4. Information Content of Volatility Forecasts: Univariate Regressions

We employ (Mincer & Zarnowitz, 1969) regressions to evaluate each model's informational content and predictive ability. The specification is:

$$RV_{t:t+k} = \alpha + \beta \hat{F}_{t:t+k} + e_t \tag{8}$$

where ($RV_{t:t+k}$) represents the subsequent (k)-day observed realized volatility and ($\beta \hat{F}_{t:t+k}$) denotes the (k)-day ahead volatility forecast. Statistical significance of the slope coefficient indicates forecast informativeness. We apply (Newey & West, 1986) heteroskedasticity and autocorrelation consistent standard errors for all forecast horizons to ensure robust inference.

2.5. Encompassing Regressions

Encompassing regressions extend univariate specifications by incorporating forecasts from two distinct models simultaneously (Patton, 2011). The equation becomes:

$$RV_{t:t+k} = \alpha + \beta_1 \hat{F}_{t:t+k} + \beta_2 \hat{F}_{t:t+k} + e_t \tag{9}$$

where ($\beta_1 \hat{F}_{t:t+k}$) and ($\beta_2 \hat{F}_{t:t+k}$) represent forecasts from different models. This framework directly tests whether one forecast set subsumes another's information content. If (β_1) is significant while (β_2) is insignificant, the first model encompasses the second. We compute encompassing tests for all pairwise model combinations across LRE, GARCH, IGARCH, EGARCH, GJR-GARCH, and HAR specifications.

2.6. Out-of-Sample Forecast Evaluation

To evaluate predictive performance, we implement a rolling-window estimation framework with a fixed estimation window of 300 observations. This window length was selected to balance the bias–variance trade-off inherent in volatility modeling: shorter windows may yield unstable parameter estimates, while excessively long windows may dilute structural changes and regime shifts that characterize cryptocurrency markets. The 300-observation window ensures parameter stability while preserving a sufficiently large out-of-sample period for statistically reliable forecast evaluation.

For each cryptocurrency, forecasts are generated recursively by rolling the estimation window forward one observation at a time. Given 761 total observations, this procedure produces 461 out-of-sample forecasts after accounting for the initial estimation window and model conditioning requirements. This approach allows for dynamic parameter updating and closely mimics real-time forecasting conditions.

To address potential serial correlation and heteroskedasticity arising in multi-step-ahead forecasts, heteroskedasticity and autocorrelation consistent (HAC) standard errors following (Newey & West, 1987) are employed. These corrections ensure valid statistical inference in the presence of overlapping forecast horizons. Forecast accuracy is evaluated using two complementary loss functions:

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(RV_{t:t+k} - \hat{F}_{t:t+k}\right)^2} \quad (10)$$

Quasi-Likelihood Loss (QLIKE)

$$QLIKE = \frac{1}{N}\sum_{t=1}^{N}\left[log\hat{F}_{t:t+k} + \frac{RV_{t:t+k}}{\hat{F}_{t:t+k}}\right] \quad (11)$$

where N denotes the number of out-of-sample forecasts, $RV_{t:t+k}$ represents realized volatility over horizon k, and $\hat{F}_{t:t+k}$ denotes the corresponding volatility forecast.

RMSE measures the magnitude of forecast errors and provides an intuitive metric of overall deviation. In contrast, QLIKE is particularly appropriate for volatility evaluation because it is robust to measurement error in realized volatility proxies and does not excessively penalize large forecast values (Patton, 2011). For this reason, QLIKE is widely regarded as a reliable loss function in volatility forecasting studies.

To formally compare predictive accuracy across competing models, we apply the Diebold–Mariano test under the null hypothesis of equal predictive performance (Diebold & Mariano, 2002). The DM statistic is asymptotically normally distributed and evaluates whether differences in loss functions between models are statistically significant. This framework allows us to determine whether observed forecast improvements are economically and statistically meaningful.

All empirical analyses were conducted using the R statistical software (R 4.1.0) environment.

3. Results

To enhance readability, the main text reports condensed summary tables, while detailed regression results are provided in Appendix A for completeness.

3.1. Univariate Regression Results

3.1.1. One-Day Forecast Horizon

Table 2 summarizes the performance of competing volatility models at the 1-day forecast horizon. Overall, the HAR model exhibits the highest average explanatory power, followed closely by EGARCH and GARCH. In terms of dominance across cryptocurrencies, GARCH achieves the highest frequency of best performance, while HAR leads for a smaller subset of assets.

Table 2. Summary of Model Performance (1-Day Horizon).

Model	Avg. Adj. R^2	Rank	Dominance (%)
HAR	37.31%	1	25.00%
EGARCH	36.80%	2	16.67%
GARCH	36.72%	3	33.33%
GJR-GARCH	36.42%	4	—
LRE	35.68%	5	—
IGARCH	34.21%	6	—

Note: Dominance (%) indicates the proportion of cryptocurrencies for which each model provides the highest explanatory power.

These findings suggest that short-horizon volatility dynamics are primarily driven by high-frequency information aggregation, which is effectively captured by the HAR frame-

work. The relatively strong performance of EGARCH further indicates that asymmetric effects play a role in short-term volatility behavior, although to a lesser extent.

While HAR achieves the highest average performance, this superiority should be interpreted as conditional rather than universal. Cross-sectional differences in liquidity, trading intensity, and market capitalization contribute to variation in model performance across cryptocurrencies.

In contrast, IGARCH exhibits comparatively weaker and less stable performance. The imposed unit-root persistence constraint appears overly restrictive in cryptocurrency markets characterized by structural shifts and nonlinear dynamics. In particular, estimation instability observed for certain assets highlights limitations of the IGARCH specification in capturing short-term volatility behavior.

These results indicate that models incorporating flexible persistence and asymmetric adjustments—particularly EGARCH—provide more robust representations of short-horizon volatility dynamics in digital asset markets. Detailed coefficient-level results are reported in Appendix A (Table A1).

3.1.2. Seven-Day Forecast Horizon

Table 3 summarizes the performance of competing volatility models at the 7-day forecast horizon. Overall, EGARCH exhibits the strongest performance across models, achieving the highest average explanatory power and dominating across the majority of cryptocurrencies. This result highlights the increasing importance of asymmetric volatility effects at medium-term horizons.

Table 3. Summary of Model Performance (7-Day Horizon).

Model	Avg. Adj. R^2	Rank	Dominance (%)
EGARCH	25.79%	1	58.33%
GJR-GARCH	24.18%	2	16.67%
HAR	23.98%	3	25.00%
GARCH	22.73%	4	—
IGARCH	22.23%	5	—
LRE	18.51%	6	—

Note: Dominance (%) indicates the proportion of cryptocurrencies for which each model provides the highest explanatory power.

HAR ranks second in performance, indicating that high-frequency information continues to contribute to volatility prediction, although its relative importance declines compared to the short-horizon case. GJR-GARCH also performs competitively, further supporting the relevance of asymmetry in modeling medium-term volatility dynamics. While EGARCH demonstrates clear dominance, this superiority should be interpreted as conditional rather than universal. Structural differences across cryptocurrencies, including variations in liquidity, trading intensity, and market maturity, contribute to heterogeneity in model performance.

These findings suggest that medium-horizon volatility is increasingly driven by nonlinear persistence and asymmetric shock transmission, which are more effectively captured by EGARCH-type specifications than by symmetric or purely realized volatility models.

Detailed coefficient-level results are reported in Appendix A (Table A2).

3.1.3. Thirty-Day Forecast Horizon

Table 4 summarizes the performance of competing volatility models at the 30-day forecast horizon. EGARCH exhibits the strongest performance at this horizon, achieving the highest average explanatory power and dominating across the majority of cryptocurrencies.

This result reflects the increasing importance of asymmetric persistence mechanisms in capturing longer-term volatility dynamics.

Table 4. Summary of Model Performance (30-Day Horizon).

Model	Avg. Adj. R^2	Rank	Dominance (%)
EGARCH	9.38%	1	66.67%
HAR	8.71%	2	16.67%
IGARCH	7.95%	3	16.67%
GJR-GARCH	7.81%	4	—
GARCH	7.55%	5	—
LRE	2.72%	6	—

Note: Dominance (%) indicates the proportion of cryptocurrencies for which each model provides the highest explanatory power.

HAR ranks second, while IGARCH shows moderate performance for a limited subset of assets. These results suggest that although high-frequency information contributes to volatility forecasting, its predictive power diminishes as the forecast horizon increases, giving way to more persistent and nonlinear volatility components.

Overall, explanatory power declines substantially across all models at the 30-day horizon, highlighting the inherent difficulty of forecasting long-term volatility using time-series approaches. As the forecast horizon increases, short-run volatility clustering and high-frequency information become less informative, while persistent structural factors play a more dominant role.

Accordingly, although relative performance differences across models remain statistically identifiable, the economic magnitude of predictive gains is limited. This finding underscores the importance of distinguishing statistical significance from practical relevance when interpreting long-horizon volatility forecasts. Detailed coefficient-level results are reported in Appendix A (Table A3).

3.2. Encompassing Regression Results

Encompassing tests evaluate whether combining models enhances predictive information beyond univariate specifications.

3.2.1. One-Day Forecast Horizon

Table 5 summarizes the results of the encompassing regressions at the 1-day forecast horizon. Full encompassing regression results are reported in Appendix A (Table A4).

Table 5. Summary of Encompassing Regression Performance (1-Day Horizon).

Model Combination	Avg. Adj. R^2	Rank
LRE + EGARCH	41.54%	1
LRE + GARCH	41.22%	2
LRE + GJR-GARCH	41.08%	3
HAR + EGARCH	40.96%	4
HAR + GARCH	40.61%	5
HAR + GJR-GARCH	40.55%	6
LRE + IGARCH	40.09%	7
HAR + IGARCH	39.52%	8

Note: Average adjusted R^2 is computed across all cryptocurrencies.

Overall, model combinations improve predictive performance relative to individual specifications, confirming the presence of complementary information across volatility

models. In particular, combinations involving EGARCH consistently achieve the highest explanatory power, as reflected in the aggregate results.

The LRE–EGARCH specification records the strongest average performance, followed closely by LRE–GJR and HAR–EGARCH combinations. These findings indicate that integrating asymmetric volatility dynamics with either realized or heterogeneous autoregressive components enhances short-horizon volatility forecasting.

The strong performance of EGARCH-based combinations highlights the importance of capturing asymmetric responses to market shocks, while the contribution of HAR and LRE components reflects the role of high-frequency information in short-term volatility dynamics.

Overall, the results provide robust evidence that combining models yields measurable gains in explanatory power, particularly when asymmetric and high-frequency components are jointly incorporated. Detailed coefficient-level results are reported in Appendix A (Table A4).

3.2.2. Seven-Day Forecast Horizon

Table 6 summarizes the results of the encompassing regressions at the 7-day forecast horizon. It presents condensed summary statistics, while full encompassing regression results are reported in Appendix A (Table A5). Overall, model combinations continue to improve predictive performance relative to individual specifications, confirming the presence of complementary information across volatility models at the medium-term horizon.

Table 6. Summary of Encompassing Regression Performance (7-Day Horizon).

Model Combination	Avg. Adj. R^2	Rank
HAR + EGARCH	25.78%	1
HAR + GJR-GARCH	24.91%	2
HAR + GARCH	24.77%	3
LRE + EGARCH	24.60%	4
HAR + IGARCH	24.34%	5
LRE + GJR-GARCH	23.41%	6
LRE + GARCH	23.27%	7
LRE + IGARCH	22.07%	8

Note: Average adjusted R^2 is computed across all cryptocurrencies.

In contrast to the 1-day results, HAR-based combinations dominate at the 7-day horizon, with the HAR–EGARCH specification achieving the highest average explanatory power. This shift indicates that heterogeneous autoregressive structures remain highly relevant at medium horizons, particularly when combined with asymmetric volatility dynamics.

The strong performance of HAR–EGARCH and other HAR-based combinations suggests that medium-term volatility is driven by a combination of persistent multi-scale dynamics and asymmetric responses to market shocks. While EGARCH remains an essential component in capturing nonlinear persistence, its effectiveness is enhanced when integrated with HAR-type structures.

Overall, the results highlight a transition in volatility dynamics from high-frequency-driven behavior at short horizons to more structured and persistent processes at medium horizons. This finding reinforces the importance of model complementarity and horizon-dependent model selection in cryptocurrency volatility forecasting.

3.2.3. Thirty-Day Forecast Horizon

Table 7 summarizes the results of the encompassing regressions at the 30-day forecast horizon. Table 7 presents condensed summary statistics, while full encompassing regression results are reported in Appendix A (Table A6). At the long-horizon level, the benefits of model combination become more limited, as reflected in the relatively low explanatory power across all specifications. While combinations involving EGARCH continue to perform comparatively better, the overall differences between models are modest.

Table 7. Summary of Encompassing Regression Performance (30-Day Horizon).

Model Combination	Avg. Adj. R^2	Rank
HAR + EGARCH	10.44%	1
LRE + EGARCH	10.44%	1
HAR + IGARCH	9.82%	3
HAR + GJR-GARCH	9.39%	4
HAR + GARCH	9.22%	5
LRE + GJR-GARCH	8.40%	6
LRE + IGARCH	8.31%	7
LRE + GARCH	8.13%	8

Note: Average adjusted R^2 is computed across all cryptocurrencies.

Both HAR–EGARCH and LRE–EGARCH achieve the highest average explanatory power, indicating that asymmetric volatility dynamics remain relevant even at longer horizons. However, the convergence in performance across model combinations suggests that the incremental gains from combining models diminish as the forecast horizon increases.

The relatively stronger performance of HAR-based combinations compared to pure LRE specifications indicates that multi-scale volatility structures continue to play a role, although their predictive contribution is substantially weaker than at shorter horizons.

Overall, these results reinforce the earlier findings that long-horizon volatility forecasting is inherently challenging. As volatility dynamics become increasingly driven by persistent structural factors, the marginal benefit of combining models declines, and differences in predictive performance become economically less meaningful.

3.3. Out-of-Sample Forecast Performance

3.3.1. One-Day Forecast Horizon

Table 8 summarizes the out-of-sample forecasting performance at the 1-day horizon. The table presents condensed summary statistics, while full out-of-sample results are reported in Appendix A (Table A7).

Table 8. Summary of Out-of-Sample Forecast Performance (1-Day Horizon).

Model	Best RMSE (%)	Best QLIKE (%)	Overall Rank
HAR	50.00%	58.33%	1
EGARCH	33.33%	25.00%	2
GARCH	8.33%	8.33%	3
GJR-GARCH	8.33%	8.33%	4
LRE	0.00%	0.00%	5
IGARCH	0.00%	0.00%	6

Note: Percentages represent the proportion of cryptocurrencies for which each model achieves the lowest forecast error.

Overall, the HAR model delivers the strongest forecasting performance, consistently achieving the lowest prediction errors across the majority of cryptocurrencies under both RMSE and QLIKE loss functions. This result highlights the importance of high-frequency

information in improving short-horizon volatility forecasts and confirms the robustness of HAR-based specifications across different types of digital assets. EGARCH ranks second in performance, with relatively stronger results for major cryptocurrencies. This suggests that large-cap assets may exhibit more pronounced asymmetric volatility dynamics, which are effectively captured by EGARCH models.

In contrast, IGARCH consistently underperforms across both evaluation metrics, indicating that its imposed unit-root persistence structure is not well suited for the rapidly evolving and nonlinear nature of cryptocurrency volatility.

The results are consistent across both loss functions, reinforcing the reliability of the findings. Statistical testing further supports these conclusions, indicating that the superior performance of HAR and EGARCH models is not only economically meaningful but also statistically significant. These findings provide strong evidence that high-frequency information is the primary driver of short-horizon volatility predictability in cryptocurrency markets.

3.3.2. Seven-Day Forecast Horizon

Table 9 summarizes the out-of-sample forecasting performance at the 7-day horizon. It presents condensed summary statistics, while full out-of-sample results are reported in Appendix A (Table A8).

Table 9. Summary of Out-of-Sample Forecast Performance (7-Day Horizon).

Model	Best RMSE (%)	Best QLIKE (%)	Overall Rank
HAR	58.33%	58.33%	1
EGARCH	33.33%	25.00%	2
GARCH	8.33%	8.33%	3
GJR-GARCH	0.00%	8.33%	4
LRE	0.00%	0.00%	5
IGARCH	0.00%	0.00%	6

Note: Percentages represent the proportion of cryptocurrencies for which each model achieves the lowest forecast error.

Overall, the HAR model continues to deliver the strongest forecasting performance, achieving the lowest prediction errors for the majority of cryptocurrencies under both RMSE and QLIKE loss functions. This result indicates that heterogeneous autoregressive structures remain highly effective at medium horizons, capturing multi-scale volatility dynamics.

EGARCH ranks second, exhibiting relatively strong performance for a subset of assets. This finding suggests that asymmetric volatility effects continue to play an important role at the 7-day horizon, although their contribution is less dominant than at shorter horizons.

In contrast, IGARCH again demonstrates consistently weak performances, reinforcing the limitations of imposing a unit-root persistence structure in cryptocurrency markets. Similarly, LRE performs poorly under the QLIKE loss function, indicating that simple lagged realized volatility measures are insufficient to capture medium-term volatility dynamics.

Overall, these findings confirm that volatility predictability at the 7-day horizon is driven by a combination of heterogeneous persistence and asymmetric effects, with HAR-based models providing the most robust performance. These findings suggest that medium-horizon volatility predictability arises from multi-scale persistence dynamics rather than purely high-frequency information.

3.3.3. Thirty-Day Forecast Horizon

Table 10 summarizes the out-of-sample forecasting performance at the 30-day horizon. It presents condensed summary statistics, while full out-of-sample results are reported in Appendix A (Table A9).

Table 10. Summary of Out-of-Sample Forecast Performance (30-Day Horizon).

Model	Best RMSE (%)	Best QLIKE (%)	Overall Rank
HAR	75.00%	75.00%	1
GJR-GARCH	16.67%	16.67%	2
EGARCH	8.33%	8.33%	3
GARCH	0.00%	0.00%	4
LRE	0.00%	0.00%	5
IGARCH	0.00%	0.00%	6

Note: Percentages represent the proportion of cryptocurrencies for which each model achieves the lowest forecast error.

At the long-horizon level, the HAR model demonstrates clear dominance, achieving the lowest forecast errors for the majority of cryptocurrencies under both RMSE and QLIKE loss functions. This result indicates that HAR's multi-component structure, which captures daily, weekly, and monthly volatility dynamics, is particularly effective in modeling slow-moving volatility processes.

While GJR-GARCH and EGARCH exhibit relatively stronger performance for a limited subset of assets, their overall contribution remains secondary compared to HAR. This suggests that, although asymmetric effects remain relevant, long-horizon volatility is primarily driven by persistent and multi-scale dynamics rather than short-term nonlinearities.

In contrast, IGARCH continues to perform poorly, reinforcing the inadequacy of rigid persistence assumptions in capturing long-term cryptocurrency volatility. Similarly, simpler specifications such as LRE fail to deliver consistent improvements, indicating that more structured modeling approaches are required at longer horizons.

Overall, the results highlight that, despite the general decline in predictive accuracy as the forecast horizon increases, models incorporating multi-scale persistence—such as HAR—provide the most robust framework for long-horizon volatility forecasting. These findings suggest that long-horizon volatility predictability is primarily governed by persistent multi-scale dynamics rather than short-term fluctuations.

3.4. Temporal Scope and Regime Considerations

The empirical analysis focuses on the 2018–2020 period, which represents a transitional yet predominantly pre-institutionalized phase of cryptocurrency market development. During this regime, market dynamics were largely driven by retail participation, speculative trading behavior, and evolving exchange microstructure conditions. As such, the results obtained in this study should be interpreted as conditional on this specific structural environment rather than as universally generalizable findings.

Such structural evolution may influence volatility persistence, asymmetry, and horizon-dependent dynamics. For instance, greater derivative market depth may dampen short-run volatility clustering while potentially strengthening longer-run spillover effects. Consequently, the model rankings identified in this study should be interpreted as conditional on the structural characteristics of the analyzed regime.

Future research should examine whether the relative dominance of HAR at short horizons and EGARCH at longer horizons remains stable under post-2020 institutional conditions. Incorporating regime-switching frameworks or structural break models may

provide additional insight into volatility formation across evolving cryptocurrency market environments.

4. Economic Interpretation of Horizon- and Asset-Specific Model Performance

The empirical results presented in Section 3 reveal systematic variation in forecasting performance across models, horizons, and cryptocurrencies. Rather than reflecting purely statistical differences, these patterns are consistent with economically distinct volatility mechanisms operating at different temporal scales and across heterogeneous digital assets. This section provides an economic interpretation of the main findings.

4.1. Short-Horizon Forecasting and the Role of Realized Volatility

At the 1-day forecast horizon, the HAR model demonstrates strong explanatory power across a substantial subset of cryptocurrencies (Table 2). This result is consistent with the dominance of short-term volatility clustering and heterogeneous information arrival in cryptocurrency markets.

Cryptocurrency markets operate continuously and are characterized by rapid information diffusion and speculative trading activity. At short horizons, volatility is largely driven by recent realized shocks, order-flow imbalances, and heterogeneous trader reactions. The HAR framework explicitly incorporates daily, weekly, and monthly realized volatility components, thereby approximating long-memory behavior through a parsimonious hierarchical structure.

From an economic perspective, the HAR specification captures the aggregation of volatility across agents with different investment horizons. When short-term realized fluctuations dominate volatility dynamics, the inclusion of high-frequency-based realized measures improves predictive performance. The relative superiority of HAR at the daily horizon therefore reflects the informational content embedded in recent realized volatility.

4.2. Medium- and Long-Horizon Forecasts: Asymmetry and Persistence

As the forecast horizon extends to 7-day and 30-day intervals (Tables 3 and 4), the EGARCH model exhibits increasing relative dominance, particularly for dominant cryptocurrencies. This shift suggests a transition from microstructure-driven volatility to persistence and asymmetric shock propagation.

Cryptocurrency markets display nonlinear responses to shocks, including evidence of asymmetric volatility effects documented in prior literature. The EGARCH specification accommodates such asymmetries through its logarithmic variance formulation and allows for differential responses to positive and negative innovations without imposing non-negativity constraints.

Over medium and longer horizons, volatility reflects the cumulative effects of shocks, sentiment adjustments, and regime-dependent persistence. In this setting, asymmetric propagation mechanisms become more influential than short-term realized fluctuations. The improved relative performance of EGARCH at extended horizons is therefore consistent with a volatility process characterized by nonlinear persistence and asymmetric risk transmission.

4.3. Cross-Sectional Heterogeneity Across Cryptocurrencies

Model performance also varies systematically across cryptocurrencies with different market capitalizations and liquidity characteristics. High-market-cap assets, such as Bitcoin and Ethereum, exhibit more structured volatility dynamics, reflecting deeper liquidity, broader participation, and stronger integration with global financial conditions.

These features amplify persistent and asymmetric volatility responses, favoring models such as EGARCH that explicitly account for nonlinear shock effects. In contrast, less-dominant cryptocurrencies often display higher idiosyncratic noise and episodic liquidity shocks. For these assets, short-memory and realized-volatility-based specifications remain comparatively competitive, particularly at shorter horizons. The absence of a universally dominant model thus reflects structural heterogeneity across digital assets rather than empirical inconsistency.

4.4. Complementarity Between HAR and EGARCH

The encompassing regressions reported in Section 3.2 indicate that combinations of HAR and EGARCH frequently enhance explanatory power relative to individual models. This complementarity is economically meaningful.

The HAR model captures heterogeneous information aggregation across multiple time scales, while EGARCH models asymmetric and persistent shock transmission. Their combination integrates two fundamental components of cryptocurrency volatility: multi-horizon realized fluctuations and nonlinear innovation effects.

The superior performance of the HAR + EGARCH pairing suggests that cryptocurrency volatility is best characterized as a multi-layered process in which realized short-term dynamics interact with asymmetric persistence mechanisms. This result provides an explanation for why model combinations outperform standalone specifications in several cases.

4.5. Structural Heterogeneity and Model Performance

The variation in model performance across cryptocurrencies may also reflect structural heterogeneity in market capitalization, liquidity conditions, trading activity, and protocol design. High-market-cap assets typically exhibit deeper liquidity and broader institutional participation, potentially amplifying asymmetric persistence mechanisms captured by EGARCH-type models. In contrast, smaller-cap assets may display higher idiosyncratic volatility and episodic liquidity shocks, conditions under which realized-volatility-based models may remain competitive. Although these structural characteristics are not explicitly modeled within a pooled framework, the asset-by-asset estimation strategy permits conditional heterogeneity in volatility dynamics. Future research may formally test these relationships using panel or hierarchical volatility specifications.

4.6. Implications for Volatility Modeling in Digital Asset Markets

Overall, the horizon-dependent and asset-specific variation in model performance indicates that cryptocurrency volatility is governed by evolving mechanisms across temporal scales. Short-horizon volatility is primarily influenced by realized fluctuations and heterogeneous trader behavior, whereas longer-horizon volatility reflects asymmetric persistence and regime-dependent dynamics.

Accordingly, model selection in cryptocurrency risk management and portfolio applications should account for both forecast horizon and asset characteristics. The empirical findings therefore contribute not only to comparative model evaluation but also to a structural understanding of volatility formation in digital asset markets.

5. Discussion

The empirical findings provide structured evidence regarding horizon-dependent volatility dynamics in cryptocurrency markets. Consistent with H1, explanatory power declines as the forecast horizon increases across all model specifications. This result reflects the well-documented difficulty of long-horizon volatility forecasting and the diminishing informational relevance of high-frequency clustering effects over extended time frames.

The evidence broadly supports H2, indicating that asymmetric models—particularly EGARCH—demonstrate relatively stronger performance at medium and longer horizons. This suggests that nonlinear persistence mechanisms and asymmetric shock responses play an increasingly important role as volatility accumulates over time. The exponential structure of EGARCH allows for flexible shock transmission without imposing strict non-negativity constraints, which may enhance its stability under heterogeneous cryptocurrency volatility regimes.

In line with H3, realized volatility-based models, especially HAR, exhibit comparatively strong performance at the 1-day horizon. This supports the heterogeneous market hypothesis, whereby volatility reflects multi-scale information aggregation across daily, weekly, and monthly components. High-frequency data appears particularly informative for short-run volatility dynamics, where microstructure and trading intensity effects remain highly relevant.

The encompassing results provide evidence consistent with H4, demonstrating that combining HAR with EGARCH frequently enhances explanatory power. This complementarity suggests that realized multi-scale information and asymmetric conditional variance dynamics capture distinct but overlapping components of the volatility process.

From a broader methodological perspective, the findings underscore that cryptocurrency volatility is neither purely long-memory nor purely asymmetric; instead, it reflects a combination of heterogeneous information arrival, nonlinear persistence, and asset-specific structural characteristics. Consequently, model selection should be conditional on forecast horizon and asset profile rather than based on universal ranking criteria.

These results contribute to the theoretical understanding of volatility formation in digital asset markets by linking statistical performance differences to underlying structural mechanisms rather than treating model rankings as purely empirical outcomes.

6. Conclusions

This study provides a comprehensive evaluation of six volatility forecasting models—GARCH, IGARCH, EGARCH, GJR-GARCH, LRE, and HAR—applied to twelve cryptocurrencies using high-frequency data across 1-day, 7-day, and 30-day forecast horizons. The results demonstrate that forecasting performance varies systematically across horizons and assets, with no single model exhibiting universal dominance.

Importantly, the findings extend beyond comparative model ranking by offering an economic interpretation of volatility dynamics in cryptocurrency markets. At short horizons, volatility is primarily driven by high-frequency information and recent realized fluctuations. In this context, the HAR model delivers superior performance due to its ability to capture multi-scale realized volatility. As the forecast horizon increases, volatility dynamics become increasingly influenced by persistence and asymmetric shock transmission. The improved relative performance of EGARCH at medium horizons is consistent with nonlinear adjustment mechanisms and regime-dependent behavior.

The analysis further reveals substantial cross-sectional heterogeneity across cryptocurrencies. Large-cap assets exhibit more persistent and asymmetric volatility patterns, whereas smaller and less-liquid cryptocurrencies display more idiosyncratic and short-memory dynamics. This heterogeneity explains why model performance is asset-specific rather than universally consistent across the market.

Encompassing regression results provide strong evidence of model complementarity. In particular, combinations of HAR and EGARCH frequently enhance explanatory power, indicating that cryptocurrency volatility is best understood as a multi-layered process in which high-frequency information interacts with asymmetric persistence mechanisms.

https://doi.org/10.3390/ijfs14040090

From a practical perspective, these findings highlight that model selection should be conditional on both forecast horizon and asset characteristics. Realized-volatility-based models are particularly effective for short-term forecasting and trading applications, while models incorporating asymmetric persistence provide more robust performance at medium horizons. At longer horizons, however, predictive accuracy declines across all models, emphasizing the inherent difficulty of long-term volatility forecasting.

Although the sample period ends in 2020, it captures a critical phase in the development of cryptocurrency markets, including the COVID-19 volatility shock. This environment provides a meaningful setting for evaluating model performance under heightened uncertainty. Future research may extend the analysis to more recent periods to assess whether increasing institutionalization has altered volatility dynamics.

Overall, this study contributes to the literature by linking volatility model performance to underlying economic mechanisms rather than relying solely on statistical comparison. By integrating high-frequency realized measures with asymmetric conditional variance dynamics, the paper provides a coherent framework for understanding horizon-dependent and asset-specific volatility behavior in digital asset markets.

Importantly, the findings of this study are conditional on the specific structural characteristics of the 2018–2020 sample period. While this period captures significant volatility episodes, including the COVID-19 shock, it precedes the rapid institutionalization and structural transformation of cryptocurrency markets observed in subsequent years. As a result, the reported model performance and volatility dynamics should be interpreted as regime-specific and may not fully generalize to alternative market conditions.

Limitations and Directions for Future Research

Several limitations warrant consideration. First, although the sample period (2018–2020) captures major market phases, including the COVID-19 shock, it precedes the accelerated institutionalization of cryptocurrency markets characterized by greater regulatory clarity, derivative market expansion, and increased institutional participation. Structural changes in liquidity and market microstructure after 2020 may influence volatility dynamics and model performance. Accordingly, the results should be interpreted as representative of the pre-institutionalization regime. Future research may extend the analysis to post-2020 data to examine regime stability and structural shifts in volatility forecasting performance. Second, although cross-sectional heterogeneity in model performance is documented, the framework remains asset-specific and univariate. Panel or hierarchical approaches incorporating asset-level characteristics represent promising extensions.

Second, realized volatility constructed from 5 min returns is employed as a proxy for latent volatility. While this approach is standard in high-frequency finance and ensures internal consistency across model comparisons, realized measures may incorporate microstructure noise, jump components, and intraday seasonal effects. Although 5 min sampling mitigates extreme noise relative to ultra-high-frequency data, it may not represent the optimal interval for all cryptocurrencies given heterogeneous liquidity conditions. Future studies may refine volatility measurement using jump-robust or noise-corrected estimators and explore asset-specific sampling frequencies.

These extensions would deepen understanding of the structural drivers of volatility in digital asset markets while preserving the comparative insights developed in this study.

Author Contributions: Conceptualization, A.A. and H.A.; methodology, A.A.; software, A.A.; validation, A.A. and H.A.; formal analysis, A.A.; investigation, A.A.; resources, A.A.; data curation, A.A.; writing—original draft preparation, A.A.; writing—review and editing, A.A. and H.A.; visualization, A.A.; supervision, H.A.; project administration, A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) through the Deputyship of Scientific Research and Publication, grant number IMSIU-DDRSP2604.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated and/or analyzed during the current study are publicly available from "Kraken" "https://www.kraken.com/" (accessed on 12 October 2020).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GARCH	Standard Generalized Autoregressive Conditional Heteroskedastic
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedastic
IGARCH	Integrated Generalized Autoregressive Conditional Heteroskedastic
GJR-GARCH	Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedastic
LRE	Lagged Realized Volatility
HAR	Heterogeneous Autoregressive
RMSE	Root Mean Squared Error
QLIKE	Quasi-likelihood
CC	Cryptocurrency

Appendix A. Detailed Regression Results

To enhance the readability of the main text, detailed regression outputs are reported in this appendix. While the main manuscript presents condensed summary tables highlighting the key comparative findings across models and forecast horizons, this appendix provides the full coefficient-level results for completeness and transparency.

Tables A1–A3 report the full Mincer–Zarnowitz regression results for the 1-day, 7-day, and 30-day forecast horizons, respectively. Each table includes estimated intercepts and slope coefficients, corresponding t-statistics, and adjusted R^2 values for all cryptocurrencies and model specifications.

Tables A4–A9 present the encompassing regression results across all model combinations. These tables provide detailed evidence on the informational contribution and complementarity between competing volatility forecasting models.

All regressions are estimated using heteroskedasticity and autocorrelation consistent (HAC) standard errors following (Newey & West, 1987) to ensure robust statistical inference across forecast horizons. These detailed results support the summary findings reported in the main text and allow for full replication and verification of the empirical analysis.

Table A1. Mincer–Zarnowitz Regression with Newey–West Standard Errors for 1-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	**−0.022** (−4.14)	**−0.007** (−1.99)	**−0.029** (−4.89)	**−0.0193** (−3.70)	**0.011** (4.81)	0.000 (−0.000)
β	**1.474** (9.14)	**0.955** (9.27)	**1.672** (9.46)	**1.394** (8.93)	**0.637** (7.56)	**1.000** (9.38)
$adj.\ R^2$	47.45%	48.53%	50.08%	47.51%	40.49%	43.74%

Table A1. *Cont.*

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
ETH						
α	**−0.028** (−3.59)	−0.004 (−0.92)	**−0.039** (−4.45)	**−0.024** (−3.05)	**0.016** (5.46)	0.000 (−0.000)
β	**1.464** (8.38)	**0.876** (8.25)	**1.701** (8.76)	**1.378** (7.86)	**0.606** (7.74)	**1.000** (8.48)
adj. R^2	41.04%	36.18%	40.89%	40.21%	36.60%	38.40%
XRP						
α	**−0.013** (−2.14)	0.000 (0.03)	**−0.015** (−2.48)	−0.010 (−1.68)	**0.018** (7.61)	0.000 (0.000)
β	**1.247** (8.07)	**0.867** (8.20)	**1.303** (8.43)	**1.183** (7.57)	**0.531** (7.95)	**1.000** (7.74)
adj. R^2	33.43%	31.99%	33.30%	32.05%	28.15%	26.50%
LTC						
α	**−0.029** (−2.80)	0.000 (0.07)	**−0.039** (−3.58)	**−0.026** (−2.55)	**0.019** (6.14)	0.000 (0.000)
β	**1.464** (6.73)	**0.809** (6.70)	**1.662** (7.35)	**1.406** (6.56)	**0.551** (7.02)	**1.000** (7.85)
adj. R^2	33.97%	20.31%	35.74%	34.29%	30.31%	32.58%
BCH						
α	**−0.029** (−3.06)	−0.003 (−0.60)	**−0.030** (−4.07)	**−0.029** (−3.09)	**0.015** (5.15)	0.000 (0.000)
β	**1.367** (7.64)	**0.823** (8.28)	**1.385** (9.68)	**1.372** (7.67)	**0.674** (9.66)	**1.000** (10.85)
adj. R^2	37.32%	34.33%	36.88%	37.62%	45.37%	47.43%
EOS						
α	**−0.048** (−3.68)	−0.003 (−0.50)	**−0.051** (−4.42)	**−0.047** (−3.28)	**0.023** (6.62)	0.000 (−0.000)
β	**1.767** (6.89)	**0.855** (6.81)	**1.841** (7.99)	**1.743** (6.25)	**0.482** (5.81)	**1.000** (6.66)
adj. R^2	23.75%	15.80%	22.90%	24.43%	23.11%	24.87%
XMR						
α	−0.005 (−0.91)	0.005 (1.32)	−0.007 (−1.17)	−0.004 (−0.70)	**0.015** (4.70)	0.000 (0.000)
β	**1.038** (7.52)	**0.732** (7.60)	**1.083** (7.54)	**1.010** (7.39)	**0.613** (6.94)	**1.000** (8.50)
adj. R^2	40.84%	40.63%	39.64%	41.10%	37.59%	40.37%
DASH						
α	0.001 (0.24)	0.006 (1.87)	−0.004 (−0.99)	0.000 (0.17)	**0.014** (5.20)	0.000 (−0.000)
β	**0.890** (9.51)	**0.729** (9.54)	**1.016** (9.90)	**0.900** (9.29)	**0.667** (9.33)	**1.000** (10.27)
adj. R^2	43.16%	40.99%	39.90%	41.39%	44.50%	45.86%
ZEC						
α	**−0.017** (−2.56)	−0.002 (−0.47)	**−0.029** (−3.72)	**−0.023** (−3.10)	**0.016** (4.96)	0.000 (−0.000)
β	**1.247** (8.73)	**0.868** (8.89)	**1.491** (8.96)	**1.353** (8.76)	**0.645** (8.23)	**1.000** (8.66)
adj. R^2	40.56%	39.31%	40.67%	41.22%	41.62%	42.57%
ETC						
α	**−0.013** (−2.09)	0.004 (1.19)	**−0.024** (−3.65)	**−0.013** (−2.17)	**0.018** (7.09)	0.000 (0.000)
β	**1.168** (8.95)	**0.730** (9.18)	**1.403** (9.92)	**1.177** (9.07)	**0.596** (9.69)	**1.000** (11.00)
adj. R^2	33.45%	33.83%	34.25%	33.14%	35.52%	38.29%
REP						
α	0.006 (1.30)	**0.017** (4.74)	−0.002 (−0.57)	0.007 (1.71)	**0.022** (9.56)	0.000 (−0.000)
β	**0.832** (9.13)	**0.599** (9.77)	**0.998** (11.97)	**0.810** (9.61)	**0.592** (12.84)	**1.000** (13.63)
adj. R^2	34.33%	34.40%	36.03%	32.52%	35.06%	36.39%

Table A1. *Cont.*

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
Aggregate Results						
Average α	−0.017	0.001	−0.024	−0.017	0.017	0.000
Average β	1.264	0.804	1.414	1.249	0.595	1.000
Average $adj.\ R^2$	36.72%	34.21%	36.80%	36.42%	35.68%	37.31%

Note: IGARCH aggregate averages exclude Stellar (XLM) due to numerical instability under the IGARCH constraint ($\alpha + \beta = 1$), which generated implausible Mincer–Zarnowitz slope estimates. Also, each panel corresponds to a different cryptocurrency. Each column shows the estimation results for each forecasting model. α and β stands for the intercept and slope of the regression, while the row $adj.\ R^2$ shows the adjusted R^2 coefficient of the regression. t-statistics estimations are reported in parentheses. The average values of the intercepts, slopes, and adjusted R squared across cryptocurrencies for each forecasting model are reported at the end of the table. Significant coefficients at the 5% level are highlighted in bold. Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors was used for all the regressions.

Table A2. Mincer–Zarnowitz Regression with Newey–West Standard Errors for 7-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	−0.012 (−1.43)	**0.014** (2.31)	**−0.026** (−2.94)	−0.007 (−1.12)	**0.042** (7.60)	0.000 (−0.000)
β	**1.047** (10.89)	**0.683** (10.98)	**1.200** (11.59)	**0.996** (14.59)	**0.499** (10.28)	**1.000** (14.32)
$adj.\ R^2$	32.13%	33.35%	34.62%	32.58%	24.54%	29.25%
ETH						
α	−0.006 (−0.48)	**0.034** (3.29)	−0.027 (−1.67)	0.001 (0.13)	**0.063** (9.53)	0.000 (0.000)
β	**0.963** (9.51)	**0.580** (7.31)	**1.138** (8.30)	**0.903** (10.37)	**0.443** (8.82)	**1.000** (11.05)
$adj.\ R^2$	26.42%	23.58%	27.18%	25.68%	19.50%	24.91%
XRP						
α	**0.026** (2.49)	**0.047** (5.51)	0.019 (1.83)	**0.030** (2.71)	**0.073** (10.35)	0.000 (−0.000)
β	**0.779** (8.00)	**0.547** (7.46)	**0.848** (8.26)	**0.745** (7.28)	**0.354** (6.82)	**1.000** (7.72)
$adj.\ R^2$	19.99%	19.50%	21.59%	19.45%	12.33%	14.93%
LTC						
α	0.005 (0.29)	**0.046** (2.89)	−0.016 (−0.78)	0.008 (0.57)	**0.077** (9.11)	0.000 (−0.000)
β	**0.885** (6.39)	**0.539** (4.61)	**1.047** (6.64)	**0.859** (7.43)	**0.373** (6.86)	**1.000** (8.56)
$adj.\ R^2$	19.64%	14.23%	22.45%	20.29%	13.58%	18.58%
BCH						
α	0.002 (0.09)	**0.044** (2.61)	−0.010 (−0.42)	0.001 (0.07)	**0.070** (7.56)	0.000 (−0.000)
β	**0.892** (4.73)	**0.553** (4.99)	**0.970** (5.68)	**0.896** (4.76)	**0.481** (7.28)	**1.000** (8.33)
$adj.\ R^2$	21.89%	21.41%	24.95%	22.11%	22.83%	30.58%
EOS						
α	−0.031 (−1.09)	**0.045** (2.38)	−0.058 (−1.92)	−0.029 (−0.97)	**0.083** (8.97)	0.000 (0.000)
β	**1.141** (5.46)	**0.553** (4.29)	**1.340** (5.94)	**1.127** (5.10)	**0.340** (5.65)	**1.000** (6.96)
$adj.\ R^2$	16.04%	10.70%	19.68%	16.53%	11.24%	15.20%
XMR						
α	**0.023** (2.44)	**0.043** (6.03)	0.016 (1.42)	**0.025** (2.96)	**0.056** (8.49)	0.000 (0.000)
β	**0.757** (8.53)	**0.536** (8.33)	**0.819** (7.47)	**0.738** (9.28)	**0.492** (9.15)	**1.000** (13.21)
$adj.\ R^2$	31.45%	31.54%	32.81%	31.76%	24.26%	29.38%

Table A2. *Cont.*

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
DASH						
α	**0.041** (3.76)	**0.050** (5.14)	**0.025** (1.98)	**0.040** (3.32)	**0.062** (7.64)	0.000 (0.000)
β	**0.636** (6.84)	**0.531** (6.61)	**0.769** (6.72)	**0.649** (6.31)	**0.491** (7.16)	**1.000** (11.12)
adj. R^2	30.66%	30.20%	31.79%	29.95%	23.88%	30.04%
ZEC						
α	0.026 (1.70)	**0.049** (4.23)	0.005 (0.33)	0.015 (1.01)	**0.078** (9.45)	0.000 (0.000)
β	**0.757** (6.05)	**0.543** (6.36)	**0.913** (6.33)	**0.834** (6.83)	**0.392** (6.60)	**1.000** (10.91)
adj. R^2	21.92%	22.56%	22.39%	23.02%	15.14%	22.71%
ETC						
α	**0.026** (2.15)	**0.057** (6.43)	0.003 (0.23)	0.025 (1.92)	**0.069** (8.73)	0.000 (−0.000)
β	**0.765** (8.46)	**0.481** (8.47)	**0.943** (8.68)	**0.777** (8.03)	**0.454** (7.75)	**1.000** (10.35)
adj. R^2	21.80%	22.36%	23.54%	21.98%	20.42%	26.05%
REP						
α	**0.088** (6.15)	**0.102** (9.08)	**0.076** (5.26)	**0.089** (6.33)	**0.104** (9.01)	0.000 (0.000)
β	**0.427** (4.80)	**0.310** (5.01)	**0.510** (5.67)	**0.426** (4.95)	**0.322** (5.07)	**1.000** (7.47)
adj. R^2	15.00%	15.35%	15.65%	14.99%	10.12%	16.73%
Aggregate Results						
Average α	0.019	0.047	0.002	0.019	0.069	0.000
Average β	0.782	0.543	0.943	0.807	0.428	1.000
Average *adj.* R^2	22.73%	22.23%	25.79%	24.18%	18.51%	23.98%

Note: IGARCH aggregate averages exclude Stellar (XLM) due to numerical instability under the IGARCH constraint ($\alpha + \beta = 1$), which generated implausible Mincer–Zarnowitz slope estimates.

Table A3. Mincer–Zarnowitz Regression with Newey–West Standard Errors for 30-day forecast horizon.

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
BTC						
α	**0.097** (3.55)	**0.122** (5.52)	**0.079** (3.10)	**0.099** (4.05)	**0.158** (5.32)	0.000 (−0.000)
β	**0.464** (5.15)	**0.304** (5.38)	**0.557** (5.58)	**0.455** (6.36)	0.172 (1.80)	**1.000** (4.76)
adj. R^2	9.26%	9.75%	10.99%	10.03%	2.72%	8.16%
ETH						
α	**0.143** (4.72)	**0.178** (7.31)	**0.114** (2.80)	**0.150** (5.54)	**0.205** (7.13)	0.000 (0.000)
β	**0.394** (3.49)	**0.235** (2.87)	**0.507** (3.01)	**0.367** (3.74)	0.159 (1.50)	**1.000** (3.66)
adj. R^2	7.45%	6.52%	9.14%	7.15%	2.22%	8.95%
XRP						
α	**0.171** (6.05)	**0.189** (7.72)	**0.164** (5.56)	**0.177** (6.20)	**0.193** (6.40)	0.000 (0.000)
β	**0.319** (3.33)	**0.226** (3.13)	**0.354** (3.24)	**0.294** (3.16)	0.175 (1.74)	**1.000** (2.47)
adj. R^2	6.36%	6.33%	7.17%	5.75%	3.51%	5.77%
LTC						
α	**0.148** (3.24)	**0.178** (4.22)	**0.113** (2.26)	**0.151** (3.77)	**0.214** (5.27)	0.000 (0.000)
β	**0.418** (2.82)	**0.288** (2.24)	**0.545** (3.13)	**0.407** (3.15)	0.190 (1.35)	**1.000** (3.21)
adj. R^2	7.35%	6.84%	10.22%	7.63%	3.03%	9.50%
BCH						
α	**0.167** (2.83)	**0.200** (4.38)	**0.136** (2.15)	**0.166** (2.81)	**0.208** (3.98)	0.000 (0.000)
β	**0.416** (2.36)	**0.280** (2.38)	**0.513** (2.66)	**0.419** (2.37)	**0.298** (1.95)	**1.000** (3.19)
adj. R^2	7.27%	8.39%	10.70%	7.39%	8.10%	13.97%

Table A3. *Cont.*

Cryptocurrency	GARCH	IGARCH	EGARCH	GJR-GARCH	LRE	HAR
EOS						
α	0.130 (1.92)	**0.209** (4.21)	0.078 (1.04)	0.120 (1.84)	**0.250** (6.52)	0.000 (0.000)
β	**0.501** (2.24)	0.212 (1.46)	**0.682** (2.63)	**0.535** (2.45)	0.089 (0.77)	**1.000** (2.82)
adj. R^2	5.46%	2.71%	9.08%	6.60%	0.56%	7.47%
XMR						
α	**0.152** (6.04)	**0.171** (8.48)	**0.135** (4.98)	**0.151** (6.32)	**0.199** (6.36)	0.000 (−0.000)
β	**0.342** (3.54)	**0.243** (3.53)	**0.415** (3.55)	**0.348** (3.85)	0.153 (1.30)	**1.000** (4.11)
adj. R^2	9.76%	9.92%	12.87%	10.74%	2.03%	11.10%
DASH						
α	**0.164** (6.10)	**0.173** (6.99)	**0.138** (4.83)	**0.162** (5.77)	**0.198** (5.51)	0.000 (0.000)
β	**0.369** (4.46)	0.318 (4.45)	**0.474** (4.52)	**0.381** (4.31)	**0.248** (2.12)	**1.000** (4.20)
adj. R^2	15.58%	16.40%	18.23%	15.60%	5.50%	12.93%
ZEC						
α	**0.174** (5.48)	**0.195** (7.64)	**0.154** (4.51)	**0.162** (4.96)	**0.235** (7.02)	0.000 (0.000)
β	**0.368** (3.46)	**0.268** (3.71)	**0.442** (3.65)	**0.408** (3.79)	0.152 (1.51)	**1.000** (3.83)
adj. R^2	8.62%	9.18%	8.73%	9.16%	2.00%	8.32%
ETC						
α	**0.175** (5.22)	**0.204** (8.05)	**0.146** (3.74)	**0.174** (5.05)	**0.238** (5.57)	0.000 (0.000)
β	**0.366** (3.48)	**0.233** (3.56)	**0.472** (3.58)	**0.368** (3.42)	0.151 (1.04)	**1.000** (3.56)
adj. R^2	8.35%	8.83%	9.93%	8.28%	2.11%	8.39%
REP						
α	**0.291** (13.01)	**0.300** (15.72)	**0.282** (12.04)	**0.291** (13.10)	**0.367** (6.42)	0.000 (−0.000)
β	0.124 (1.90)	0.090 (1.88)	**0.154** (2.12)	0.126 (1.96)	−0.106 (−0.59)	**1.000** (2.93)
adj. R^2	2.49%	2.56%	2.83%	2.62%	0.90%	6.07%
Aggregate Results						
Average α	0.169	0.193	0.146	0.168	0.228	0.000
Average β	0.357	0.245	0.446	0.360	0.138	1.000
Average *adj.* R^2	7.55%	7.95%	9.38%	7.81%	2.72%	8.71%

Note: IGARCH aggregate averages exclude Stellar (XLM) due to numerical instability under the IGARCH constraint ($\alpha + \beta = 1$), which generated implausible Mincer–Zarnowitz slope estimates.

Table A4. Full Encompassing Regression Results (1-Day Horizon).

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
BTC								
α	**−0.015** (−2.85)	−0.004 (−1.30)	**−0.023** (−2.88)	**−0.013** (−2.14)	**−0.017** (−2.44)	−0.006 (−1.79)	**−0.025** (−2.55)	**−0.015** (−2.03)
β_1	**0.218** (2.38)	**0.188** (2.11)	0.140 (1.32)	0.206 (1.90)	0.329 (1.63)	0.281 (1.45)	0.199 (0.79)	0.332 (1.30)
β_2	**1.092** (5.48)	**0.741** (5.64)	**1.393** (4.53)	**1.047** (4.30)	**1.057** (3.01)	**0.727** (3.26)	**1.401** (2.86)	**1.000** (2.43)
adj. R^2	48.97%	49.57%	50.62%	48.80%	48.52%	49.34%	50.84%	48.72%

Table A4. *Cont.*

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
ETH								
α	**−0.016**	0.000	**−0.023**	−0.013	−0.020	−0.005	**−0.027**	−0.017
	(−2.02)	(0.14)	(−2.41)	(−1.47)	(−1.94)	(−1.05)	(−2.05)	(−1.58)
β_1	**0.264**	**0.354**	**0.266**	**0.276**	**0.439**	**0.656**	**0.454**	**0.494**
	(2.96)	(4.26)	(2.90)	(2.80)	(2.00)	(3.88)	(2.03)	(2.05)
β_2	**0.988**	**0.495**	**1.143**	**0.902**	**0.920**	**0.371**	**1.052**	**0.800**
	(4.46)	(4.86)	(4.31)	(3.67)	(2.40)	(2.27)	(2.33)	(1.97)
adj. R^2	43.60%	41.78%	43.48%	42.99%	42.06%	40.14%	41.93%	41.69%
XRP								
α	−0.006	0.002	−0.008	−0.004	**−0.013**	−0.004	**−0.014**	**−0.013**
	(−1.10)	(0.76)	(−1.34)	(−0.73)	(−2.33)	(−1.02)	(−3.10)	(−2.61)
β_1	**0.222**	**0.253**	**0.235**	**0.256**	**0.421**	**0.496**	**0.508**	**0.489**
	(3.49)	(4.01)	(3.39)	(3.80)	(2.55)	(3.10)	(3.32)	(3.16)
β_2	**0.887**	**0.585**	**0.916**	**0.798**	**0.868**	**0.532**	**0.812**	**0.803**
	(4.81)	(5.12)	(4.91)	(4.50)	(3.60)	(3.65)	(4.82)	(4.12)
adj. R^2	35.53%	34.92%	35.83%	35.12%	30.98%	30.21%	31.02%	30.68%
LTC								
α	−0.016	0.005	**−0.026**	−0.014	−0.022	−0.004	**−0.031**	−0.020
	(−1.51)	(1.24)	(−1.99)	(−1.21)	(−1.82)	(−0.82)	**(−2.11)**	(−1.58)
β_1	**0.249**	**0.435**	**0.198**	**0.238**	**0.464**	**0.875**	0.350	0.447
	(3.19)	(5.61)	(2.31)	(2.63)	(2.38)	(6.04)	(1.57)	(1.88)
β_2	**0.981**	**0.367**	**1.219**	**0.958**	**0.904**	**0.181**	**1.194**	**0.889**
	(3.85)	(5.27)	(3.87)	(3.23)	(2.41)	(2.14)	(2.54)	(2.04)
adj. R^2	36.40%	33.09%	37.05%	36.40%	36.17%	33.00%	37.07%	36.32%
BCH								
α	−0.005	0.004	−0.007	−0.006	−0.012	−0.003	−0.012	−0.012
	(−0.71)	(1.08)	(−1.18)	(−0.73)	(−1.39)	(−0.86)	(−1.91)	(−1.39)
β_1	**0.493**	**0.521**	**0.494**	**0.490**	**0.799**	**0.864**	**0.803**	**0.794**
	(5.01)	(5.82)	(5.12)	(4.94)	(5.13)	(6.08)	(5.08)	(5.04)
β_2	**0.536**	**0.297**	**0.558**	**0.543**	0.385	0.165	0.388	0.394
	(2.67)	(3.14)	(3.38)	(2.66)	(1.55)	(1.38)	(1.84)	(1.56)
adj. R^2	47.79%	47.48%	48.07%	47.83%	48.39%	47.87%	48.36%	48.43%
EOS								
α	**−0.026**	0.002	**−0.027**	**−0.025**	**−0.032**	−0.008	**−0.033**	**−0.032**
	(−2.47)	(0.63)	**(−3.22)**	(−2.02)	**(−2.67)**	(−1.49)	**(−3.42)**	**(−2.20)**
β_1	**0.286**	**0.376**	**0.300**	**0.274**	**0.613**	**0.826**	**0.643**	**0.585**
	(3.88)	(4.62)	(3.78)	(3.76)	(3.84)	(4.91)	**(3.75)**	(3.46)
β_2	**1.103**	**0.443**	**1.130**	**1.105**	**0.939**	**0.296**	**0.939**	**0.961**
	(4.97)	(4.79)	(5.91)	(4.12)	(3.23)	(2.65)	**(3.76)**	(2.65)
adj. R^2	28.51%	26.18%	28.41%	28.57%	27.73%	25.92%	27.51%	27.85%
XRM								
α	−0.001	0.005	−0.002	−0.0005	−0.006	−0.0006	−0.007	−0.005
	(−0.25)	(1.43)	(−0.40)	(−0.10)	(−1.14)	(−0.15)	(−1.30)	(−1.04)
β_1	**0.308**	**0.310**	**0.327**	**0.302**	**0.537**	**0.541**	**0.576**	**0.524**
	(3.08)	(3.16)	(3.42)	(2.87)	(2.54)	(2.67)	(3.05)	(2.28)
β_2	**0.666**	**0.468**	**0.671**	**0.654**	**0.572**	**0.401**	**0.566**	0.569
	(3.80)	(3.90)	(3.87)	(3.53)	(2.09)	(2.17)	(2.16)	(1.95)
adj. R^2	45.12%	45.02%	44.60%	45.15%	44.06%	44.03%	43.79%	44.24%

Table A4. *Cont.*

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
XLM								
α	−0.003	1.377	−0.008	−0.004	−0.013	0.710	**−0.019**	−0.014
	(−0.39)	(1.84)	(−1.00)	(−0.53)	(−1.87)	(0.96)	**(−2.33)**	(−1.91)
β_1	**0.288**	**0.541**	**0.292**	**0.283**	**0.549**	**0.998**	**0.562**	**0.539**
	(3.50)	(8.72)	(3.88)	(3.37)	(3.34)	(8.89)	(3.86)	(3.18)
β_2	**0.745**	27.792	**0.865**	**0.779**	**0.707**	14.556	**0.820**	**0.740**
	(3.30)	(−1.81)	**(3.59)**	(3.28)	**(2.73)**	(−0.96)	**(3.07)**	**(2.70)**
adj. R^2	34.82%	30.02%	35.06%	34.90%	35.14%	30.71%	35.53%	35.19%
DASH								
α	0.004	**0.007**	0.001	0.004	−0.002	−0.001	−0.005	−0.002
	(1.17)	(2.35)	(0.40)	(1.20)	(−0.68)	(−0.22)	(−1.36)	(−0.75)
β_1	**0.391**	**0.426**	**0.441**	**0.421**	**0.642**	**0.712**	**0.724**	**0.698**
	(4.25)	(4.82)	(5.33)	(4.78)	(3.87)	(4.56)	(5.15)	(4.52)
β_2	**0.464**	**0.351**	**0.486**	**0.438**	**0.378**	**0.260**	**0.363**	**0.335**
	(3.98)	(4.10)	(4.66)	(4.02)	(2.37)	(2.23)	(2.67)	(2.30)
adj. R^2	48.63%	48.17%	48.49%	48.25%	47.81%	47.26%	47.46%	47.40%
ZEC								
α	−0.005	0.003	−0.011	−0.008	**−0.013**	−0.005	**−0.019**	**−0.016**
	(−0.82)	(0.81)	(−1.60)	(−1.12)	**(−2.05)**	(−1.11)	**(−2.49)**	**(−2.07)**
β_1	**0.378**	**0.398**	**0.376**	**0.365**	**0.600**	**0.644**	**0.600**	**0.576**
	(3.82)	(4.19)	(3.90)	(3.60)	(3.57)	(3.89)	(3.63)	(3.22)
β_2	**0.663**	**0.438**	**0.798**	**0.737**	**0.614**	**0.384**	**0.733**	**0.690**
	(3.70)	(4.08)	(3.96)	(3.55)	(2.86)	(2.85)	(2.97)	(2.67)
adj. R^2	45.91%	45.50%	45.99%	45.98%	45.65%	44.91%	45.58%	45.68%
ETC								
α	−0.002	0.007	0.009	−0.002	0.01	−0.002	**0.016**	0.01
	(−0.37)	(1.82)	(−1.37)	(−0.44)	(−1.58)	(−0.67)	**(−2.35)**	(−1.72)
β_1	**0.371**	**0.366**	**0.359**	**0.376**	**0.688**	**0.678**	**0.657**	**0.695**
	(4.54)	(4.47)	(4.60)	(4.79)	(4.58)	(4.57)	(4.72)	(4.96)
β_2	**0.618**	**0.390**	**0.766**	**0.620**	**0.489**	**0.313**	**0.637**	**0.489**
	(3.57)	(3.67)	(4.29)	(3.86)	(2.20)	(2.34)	(2.86)	(2.42)
adj. R^2	39.78%	39.82%	40.11%	39.83%	40.40%	40.51%	40.79%	40.41%
REP								
α	**0.008**	**0.014**	0.002	**0.009**	−0.004	0.001	**−0.009**	−0.004
	(2.02)	(4.77)	(0.69)	(2.37)	(−0.97)	(0.47)	**(−2.30)**	(−1.01)
β_1	**0.348**	**0.347**	**0.326**	**0.376**	**0.595**	**0.593**	**0.557**	**0.643**
	(4.81)	(4.84)	(4.93)	(5.57)	(4.74)	(4.71)	(5.03)	(5.52)
β_2	**0.461**	**0.332**	**0.596**	**0.421**	**0.451**	**0.323**	**0.588**	**0.409**
	(3.86)	(4.04)	(6.22)	(4.03)	(3.48)	(3.56)	(5.68)	(3.55)
adj. R^2	39.57%	39.56%	40.80%	39.14%	40.42%	40.31%	41.69%	39.96%
Aggregate Results								
Average α	−0.007	0.119	−0.012	−0.006	−0.014	0.056	−0.018	−0.013
Average β_1	0.318	0.376	0.313	0.322	0.556	0.68	0.553	0.568
Average β_2	0.767	−1.907	0.878	0.75	0.69	−0.884	0.791	0.673
Average *adj.* R^2	41.22%	40.09%	41.54%	41.08%	40.61%	39.52%	40.96%	40.55%

Table A5. Encompassing regressions for volatility forecasts: 7-day forecast horizon with Newey–West Standard Error (7-lag).

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
BTC								
α	−0.012	**0.014**	−0.025	−0.005	−0.012	0.010	**−0.026**	−0.009
	(−0.99)	(2.09)	(−1.81)	(−0.59)	(−1.48)	(1.28)	(−2.66)	(−1.29)
β_1	0.002	0.006	0.028	0.042	0.287	0.199	0.100	0.258
	(0.02)	(0.05)	(0.26)	(0.35)	(1.21)	(0.85)	(0.34)	(0.83)
β_2	**1.045**	**0.679**	**1.156**	**0.936**	**0.788**	**0.569**	**1.109**	**0.781**
	(4.17)	(4.41)	(4.49)	(4.31)	(2.94)	(3.28)	(3.08)	(2.63)
adj. R^2	32.13%	33.40%	34.73%	32.69%	32.58%	33.65%	35.10%	33.16%
ETH								
α	−0.008	**0.035**	−0.030	0.004	−0.011	0.006	−0.024	−0.007
	(−0.55)	(2.89)	(−1.22)	(0.37)	(−0.88)	(0.57)	(−1.36)	(−0.63)
β_1	−0.024	0.040	−0.026	0.054	**0.475**	**0.668**	0.426	**0.550**
	(−0.27)	(0.35)	(−0.23)	(0.59)	(2.10)	(3.28)	(1.61)	(2.18)
β_2	**1.002**	**0.539**	**1.186**	**0.822**	**0.564**	0.232	**0.722**	**0.467**
	(5.17)	(3.06)	(3.85)	(4.76)	(2.44)	(1.58)	(2.01)	(2.00)
adj. R^2	26.42%	23.77%	27.14%	25.74%	26.71%	25.72%	27.08%	26.43%
XRP								
α	0.023	**0.046**	0.018	**0.028**	0.011	0.025	0.004	0.007
	(1.89)	(5.21)	(1.55)	(2.37)	(0.81)	(1.76)	(0.30)	(0.53)
β_1	−0.068	−0.078	−0.028	−0.034	0.316	0.372	**0.355**	**0.394**
	(−0.64)	(−0.68)	(−0.31)	(−0.34)	(1.43)	(1.76)	(2.07)	(2.15)
β_2	**0.879**	**0.631**	**0.888**	**0.792**	**0.588**	**0.377**	**0.610**	**0.543**
	(4.40)	(3.91)	(4.91)	(4.35)	(3.06)	(2.84)	(3.96)	(3.37)
adj. R^2	20.09%	19.68%	21.57%	19.44%	17.80%	17.47%	18.67%	17.60%
LTC								
α	0.007	**0.052**	−0.017	0.010	−0.006	0.002	−0.019	−0.003
	(0.31)	(3.31)	(−0.66)	(0.55)	(−0.34)	(0.15)	(−0.99)	(−0.18)
β_1	0.021	0.192	−0.011	0.023	0.443	**0.808**	0.157	0.395
	(0.19)	(1.95)	(−0.10)	(0.20)	(1.69)	(5.05)	(0.49)	(1.29)
β_2	**0.851**	0.329	**1.070**	**0.825**	**0.559**	0.150	**0.925**	**0.583**
	(3.21)	(1.85)	(3.65)	(3.53)	(2.18)	(1.15)	(2.43)	(2.15)
adj. R^2	19.56%	15.60%	22.40%	20.24%	20.53%	18.90%	22.57%	20.98%
BCH								
α	0.028	**0.064**	0.008	0.024	−0.006	0.000	−0.014	−0.007
	(0.98)	(2.70)	(0.23)	(0.93)	(−0.33)	(0.01)	(−0.72)	(−0.35)
β_1	**0.376**	**0.461**	**0.354**	**0.363**	**0.895**	**0.938**	**0.764**	**0.888**
	(3.95)	(4.10)	(3.78)	(4.17)	(4.51)	(4.63)	(3.24)	(4.47)
β_2	0.424	0.059	0.597	0.465	0.136	0.050	0.307	0.146
	(1.54)	(0.25)	(1.80)	(1.88)	(0.70)	(0.40)	(1.24)	(0.73)
adj. R^2	23.78%	22.77%	24.61%	24.19%	30.66%	30.54%	31.22%	30.68%
Aggregate Results								
Average α	0.023	0.576	0.006	0.023	−0.001	0.354	−0.011	−0.001
Average β_1	0.091	0.134	0.080	0.098	0.534	0.640	0.450	0.530
Average β_2	0.705	−3.660	0.850	0.690	0.451	−2.424	0.613	0.454
Average *adj.* R^2	23.27%	22.07%	24.60%	23.41%	24.77%	24.34%	25.78%	24.91%

Table A6. Encompassing regressions for volatility forecasts: 30-day forecast horizon with Newey–West Standard Error (30-lag).

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
BTC								
α	**0.103**	**0.128**	**0.083**	**0.103**	0.074	0.108	0.108	0.100
	(3.49)	(4.52)	(3.10)	(3.65)	(1.16)	(1.54)	(1.62)	(1.25)
β_1	−0.024	−0.017	−0.044	−0.010	0.245	0.131	−0.229	0.025
	(−0.19)	(−0.14)	(−0.36)	(−0.09)	(0.49)	(0.27)	(−0.44)	(0.04)
β_2	**0.478**	**0.309**	**0.600**	**0.461**	0.362	**0.268**	**0.656**	**0.444**
	(4.00)	(4.02)	(3.99)	(5.10)	(1.65)	(2.03)	(2.56)	(2.13)
$adj.\ R^2$	9.10%	9.56%	11.28%	10.01%	9.16%	9.56%	11.25%	10.00%
ETH								
α	**0.139**	**0.180**	**0.106**	**0.146**	0.025	0.017	0.058	0.015
	(4.19)	(6.37)	(2.44)	(4.70)	(0.31)	(0.21)	(0.92)	(0.17)
β_1	−0.026	−0.082	−0.072	0.008	0.788	**0.892**	0.389	0.874
	(−0.24)	(−0.67)	(−0.71)	(0.08)	(1.54)	(2.01)	(0.75)	(1.56)
β_2	**0.438**	**0.304**	**0.611**	**0.377**	0.105	0.035	0.359	0.060
	(3.20)	(2.71)	(2.82)	(3.41)	(0.48)	(0.25)	(0.99)	(0.28)
$adj.\ R^2$	7.80%	7.30%	9.77%	7.28%	8.94%	8.87%	9.78%	8.87%
XRP								
α	**0.163**	**0.178**	**0.158**	**0.165**	0.036	0.047	0.055	0.029
	(4.49)	(5.47)	(4.09)	(4.41)	(0.36)	(0.49)	(0.63)	(0.31)
β_1	0.090	0.079	0.083	0.092	0.756	0.728	0.611	**0.803**
	(0.96)	(0.83)	(0.89)	(0.98)	(1.68)	(1.69)	(1.53)	(1.98)
β_2	0.228	0.164	0.262	0.220	0.096	0.073	0.167	0.080
	(1.95)	(1.81)	(1.76)	(1.82)	(0.74)	(0.72)	(0.97)	(0.64)
$adj.\ R^2$	5.41%	5.38%	5.93%	5.16%	5.80%	5.82%	6.19%	5.75%
LTC								
α	**0.145**	**0.181**	**0.110**	**0.147**	0.010	0.027	0.071	0.018
	(2.98)	(4.34)	(2.13)	(3.23)	(0.10)	(0.34)	(0.82)	(0.16)
β_1	0.048	−0.232	0.002	0.055	0.913	**0.793**	0.285	0.856
	(0.34)	(−1.05)	(0.02)	(0.41)	(1.74)	(1.99)	(0.55)	(1.54)
β_2	**0.391**	**0.496**	**0.559**	**0.377**	0.047	0.094	0.429	0.075
	(2.47)	(2.22)	(2.94)	(2.89)	(0.22)	(0.56)	(1.41)	(0.37)
$adj.\ R^2$	7.67%	8.21%	10.65%	7.96%	9.40%	9.71%	10.83%	9.44%
BCH								
α	**0.153**	**0.184**	**0.130**	**0.152**	−0.011	−0.015	0.019	−0.010
	(2.62)	(3.46)	(2.10)	(2.59)	(−0.11)	(−0.14)	(0.18)	(−0.10)
β_1	0.194	0.158	0.100	0.193	**1.139**	**1.099**	0.775	**1.128**
	(1.13)	(0.83)	(0.53)	(1.13)	(2.51)	(2.47)	(1.47)	(2.49)
β_2	0.280	0.196	**0.445**	0.285	−0.098	−0.043	0.156	−0.091
	(1.74)	(1.61)	(1.97)	(1.77)	(−0.59)	(−0.36)	(0.58)	(−0.54)
$adj.\ R^2$	10.29%	10.30%	12.33%	10.38%	13.98%	13.90%	14.11%	13.96%
EOS								
α	0.117	**0.208**	0.023	0.112	0.009	0.006	0.002	0.019
	(1.61)	(4.22)	(0.27)	(1.61)	(0.10)	(0.07)	(0.02)	(0.21)
β_1	−0.114	−0.132	−0.321	−0.105	0.741	**0.913**	0.440	0.624
	(−0.74)	(−0.73)	(−1.85)	(−0.73)	(1.92)	(2.50)	(1.08)	(1.61)
β_2	**0.661**	0.342	**1.198**	**0.671**	0.217	0.057	0.533	0.293
	(2.03)	(1.45)	(2.90)	(2.18)	(0.81)	(0.38)	(1.55)	(1.11)
$adj.\ R^2$	6.45%	3.54%	13.89%	7.54%	7.86%	7.49%	10.47%	8.25%
XRM								
α	**0.160**	**0.183**	**0.145**	**0.159**	0.041	0.052	0.074	0.056
	(5.15)	(6.12)	(4.96)	(5.17)	(0.61)	(0.73)	(1.05)	(0.77)

Table A6. *Cont.*

CC	LRE + GARCH	LRE + IGARCH	LRE + EGARCH	LRE + GJR	HAR + GARCH	HAR + IGARCH	HAR + EGARCH	HAR + GJR
β_1	−0.092	−0.093	−0.177	−0.087	0.681	0.657	0.369	0.573
	(−0.71)	(−0.72)	(−1.30)	(−0.72)	(1.81)	(1.72)	(0.84)	(1.41)
β_2	**0.409**	**0.292**	**0.559**	**0.407**	0.145	0.110	0.314	0.186
	(3.68)	(3.55)	(3.48)	(4.16)	(0.94)	(0.98)	(1.45)	(1.21)
adj. R^2	10.26%	10.49%	14.76%	11.22%	11.57%	11.67%	13.72%	12.00%
XLM								
α	**0.230**	17.731	**0.223**	**0.228**	0.045	17.227	0.035	0.046
	(5.55)	(1.43)	(5.13)	(5.43)	(0.47)	(1.49)	(0.35)	(0.48)
β_1	−0.082	−0.038	−0.077	−0.082	0.741	**0.996**	0.777	0.736
	(−0.88)	(−0.38)	(−0.82)	(−0.88)	(1.89)	(2.75)	(1.90)	(1.85)
β_2	**0.240**	−65.276	**0.264**	**0.248**	0.093	−64.439	0.096	0.097
	(2.60)	(−1.41)	(2.46)	(2.59)	(0.93)	(−1.49)	(0.80)	(0.91)
adj. R^2	3.42%	5.42%	3.11%	3.45%	4.08%	9.28%	4.03%	4.08%
DASH								
α	**0.165**	**0.179**	**0.148**	**0.165**	0.152	0.188	0.180	0.147
	(4.62)	(5.15)	(4.41)	(4.58)	(1.28)	(1.53)	(1.67)	(1.28)
β_1	0.012	−0.034	−0.109	−0.008	0.079	−0.069	−0.237	0.089
	(0.09)	(−0.25)	(−0.75)	(−0.06)	(0.13)	(−0.12)	(−0.40)	(0.15)
β_2	**0.363**	**0.336**	**0.558**	**0.387**	0.346	**0.337**	**0.562**	0.355
	(3.92)	(3.83)	(3.85)	(3.71)	(1.91)	(2.09)	(2.30)	(1.90)
adj. R^2	15.48%	16.45%	19.08%	15.53%	15.49%	16.40%	18.65%	15.55%
ZEC								
α	**0.173**	**0.199**	**0.153**	**0.162**	0.086	0.131	0.082	0.102
	(4.71)	(6.09)	(4.09)	(4.37)	(0.90)	(1.39)	(0.88)	(1.07)
β_1	0.009	−0.029	−0.016	0.002	0.459	0.305	0.402	0.330
	(0.08)	(−0.27)	(−0.16)	(0.02)	(1.05)	(0.76)	(0.86)	(0.74)
β_2	**0.367**	**0.286**	**0.466**	**0.412**	0.230	0.204	0.304	0.301
	(3.14)	(3.36)	(3.47)	(3.45	(1.34)	(1.78)	(1.39)	(1.65)
adj. R^2	8.65%	9.35%	8.97%	9.20%	9.14%	9.48%	9.32%	9.43%
ETC								
α	**0.176**	**0.205**	**0.148**	**0.176**	0.076	0.109	0.100	0.072
	(4.08)	(5.01)	(3.29)	(4.09)	(0.75)	(0.97)	(1.14)	(0.74)
β_1	0.023	0.020	−0.009	0.022	0.519	0.446	0.251	0.538
	(0.15)	(0.13)	(−0.06)	(0.14)	(1.08)	(0.91)	(0.55)	(1.15)
β_2	**0.354**	**0.228**	**0.492**	**0.356**	0.213	0.153	0.398	0.209
	(3.18)	(3.28)	(3.42)	(2.98)	(1.18)	(1.32)	(1.75)	(1.16)
adj. R^2	8.53%	9.04%	10.62%	8.41%	9.26%	9.58%	10.80%	9.23%
REP								
α	**0.336**	**0.348**	**0.326**	**0.336**	0.016	0.020	0.023	0.020
	(5.70)	(6.03)	(5.37)	(5.69)	(0.10)	(0.12)	(0.15)	(0.13)
β_1	−0.158	−0.163	−0.161	−0.159	0.930	0.919	0.887	0.907
	(−0.90)	(−0.93)	(−0.93)	(−0.90)	(1.68)	(1.64)	(1.62)	(1.72)
β_2	**0.153**	**0.114**	**0.190**	**0.157**	0.024	0.020	0.046	0.033
	(2.43)	(2.50)	(2.94)	(2.54)	(0.22)	(0.25)	(0.38)	(0.32)
adj. R^2	4.49%	4.70%	4.94%	4.65%	6.01%	6.03%	6.13%	6.07%
Aggregate Results								
Average α	0.172	1.658	0.146	0.171	0.046	1.493	0.067	0.051
Average β_1	−0.010	−0.047	−0.067	−0.007	0.666	0.651	0.393	0.624
Average β_2	0.363	−5.184	0.517	0.363	0.148	−5.261	0.335	0.170
Average *adj.* R^2	8.13%	8.31%	10.44%	8.40%	9.22%	9.82%	10.44%	9.39%

Table A7. Full Out-of-Sample Forecast Performance (1-Day Horizon).

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**	**GARCH**	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**
BTC	0.0178	0.4248 ***	**0.0172**	0.0180	0.0212	0.0188	−2.526	−0.982 ***	−2.511	−2.510	−2.523	**−2.543**
ETH	0.0207	0.2998 ***	**0.0195**	0.0255	0.0229	0.0200	−2.253	−1.463 ***	−2.257	−2.224 **	−2.266	**−2.282**
XRP	**0.0229**	0.3778 ***	0.0230	0.0258	0.0274	0.0233	−2.326	−1.120 ***	−2.332	−2.203	−2.314 **	**−2.339**
LTC	0.0242 ***	0.2731 ***	0.0224	0.0222	0.0246	**0.0214**	−2.182 ***	−1.388 ***	−2.187	−2.184	−2.197	**−2.211**
BCH	0.0306 **	0.3446 ***	0.0304 *	0.0318 **	0.0332	**0.0291**	−2.142 **	−1.223 ***	−2.130 *	−2.050 **	−2.160	**−2.189**
EOS	0.0315	0.2226 ***	0.0304	0.0331	0.0338 **	**0.0290**	−2.144	−1.510 ***	−2.149	−2.062	−2.167 **	**−2.189**
XMR	0.0179 **	0.3029 ***	**0.0166**	0.0176	0.0201	0.0177	−2.252	−1.359 ***	−2.256	−2.247	−2.258	**−2.269**
XLM	0.0246 **	0.3031 ***	0.0218	0.0258 **	0.0248	**0.0216**	−2.140 **	−1.339 ***	−2.160	−2.127 **	−2.160	**−2.171**
DASH	0.0221	0.3828 ***	0.0231	0.0297 ***	0.0241	**0.0216**	−2.190	−1.028 ***	−2.188	−2.163 ***	−2.194	**−2.207**
ZEC	0.0253 *	0.4308 ***	0.0233	0.0302 **	0.0256	**0.0231**	−2.092 *	−0.764 ***	−2.108	−2.003 **	−2.106	**−2.122**
ETC	0.0278 ***	0.2971 ***	0.0271 ***	0.0297 ***	0.0276	**0.0244**	−2.078 ***	−1.229 ***	−2.073 ***	−2.056 ***	−2.098	**−2.116**
REP	0.0313 ***	0.4491 ***	0.0703	0.0340 ***	0.0294 **	**0.0262**	−2.012 ***	−0.858 ***	−2.023	−1.990 ***	−2.010 **	**−2.035**

This table presents out-of-sample forecasting errors for the 12 cryptocurrencies using the root mean squared error (RMSE) and the quasi-likelihood (QLIKE) loss functions for 1-day forecast horizon. Each columns resemble the forecasting models. The model with the lowest forecast errors is highlighted in bold. Forecasting is based on GARCH(1,1) model, IGARCH model, the EGARCH model, the GJR-GARCH model, the lagged realized volatility (LRE), and the Heterogeneous Autoregressive (HAR) model. All forecasts are obtained from 5-min returns. Also, based on the DM test, the models that have higher forecast errors and are more statistically significant than the best models are signaled with *, ** and *** at 10%, 5%, and 1% significant levels. The same as below.

Table A8. Full Out-of-Sample Forecast Performance (7-Day Horizon).

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**	**GARCH**	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**
BTC	0.0476	1.1230 ***	0.0508 **	0.0508 ***	0.0592 ***	0.0492	−1.469	0.019 ***	−1.434 **	−1.445 ***	−1.425 ***	−1.464
ETH	0.0554 ***	0.7935 ***	0.0558 *	0.0601 ***	0.0605 ***	0.0509	−1.210 ***	−0.458 ***	−1.213 *	−1.196 ***	−1.200 ***	−1.223
XRP	0.0521	0.9958 ***	0.0539	0.0575 **	0.0644 ***	0.0519	−1.252	−0.115 ***	−1.248	−1.131 **	−1.217 ***	−1.257
LTC	0.0561 ***	0.7219 ***	0.0525	0.0565 **	0.0645 ***	0.0541	−1.146 ***	−0.385 ***	−1.153	−1.148 **	−1.127 ***	−1.147
BCH	0.0692 ***	0.9077 ***	0.0694 **	0.0726 ***	0.0731 ***	0.0655	−1.112 ***	−0.227 ***	−1.099 **	−1.032 ***	−1.102 ***	−1.126
EOS	0.0663 **	0.5845 ***	0.0637	0.0683 *	0.0796 ***	0.0659	−1.086	−0.491 ***	−1.091	−1.050	−1.066 ***	−1.097

Table A8. *Cont.*

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**	**GARCH**	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**
XMR	0.0470 ***	0.8015 ***	0.0441	0.0492 **	0.0528 ***	0.0444	−1.227 **	−0.362 ***	−1.232	−1.222 ***	−1.219 ***	−1.234
XLM	0.0540 **	0.7980 ***	0.0540 *	0.0561 ***	0.0645 ***	0.0513	−1.097 **	−0.340 ***	−1.097 *	−1.089 ***	−1.066 ***	−1.105
DASH	0.0635 **	1.0105 ***	0.0611 **	0.0757 ***	0.0681 ***	0.0569	−1.138 **	−0.035 ***	−1.143 **	−1.121 ***	−1.131 ***	−1.148
ZEC	0.0634 ***	1.1362 ***	0.0612	0.0734 ***	0.0771 ***	0.0629	−1.045 ***	0.224 ***	−1.051	−0.954 ***	−1.016 ***	−1.049
ETC	0.0654 ***	0.7804 ***	0.0670 ***	0.0647 ***	0.0710 ***	0.0580	−1.026 ***	−0.232 ***	−1.006 ***	−1.017 ***	−1.025 ***	−1.050
REP	0.0901 ***	1.1799 ***	0.2010	0.0947 **	0.0760 ***	0.0621	−0.920 ***	0.134 ***	−0.930	−0.915 **	−0.912 ***	−0.949

Table A9. Full Out-of-Sample Forecast Performance (30-Day Horizon).

	Panel A: RMSE						Panel B: QLIKE					
	GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**	**GARCH**	**IGARCH**	**EGARCH**	**GJR-GARCH**	**LRE**	**HAR**
BTC	0.1013 **	2.3338 ***	0.1103 **	0.1137 ***	0.1253 ***	0.0942	−0.682	0.782 ***	−0.646	−0.652 ***	−0.636 ***	−0.679 ***
ETH	0.1178 ***	1.6518 ***	0.1156	0.1096 ***	0.1164 ***	0.0972	−0.433 ***	0.298 ***	−0.441	−0.441 ***	−0.434 ***	−0.451
XRP	0.0946 ***	2.0638 ***	0.0970 ***	0.0952 ***	0.1009 ***	0.0847	−0.464 ***	0.641 ***	−0.456 ***	−0.393 ***	−0.462 ***	−0.476
LTC	0.1091 ***	1.5041 ***	0.0988	0.1124 **	0.1161 ***	0.1069 **	−0.380	0.373 ***	−0.389 **	−0.390	−0.379	−0.379
BCH	0.1259	1.8871 ***	0.1251	0.1245	0.1289	0.1521 ***	−0.347	0.527 ***	−0.329	−0.307	−0.348	−0.314 ***
EOS	0.1091 **	1.2146 ***	0.1096 **	0.1041	0.1266 ***	0.1092 **	−0.316	0.271 ***	−0.312	−0.309 **	−0.303 ***	−0.319
XMR	0.1047 ***	1.6699 ***	0.0959 **	0.1063 **	0.1083 ***	0.0826	−0.467 ***	0.392 ***	−0.476 **	−0.473 **	−0.468 ***	−0.484
XLM	0.0917 **	1.6530 ***	0.0993 ***	0.0930 **	0.1023 ***	0.0852	−0.329 **	0.412 ***	−0.326 ***	−0.328 **	−0.320 ***	−0.336
DASH	0.1373 **	2.0922 ***	0.1262 **	0.1471 ***	0.1356 ***	0.1133	−0.355 **	0.713 ***	−0.359 **	−0.343 ***	−0.340 ***	−0.362
ZEC	0.1179 ***	2.3496 ***	0.1174 ***	0.1313 ***	0.1314 ***	0.1075	−0.268 ***	0.962 ***	−0.267 ***	−0.205 ***	−0.253 ***	−0.275
ETC	0.1211 ***	1.6137 ***	0.1256 ***	0.1057	0.1343 ***	0.1027	−0.250 ***	0.516 ***	−0.230 ***	−0.257	−0.235 ***	−0.269
REP	0.1867 **	2.4310 ***	0.4260	0.1905 **	0.1306 ***	0.1125	−0.135 **	0.867 ***	−0.134	−0.136 **	−0.133 ***	−0.168

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