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Artificial Intelligence Models and Cryptocurrency Price Volatility: A Predictive Econometric Approach to Bitcoin and Ethereum

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ABSTRACT

This study aims to analyze the determinants of digital asset pricing by assessing the explanatory and predictive roles of generative artificial intelligence tools and financial analytics platforms relative to macroeconomic variables and traditional financial market dynamics. Particular emphasis is placed on examining whether Large Language Models (LLMs) possess an independent structural capacity to influence cryptocurrency market volatility. The study focuses on a sample comprising Bitcoin and Ethereum over the period from March 10, 2016, to March 14, 2026. Methodologically, it employs the Random Forest algorithm, a machine learning technique, to extract the relative importance of explanatory variables using the Percentage Increase in Mean Squared Error (%IncMSE) metric. The findings reveal that cryptocurrencies have become increasingly integrated into the global financial system, with financial stress indicators, energy markets, and energy costs emerging as the dominant drivers of price fluctuations. The results also indicate a limited structural impact of generative AI, suggesting that its role is primarily interpretive and reactive rather than a direct catalyst of market shocks. In contrast, on-chain analytics platforms demonstrate stronger explanatory power, as smart liquidity tracking through Nansen plays a more prominent role in explaining Ethereum dynamics, while aggregate supply indicators from Glassnode exert greater influence on Bitcoin as a monetary asset. Furthermore, the results show that Ethereum exhibits higher informational efficiency and a shorter price memory than Bitcoin, reflecting a faster process of shock absorption and price adjustment.

Keywords: Bitcoin, Ethereum, Generative Artificial Intelligence, Algorithmic Execution Platforms, Macroeconomics, Random Forest.

JEL Classification: O33, G15, G14, G12, C58.

Introduction

The global financial system is undergoing a profound structural transformation driven by the rapid maturation of digital asset markets, particularly Bitcoin and Ethereum. Once regarded as merely experimental cryptographic technologies operating within an isolated ecosystem, these assets have increasingly become organically integrated into global liquidity cycles. Consequently, they have evolved into financial instruments that are highly sensitive to macroeconomic fluctuations, episodes of financial distress, and shifts in international monetary policy.

These financial transformations coincide with an unprecedented technological disruption brought about by the artificial intelligence revolution, which has fundamentally reshaped the information architecture and price discovery mechanisms of financial markets. However, the impact of this technological shift is inherently dual in nature. On the one hand, generative AI models function as cognitive layers that reinterpret news flows, process information, and analyze market sentiment. On the other hand, specialized analytics and trading platforms rely on quantitative algorithms to monitor

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smart liquidity, analyze on-chain activity, and facilitate the direct execution of transactions within blockchain ecosystems.

Amid this complex interaction between traditional macroeconomic determinants and emerging financial technologies, a growing body of literature suggests that generative artificial intelligence may act as an independent driver of market volatility. This perspective necessitates a rigorous empirical investigation that moves beyond descriptive analysis toward advanced econometric and machine-learning modeling in order to assess the validity of such claims. More specifically, it requires measuring the actual explanatory and predictive significance of AI-driven tools and digital finance platforms relative to macroeconomic and financial variables in shaping cryptocurrency price dynamics.

Against this backdrop, the central research question of this study can be formulated as follows:

To what extent do generative artificial intelligence tools and digital financial analytics platforms contribute to explaining and predicting the price volatility of cryptocurrencies (Bitcoin and Ethereum), relative to macroeconomic variables and traditional financial market dynamics, using the Random Forest algorithm?

First: Literature Review

The existing literature on cryptocurrency market modeling consistently highlights the growing role of machine learning techniques and artificial intelligence in explaining and reducing the uncertainty associated with price volatility. (Kim et al.2016) demonstrate that unstructured data, particularly user-generated comments, possess significant explanatory power for price fluctuations and transaction intensity, thereby establishing digital discussions as leading indicators in cryptocurrency markets, with relatively simple models showing strong performance in integrating textual and financial data. In a similar vein, (Jiang et al.2017) emphasize the effectiveness of deep reinforcement learning in enhancing digital portfolio management, where neural architectures such as CNN, RNN, and LSTM achieve superior performance and higher cumulative returns compared to traditional investment strategies, reflecting the adaptability of algorithms to short-term market volatility.

(McNally et al.2018) compare deep learning models with classical approaches such as ARIMA for Bitcoin price prediction, finding only marginal improvements from neural networks, while overall predictive performance remains limited due to high levels of noise in financial data. (Valencia et al.2019) further underscore the importance of integrating social media sentiment data with market variables, showing that neural networks outperform SVM and Random Forest models in directional forecasting, thus confirming the strong sensitivity of cryptocurrencies to public sentiment and media-driven dynamics.

(Chen et al.2020) highlight that model performance is highly dependent on data structure and temporal frequency, with simpler statistical models performing better in high-dimensional daily datasets, whereas advanced machine learning models excel in high-frequency environments due to their ability to capture nonlinear dynamics. Similarly, (Hamayel and Owda.2021) document the superiority of GRU and LSTM architectures over bidirectional recurrent models in cryptocurrency price prediction, achieving high accuracy in capturing complex price patterns.

Recent reviews by (Amirzadeh et al.2022) and (Wang et al.2023) confirm that hybrid deep learning and reinforcement learning frameworks outperform traditional econometric models such as GARCH, particularly when incorporating blockchain indicators, macroeconomic variables, and sentiment measures. Likewise, (Brini and Lenz.2024) demonstrate the superiority of machine learning models in pricing cryptocurrency derivatives relative to classical models, especially when high-frequency volatility measures are integrated.

Finally, (Islam et al.2025) show that simpler models such as logistic regression may occasionally outperform more complex algorithms in noisy data environments, while also identifying clear seasonal patterns and strong sensitivity to liquidity and technical indicators. Overall, the literature

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converges on the conclusion that cryptocurrency markets are characterized by strong nonlinearity, high volatility, and significant interaction between technical, behavioral, and macroeconomic factors, with machine learning-based models consistently outperforming traditional econometric approaches.

Second: Methodology and Research Instruments

In this section, the study population is characterized through a detailed presentation of the dependent variables, followed by the specification of the key independent variables representing artificial intelligence indicators, as well as the economic and financial variables that are considered major determinants of cryptocurrency prices and significant drivers of cryptocurrency volatility, particularly for Bitcoin and Ethereum. Subsequently, the methodological approaches, empirical tests, and econometric techniques employed in estimating the study models are presented.

1. Study Variables

1.1. Dependent Variables

Bitcoin and Ethereum are selected as the dependent variables, given that they represent the most accurate proxies for overall trends in the cryptocurrency market. These two assets account for the largest share of market capitalization and liquidity and are therefore the most exposed to algorithmic trading models driven by artificial intelligence. Analyzing their volatility provides a comprehensive picture of how decentralized digital markets interact with modern predictive technologies.

1.2. Independent Variables: Artificial Intelligence

1.2.1. Indicators for Measuring Artificial Intelligence Levels

The Artificial Intelligence Index (AI Index) and the NASDAQ Composite Index (NASDAQ) are included to represent the technological dimension of the study. This selection is justified by the strong interdependence between investors' risk appetite in technology equities and artificial intelligence innovations on the one hand, and their exposure to cryptocurrency assets on the other. These indicators capture the impact of the artificial intelligence boom on capital flows, thereby enabling the measurement of how technological advancement influences price volatility in digital currencies.

1.2.2. Quantification of Generative Artificial Intelligence Variables

Technological shocks are treated as structural breaks in cryptocurrency markets by transforming successive versions of generative artificial intelligence tools into measurable ordinal variables. This approach aims to assess the direct impact of technological advancements on traders' behavior and the speed of information assimilation, which in turn is reflected in levels of price volatility. The models ChatGPT, Gemini, Claude, and DeepSeek are selected as they represent the core structure of the technological ecosystem, combining closed-source commercial models (OpenAI and Google), widely adopted by financial institutions, with open-source models that contribute to the democratization of algorithmic trading and the reduction of its implementation costs.

The evolution of ChatGPT is converted into an ordinal variable ranging from level (1) to (6), where each level reflects a major innovation shock, from initial adoption stages to advanced reasoning and multimodal processing capabilities. This quantification is designed to measure the effect of software updates on data-processing speed and market decision-making, and consequently on price volatility dynamics.

Similarly, the development of Gemini is transformed into an ordinal variable ranging from (1) to (7), given its introduction of multimodal capabilities and massive context windows (Reid, M., et al., 2024), which enable the simultaneous processing of large volumes of unstructured data, including real-time news, market data, and social media sentiment (Zhang, L., et al., 2024). This contributes to reducing

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market reaction lags and enhancing the speed of information transmission, thereby intensifying price shocks generated by high-frequency trading (Financial Market Research, 2026).

Claude is further operationalized into an 11-level ordinal variable based on its Constitutional AI architecture, which prioritizes factual reliability and minimizes hallucinations (Bai et al., 2022). This framework enables more rigorous analysis of smart contracts and on-chain data prior to trade execution (Yining Yuan et al., 2025), allowing for empirical testing of whether its reasoning capabilities contribute to shock absorption or instead reshape market microstructure through new volatility regimes driven by rapid arbitrage trading (Lopez-Lira, 2025).

In the same vein, DeepSeek developments are transformed into a 1–9 ordinal scale, reflecting the evolution of low-cost open-source models from early coding-focused systems to Mixture-of-Experts architectures and deep reasoning models. This progression has contributed to the democratization of algorithmic trading by enabling retail investors to build sophisticated trading agents previously accessible only to large financial institutions (Yang et al., 2023). The proliferation of AI-driven trading agents has further reshaped market microstructure, intensifying interactions among automated strategies and increasing financial noise and volatility induced by high-frequency trading dynamics.

1.2.3. Quantification of the Impact of Specialized Financial Analytics Platforms

On the other hand, the inclusion of specialized financial analytics platforms and on-chain data sources—namely 3Commas, Glassnode, and Nansen—as ascending quantitative variables within the econometric framework represents a key methodological shift. This extension moves the analysis from measuring the impact of general-purpose language models toward assessing the effects of domain-specific financial artificial intelligence, thereby enabling a more precise examination of behavioral dynamics in algorithmic trading environments and their associated market implications.

The 3Commas platform is one of the leading automated trading systems in the cryptocurrency market, allowing investors to design intelligent trading bots based on customizable technical indicators and algorithmic strategies, with the ability to execute orders automatically across multiple exchanges. Such systems enhance market responsiveness to price changes and reduce the influence of emotional decision-making in investment processes (3Commas, 2025).

In parallel, Glassnode provides core on-chain metrics such as Net Unrealized Profit/Loss (NUPL) and whale movement indicators. These variables are increasingly integrated into AI-driven trading systems to identify potential liquidity distribution or accumulation zones, thereby contributing to the construction of dynamic pricing models (Liu et al., 2022).

Similarly, Nansen plays a central role in analyzing institutional investor behavior and smart money flows by tracking capital movements on blockchain networks and linking transactions to influential entities and wallets. This data enables a more accurate understanding of liquidity dynamics and investment flows, offering early signals of potential shifts in market sentiment (Nansen, 2025).

1.3. Financial and Macroeconomic Independent Variables

The pricing of cryptocurrencies in U.S. dollars justifies the inclusion of the U.S. Dollar Index, as well as major currency pairs such as the Japanese yen and Swiss franc exchange rates, in order to capture the strength of traditional fiat currencies. In this context, a stronger U.S. dollar is typically associated with a decline in high-risk assets, including cryptocurrencies. U.S. Treasury bond yields are also incorporated to measure opportunity costs and risk-free interest rates, as higher interest rate environments tend to divert liquidity away from crypto markets, thereby amplifying price volatility.

In addition, precious metals—gold, silver, platinum, and palladium—are included to capture hedging behavior and liquidity reallocation between safe-haven assets and high-risk assets such as cryptocurrencies during periods of financial stress. Furthermore, energy and commodity indices,

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including crude oil, natural gas, copper, wheat, and the S&P 500 index, are incorporated to account for key macroeconomic channels such as global inflation dynamics, supply chain costs, and energy prices, which directly affect cryptocurrency mining operations and their cost structures.

The Fear and Greed Index is also introduced to quantify psychological and behavioral forces driving market dynamics. In highly volatile markets such as cryptocurrencies, sentiment plays a crucial role in triggering price shocks. The inclusion of this variable allows the model to distinguish between volatility driven by rational or algorithmic, AI-based trading behavior and that generated by irrational human-driven fear or greed.

2. Study Period and Scope

The empirical analysis covers the period from 10 March 2016 to 14 March 2026, using daily data for all dependent and independent variables. The study focuses on Bitcoin and Ethereum as representative proxies of the cryptocurrency market.

3. Methodology of the Study

Random Forest Algorithm

To estimate model parameters and test the research hypotheses, the study employs the Random Forest algorithm within the R statistical programming environment. The selection of this machine learning approach is particularly relevant for financial time series modelling due to its strong capability to handle non-linear relationships and the extreme volatility characteristic of cryptocurrency markets. In addition, the method is structurally robust against overfitting through the aggregation of predictions generated by multiple independent decision trees (Breiman, L., 2001).

To ensure statistical robustness and out-of-sample generalizability, a strict data partitioning framework is adopted. The dataset is divided into a training set (80%) used for learning market behavioral patterns, and an independent test set (20%) used to evaluate predictive performance without any estimation bias. Furthermore, to enhance model stability within the training process, a 10-fold cross-validation procedure is implemented. This resampling technique divides the training data into ten subsets (folds), allowing the model to be iteratively trained and validated, thereby reducing estimation variance and improving parameter stability (Hastie et al., 2009).

To assess the actual impact of news-related and AI-related variables on predictive efficiency, the study compares two experimental specifications: a model including news and artificial intelligence variables, and a baseline model excluding them. The difference in predictive accuracy is quantified using the Root Mean Squared Error (RMSE), which is widely regarded as an appropriate metric for highly volatile financial markets. RMSE penalizes large forecasting errors more heavily by squaring residuals prior to averaging, making it particularly sensitive to abrupt price shocks (Chai & Draxler, 2014). Accordingly, a lower RMSE in the augmented model indicates statistically improved forecasting accuracy resulting from the inclusion of news variables.

The RMSE is computed as follows:

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

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where:

- y_i represents the actual observed values
- $\hat{y}_i$ represents the predicted values
- $(y_i - \hat{y}_i)$ represents the forecasting error for each observation
- Squaring the errors ensures all values are positive and assigns greater weight to large errors
- n denotes the total number of observations (actual–predicted pairs) used in the calculation
- $(y_i - \hat{y}_i)^2$ is the squared error for each observation, capturing the magnitude of deviation with higher sensitivity to large errors

The Mean Squared Error (MSE) is calculated as(Abdellaoui et al., 2025):

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

Finally, the RMSE is obtained by taking the square root of the MSE:

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

Third: Results Analysis and Discussion

This section marks the transition from the theoretical and methodological framework to the estimation and interpretation of the machine learning models, specifically those based on the Random Forest algorithm. The primary objective is to assess the importance of generative artificial intelligence tools, specialized financial trading platforms, and a set of financial and monetary variables in forecasting cryptocurrency volatility. In particular, the analysis seeks to evaluate their explanatory power with respect to the price dynamics and volatility patterns of Bitcoin and Ethereum.

1. Analysis of the Random Forest Results for Bitcoin

Based on the outputs of the Random Forest algorithm and using the **Percentage Increase in Mean Squared Error (%IncMSE)** indicator—which measures the deterioration in predictive accuracy resulting from the exclusion of a given variable—the determinants of Bitcoin volatility can be classified into three structural levels. This measure provides a quantitative assessment of the relative importance of each explanatory variable within the forecasting framework. The following table presents the resulting classification.

Table 1: Variable Importance Results from the Random Forest Model for Bitcoin

Variable	%IncMSE	Predictive Importance Rank	Variable	%IncMSE	Predictive Importance Rank	Variable	%IncMSE	Predictive Importance Rank
VIX	26.06	1	USBONDS	19.96	10	Glassnode	4.79	19
USD_JPY	25.98	2	Goldpr	19.94	11	Nansen	4.38	20
silverpr	23.41	3	COPPERpr	18.70	12	CLAUDE	3.63	21
GASpr	23.04	4	PLATINUMpr	17.09	13	CHATGPT	3.36	22

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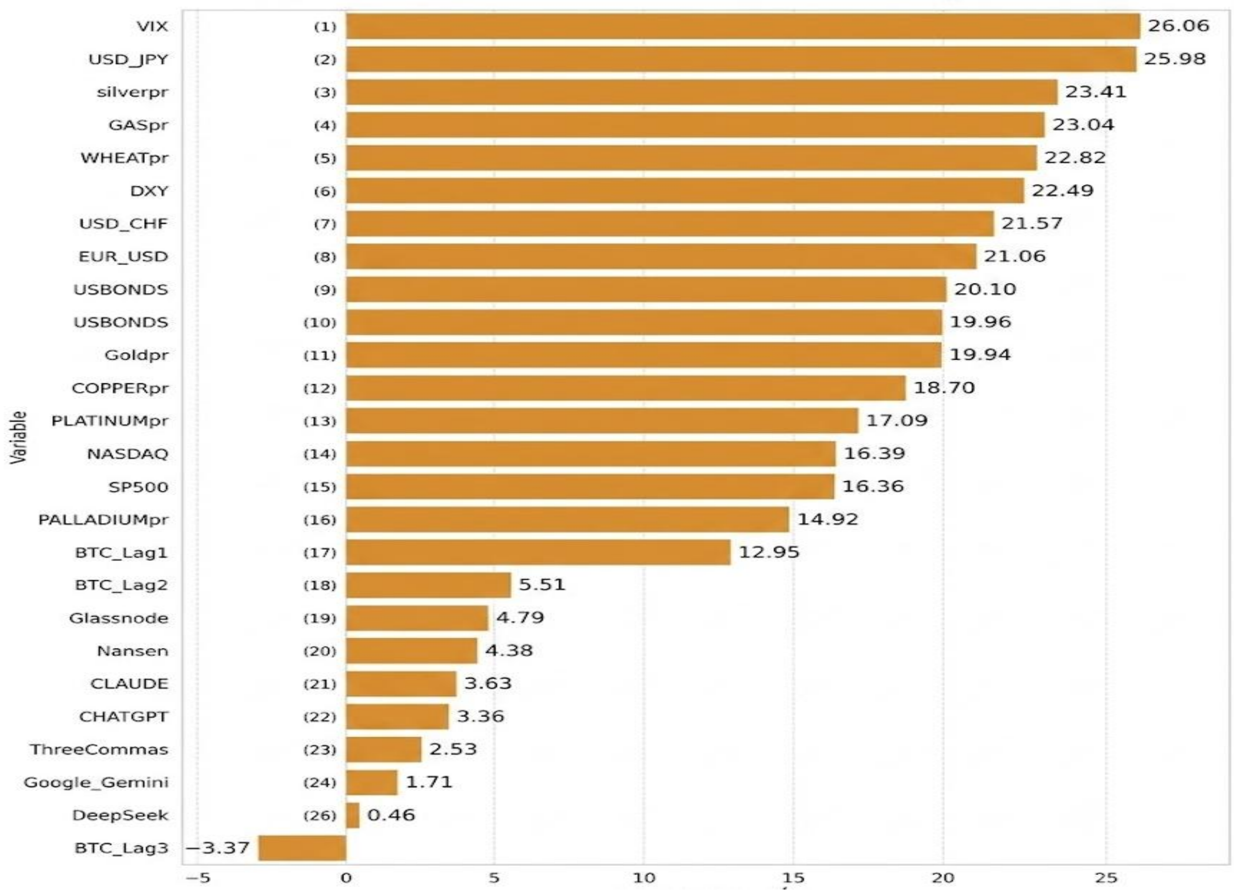
Variable	%IncMSE	Predictive Importance Rank	Variable	%IncMSE	Predictive Importance Rank	Variable	%IncMSE	Predictive Importance Rank
WHEATpr	22.82	5	NASDAQ	16.39	14	3Commas	2.53	23
DXY	22.49	6	SP500	16.36	15	Google_Gemini	1.71	24
USD_CHF	21.57	7	PALLADIUMpr	14.92	16	DeepSeek	0.46	25
EUR_USD	21.06	8	BTC_Lag1	12.95	17	BTC_Lag3	-3.37	26
USBONDS	20.10	9	BTC_Lag2	5.51	18			

Source: Authors' own elaboration based on R software outputs

This is illustrated in the following figure:

Figure 1: Variable Importance Results from the Random Forest Model for Bitcoin.



Source: Authors' own elaboration based on R software outputs

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1.1. The Dominance of Psychological Factors and Macroeconomic Dynamics in Explaining Bitcoin Volatility According to the Random Forest Model

The results reveal the predominance of macroeconomic and traditional financial market variables, confirming that Bitcoin does not operate in isolation but rather behaves as an asset that is highly sensitive to global liquidity conditions and macroeconomic cycles.

- **Volatility shocks:** The **Volatility Index (VIX)** ranked first, with the highest contribution rate (**%IncMSE = 26.06%**). This finding provides statistical evidence that Bitcoin is priced as a **risk-on asset**. Periods of heightened uncertainty and fear in traditional financial markets immediately affect Bitcoin liquidity and valuation, reflecting the close relationship between institutional investor sentiment and cryptocurrency market volatility.

- **International foreign exchange market dynamics:** Currency pairs and the U.S. Dollar Index (**USD/JPY, DXY, USD/CHF, and EUR/USD**) occupied the highest ranks, with importance values ranging from **21% to 25.98%**. The exceptional importance of the **USD/JPY** exchange rate highlights the role of carry-trade strategies and the influence of monetary policy decisions by the **Bank of Japan** and the **Federal Reserve** in directing global liquidity toward digital assets. Likewise, the significance of the **DXY** confirms that Bitcoin volatility largely reflects the inverse pricing of U.S. dollar strength.

- **Strategic commodities and safe-haven assets:** Commodities such as **silver, natural gas, wheat, and crude oil** formed a substantial explanatory block. This finding underscores the debated role of Bitcoin as an inflation hedge, as its volatility responds strongly to supply and demand shocks in the real economy as well as to energy costs that directly affect cryptocurrency mining operations.

Overall, the Random Forest results clearly indicate that Bitcoin volatility during the study period is driven less by internal cryptocurrency market factors and more by the broader global financial environment and macroeconomic conditions governing international liquidity flows and risk aversion. The **VIX** emerged as the most influential predictor (**%IncMSE = 26.06%**), suggesting that any deterioration in global risk appetite is rapidly transmitted to Bitcoin markets. This supports the contemporary view that Bitcoin functions primarily as a speculative high-risk asset rather than as an independent safe-haven asset.

This conclusion is further reinforced by the high predictive importance of foreign exchange variables and the U.S. dollar index (**USD/JPY, DXY, USD/CHF, and EUR/USD**) in explaining Bitcoin price volatility and directional movements. These results highlight Bitcoin's sensitivity to changes in global monetary conditions and interest rate differentials among major economies, particularly given the central role of the U.S. dollar in shaping global liquidity dynamics. The prominence of **USD/JPY**, in particular, reflects the growing importance of low-cost financing strategies, whereby shifts in Japanese and U.S. monetary policies reallocate capital between traditional and digital assets. Similarly, the strong contribution of the **DXY** suggests that a significant share of Bitcoin volatility is associated with the repricing of the dollar's global purchasing power and changing international monetary conditions.

1.2. The Short-Term Memory of Bitcoin Volatility According to the Random Forest Model

The lagged variables exhibit behavior consistent with the **weak-form market efficiency hypothesis**.

- The first lagged variable (**BTC_Lag1**) demonstrated a meaningful explanatory contribution (**12.95%**), indicating the presence of short-term memory effects or momentum within the market.

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- In contrast, the third lagged variable (**BTC_Lag3**) recorded a negative value (**−3.37%**). Within the Random Forest framework, a negative importance value implies that the variable introduces noise into the model and reduces forecasting accuracy. This finding suggests that Bitcoin rapidly absorbs new information and shocks, causing its predictive memory to dissipate over relatively short horizons.

The results associated with Bitcoin's lagged variables provide important insights into the dynamic structure of cryptocurrency market volatility, particularly the short-lived persistence of shocks and their rapid convergence toward dissipation. The explanatory importance of **BTC_Lag1 (12.95%)** indicates a limited degree of temporal dependence and price momentum, whereby the effects of recent information and shocks continue to influence volatility in immediately subsequent periods. This reflects a gradual market adjustment process in which new information—whether related to macroeconomic developments or cryptocurrency-specific events—is incorporated into prices over a short period, allowing a portion of volatility to be transmitted from one period to the next.

From an economic perspective, this finding is consistent with the behavioral characteristics of digital asset markets, where sequential reactions by retail and institutional investors to news and market developments generate temporary patterns of price momentum and short-term volatility persistence before information becomes fully absorbed.

The most significant result, however, is the sharp decline in the importance of subsequent lagged variables, culminating in the negative contribution of **BTC_Lag3 (−3.37%)**. Economically, this outcome is highly meaningful within the Random Forest framework. A negative value does not merely indicate weak explanatory power; rather, it suggests that the information contained in this variable provides no additional predictive value and may actually impair forecasting performance by introducing outdated historical patterns that are no longer relevant to current market conditions. This implies that Bitcoin volatility does not exhibit the long-memory characteristics often observed in traditional financial markets. Instead, it is characterized by a rapid absorption and repricing of information, rendering older shocks progressively irrelevant over relatively short time horizons.

In other words, the influence of past information decays rapidly over time, making contemporaneous events and current macroeconomic conditions far more important than distant historical price movements in explaining future volatility. These findings suggest that Bitcoin markets approximate the characteristics of **weak-form informational efficiency**, at least with respect to short-term volatility dynamics, since publicly available information appears to be incorporated into prices relatively quickly. Nevertheless, market efficiency does not appear to be complete, given the still-significant contribution of **BTC_Lag1**, which implies the existence of brief temporal windows during which past volatility can influence subsequent volatility before its effects vanish.

Consequently, Bitcoin markets do not appear to suffer from a persistent inability to process information efficiently; rather, they exhibit only a limited and temporary delay in the transmission of shocks. This delay dissipates rapidly due to the high intensity of trading activity and the continuous flow of news and information.

These findings also reflect the unique nature of cryptocurrency markets relative to traditional financial markets. Cryptocurrency trading operates continuously, twenty-four hours a day, and is characterized by high liquidity and instantaneous global information flows through digital platforms and social media. These features accelerate the absorption of shocks and the reassessment of investment expectations. As a result, contemporaneous external factors—particularly those related to global risk conditions, monetary policy, and exchange rates—possess greater explanatory power for future volatility than distant historical patterns, which explains why macroeconomic variables occupy the highest ranks in the Random Forest model while lagged variables exhibit a sharp decline in importance.

Moreover, these findings are consistent with a broad body of empirical literature suggesting that cryptocurrency markets are characterized by short-term volatility persistence followed by rapid

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dissipation of historical effects. They align with studies indicating that the predictive influence of historical information in Bitcoin markets declines over time as market efficiency improves. For example, **(Urquhart, 2016)** found that Bitcoin exhibited signs of inefficiency during its early stages of development, although subsequent evidence suggested improvements in market efficiency. Similarly, **(Nadarajah & Chu, 2017)** documented several characteristics consistent with weak-form efficiency when appropriate statistical transformations and testing procedures were applied. Furthermore, **(Bariviera, 2017)** showed that long-memory properties in Bitcoin returns gradually diminished as the market matured, with return dynamics becoming increasingly consistent with the Efficient Market Hypothesis. Therefore, the limited predictive importance of lagged variables observed in the present study—particularly the sharp decline in the contribution of more distant lags—reflects the rapid incorporation of new information and shocks into the market, making contemporary economic and financial variables more effective predictors of future volatility than distant historical information.

1.3. Interpreting the Impact of Artificial Intelligence Variables According to the Random Forest Algorithm

It should be emphasized that artificial intelligence is not merely represented by software tools such as successive versions of generative AI applications. Rather, it constitutes a massive capital-expenditure cycle and a large-scale technological infrastructure driven by dominant technology firms such as Microsoft, Alphabet, Meta Platforms, and NVIDIA. These corporations account for a substantial proportion of the Nasdaq-100 index. Consequently, any breakthrough in artificial intelligence algorithms or improvements in data-processing capabilities is rapidly reflected in the market valuation of these firms. The Nasdaq index therefore serves as a real-time quantitative proxy that translates the economic value and market impact of AI innovations into measurable financial indicators, making it one of the most effective measures of technological shocks (Pastor & Veronesi, 2009).

Furthermore, the economics of artificial intelligence and the cryptocurrency economy—particularly Bitcoin—share a common foundation based on computational power and semiconductor technologies. Periods of rapid AI expansion typically stimulate demand for advanced chips and computing infrastructure, thereby boosting the valuation of technology firms listed on Nasdaq. This process generates a positive wealth effect among technology-oriented investors and encourages liquidity flows toward digital assets that exhibit a similar risk profile. Consequently, fluctuations in the Nasdaq index can be interpreted as a reflection of investors' risk appetite toward frontier technological innovations, with Bitcoin representing one of the most closely associated speculative assets (Adrian et al., 2022).

It is also important to distinguish between AI-driven analytical platforms and broader technology-market indicators. While platforms such as Glassnode capture real-time blockchain activity, the Nasdaq index primarily prices future expectations. When financial markets value technology stocks based on anticipated productivity gains and economic transformation generated by generative AI, these expectations often spill over into cryptocurrency markets, which are increasingly perceived as components of the future digital economy. This mechanism helps explain why Nasdaq exhibits greater explanatory power for Bitcoin volatility than the S&P 500, whose composition remains more heavily weighted toward mature sectors that are comparatively less responsive to technological disruptions.

On the other hand, the empirical results indicate that AI-related variables and analytical platforms (Glassnode, Claude, ChatGPT, and DeepSeek) occupy relatively low positions in the importance ranking, with explanatory contributions generally below 5%. From an analytical perspective, this finding should not be interpreted as evidence against the hypothesis that artificial intelligence influences Bitcoin volatility. Rather, it reveals important insights regarding the microstructure of the cryptocurrency market.

First, artificial intelligence appears to function primarily as an information-transmission mechanism rather than a fundamental driver of market volatility. Generative AI tools and analytical platforms accelerate the processing of large datasets and support decision-making processes. AI-driven trading

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systems typically analyze information derived from volatility indices, exchange rates, interest rates, and other macro-financial indicators before generating trading signals. Consequently, the Random Forest algorithm identifies the underlying economic determinants of market fluctuations while assigning lower importance to the technological tools that merely facilitate the transmission and processing of information.

Second, the results suggest a distinction between the short-term and structural effects of artificial intelligence. Generative AI applications and algorithmic trading systems may amplify market reactions to news and information, thereby generating substantial volatility over very short horizons measured in minutes or hours. However, these effects tend to dissipate rapidly. Over longer time horizons, macroeconomic fundamentals, monetary policy conditions, and global liquidity dynamics remain the dominant determinants of cryptocurrency price volatility.

The relatively low ranking of AI variables therefore implies that artificial intelligence does not constitute an autonomous source of market shocks. Instead, it acts as an advanced mechanism for information processing and accelerating the incorporation of information into asset prices. Most AI-based trading and analytical systems derive their decisions from existing economic and financial data rather than generating independent market signals. As a result, when the Random Forest algorithm evaluates variable importance, it prioritizes the underlying drivers of volatility while assigning lower significance to technologies that merely facilitate information transmission.

These findings further highlight a fundamental distinction between the instantaneous and structural roles of artificial intelligence within cryptocurrency markets. While AI applications may increase the speed of information diffusion and contribute to short-lived volatility episodes, they do not appear to generate independent long-term volatility patterns. Rather, their principal contribution lies in enhancing price discovery and improving market efficiency through faster information incorporation (Fang et al., 2022). This explains why AI-related variables fail to achieve predictive importance comparable to indicators such as the VIX, DXY, or major commodity prices in explaining overall Bitcoin volatility.

Moreover, the results reflect the increasing maturity of the Bitcoin market. As institutional adoption of AI-based analytical and quantitative tools has become widespread, these technologies have evolved into standard components of market infrastructure rather than unique sources of informational advantage. Once a technology becomes broadly accessible to market participants, its independent explanatory power naturally declines because its effects become implicitly embedded in market prices. Consequently, the economic value of artificial intelligence is manifested less through its ability to alter broad market trends and more through its capacity to accelerate market reactions and reduce the time lag between information arrival and price adjustment.

1.4. Explaining the Higher Predictive Importance of Digital Asset Analytics and Trading Platforms Relative to Generative AI Tools in Forecasting Bitcoin Volatility According to the Random Forest Algorithm

The empirical results indicate that digital asset analytics and trading platforms exhibit greater predictive importance for Bitcoin volatility than generative AI tools. This outcome should not be interpreted as evidence of technological superiority of these platforms over AI models. Rather, it reflects the structure of information generation and transmission within the Bitcoin market and the manner in which information is transformed into pricing signals within the Random Forest framework.

The platforms that rank highest within this category—Glassnode, Nansen, and ThreeCommas—are not primarily artificial intelligence systems. Instead, they function as direct or near-direct sources of market information. In contrast, models such as Claude, ChatGPT, Gemini, and DeepSeek constitute secondary interpretative layers that rely on information already generated by the market.

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The superior performance of Glassnode (rank 19), Nansen (rank 20), and ThreeCommas (rank 23) can be explained by the nature of the signals they provide. Glassnode and Nansen specialize in on-chain analytics and deliver quasi-fundamental information concerning wallet flows, whale activity, supply distribution, and liquidity movements across blockchain networks. These indicators are directly linked to the underlying supply-and-demand dynamics of Bitcoin and therefore possess a closer causal and temporal relationship with volatility generation than higher-level interpretative tools (Liu et al., 2022).

Similarly, ThreeCommas functions as an automated trading and portfolio-management platform that reflects actual execution behavior within the market. By capturing trading decisions and algorithmic execution processes, it provides insights into realized market behavior rather than merely analyzing market conditions. This characteristic grants it relatively greater explanatory power than generative AI systems.

In contrast, generative AI models such as Claude (rank 21), ChatGPT (rank 22), Gemini (rank 24), and DeepSeek (rank 25) occupy lower positions because their primary role is not to generate original financial signals but rather to interpret existing information. These models rely predominantly on news articles, analytical reports, and general market indicators rather than possessing direct access to real-time transaction flows or granular behavioral data. Consequently, they function primarily as cognitive and interpretative layers rather than generators of original market information (Makarov & Schoar, 2020).

From a market-structure perspective, the Random Forest algorithm assigns greater importance to variables that contain information closest to the point of price formation. This explains why Glassnode and Nansen outperform generative AI tools: they capture actual supply dynamics within blockchain networks, while ThreeCommas reflects real trading execution behavior. Generative AI systems, by contrast, operate further downstream in the information-production chain, where raw data are transformed into interpretation, summarization, and recommendations.

This ranking can also be explained by differences in information-transmission timing. Variables that are temporally closer to market events—such as wallet transfers, liquidity movements, and trading orders—possess greater explanatory power for short-term volatility. Generative AI models inherently face a relative delay because they depend on collecting, processing, and synthesizing information. Consequently, they are better suited for qualitative interpretation and strategic analysis than for direct prediction of high-frequency volatility fluctuations.

Ultimately, this ranking reflects a fundamental structural characteristic of the Bitcoin market: market volatility is driven primarily by what occurs within the market itself rather than by external commentary or interpretation of market developments. As a result, advanced analytics and automated trading platforms occupy an intermediate position between primary market data and higher-level interpretative systems, whereas generative AI tools remain positioned further downstream in the financial signal-production process rather than at its origin.

2. Analysis of Random Forest Results for Ethereum

In continuation of the adopted econometric approach, Table (2) and Figure (2) present the ranking of explanatory variables for Ethereum (ETH) volatility based on the Mean Increase in Squared Error (%IncMSE) index

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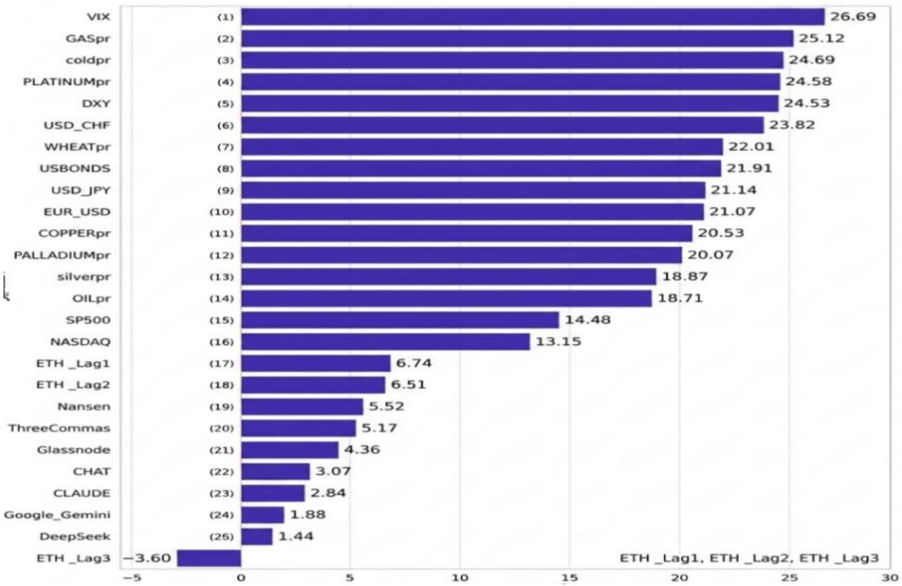
Table 2: Variable Importance Results from the Random Forest Model for Ethereum

Variable	%IncMSE	Importance Rank	Variable	%IncMSE	Importance Rank	Variable	%IncMSE	Importance Rank
VIX	26.69	1	EUR_USD	21.07	10	Nansen	5.52	19
GASpr	25.12	2	COPPERpr	20.53	11	3Commas	5.17	20
coldpr	24.69	3	PALLADIUMpr	20.07	12	Glassnode	4.36	21
PLATINUMpr	24.58	4	silverpr	18.87	13	ChatGPT	3.07	22
DXY	24.53	5	OILpr	18.71	14	Claude	2.84	23
USD_CHF	23.82	6	SP500	14.48	15	Google Gemini	1.88	24
WHEATpr	22.01	7	NASDAQ	13.15	16	DeepSeek	1.44	25
USBONDS	21.91	8	ETH _Lag1	6.74	17	ETH Lag3	-3.60	26
USD_JPY	21.14	9	ETH _Lag2	6.51	18			

Source: Authors' own elaboration based on R software outputs

This is illustrated in the following figure:

Figure 2: Variable Importance Results from the Random Forest Model for Ethereum.



Source: Authors' own elaboration based on R software outputs

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Although the results exhibit a general structural similarity to Bitcoin—namely the dominance of macroeconomic factors and the relatively delayed importance of artificial intelligence variables—the Ethereum output reveals a distinct pricing footprint that can be interpreted through the following economic dimensions:

2.1. Excess Sensitivity to Global Volatility and Ethereum as a Technological Commodity

The results indicate that Ethereum is not priced solely as a digital financial asset, but rather as a technologically embedded infrastructure highly exposed to real-economy dynamics and energy shocks:

- **Dominance of the volatility index:** The VIX index ranks first in importance (26.69%), with an even higher relative impact than in Bitcoin. This suggests that Ethereum exhibits a higher risk coefficient, making it more vulnerable to rapid institutional liquidity withdrawals during episodes of financial stress and market panic.

- **Surge in energy and industrial metal variables:** Unlike Bitcoin, natural gas prices (GASpr) rank second (25.12%), followed by gold prices (Goldpr) in third place and platinum prices (PLATINUMpr) in fourth place. Economically, Ethereum operates as a global computational infrastructure driven by smart contracts, which makes its cost structure highly sensitive to global energy prices. Moreover, the strong significance of industrial metals such as platinum and copper supports the interpretation of Ethereum as a quasi-industrial digital commodity whose valuation is closely linked to real technological production cycles (Corbet et al., 2020).

2.2. Exchange Rate Dynamics and Weak Price Memory

- Major currency pairs and the US dollar index (DXY, USD_CHF, USD_JPY, EUR_USD) maintain prominent positions in the ranking (positions 5 to 10), confirming that cryptocurrency liquidity remains structurally dominated by the US dollar and is strongly influenced by monetary policy conditions set by major central banks.

- Regarding lagged variables, ETH_Lag1 and ETH_Lag2 show weak explanatory power (6.74% and 6.51% respectively), while ETH_Lag3 records a negative value (-3.60%). This rapid decay in predictive memory indicates that Ethereum markets exhibit high informational efficiency, with prices quickly absorbing new information and showing limited reliance on historical dynamics to generate short-term volatility.

2.3. The Superiority of Decentralized Finance Platforms over Generative AI Models

Ethereum-related results also reshape the ranking of specialized analytical platforms in line with its technological architecture:

- **Nansen's outperformance over Glassnode:** Nansen ranks 19th, ahead of ThreeCommas (20th) and Glassnode (21st). From an academic standpoint, this reflects the fact that Nansen specializes in tracking decentralized finance (DeFi) portfolios and non-fungible token (NFT) flows, both of which are primarily built on the Ethereum network (ERC-20 standard). Its higher explanatory power indicates a superior ability to capture smart liquidity movements within the Ethereum ecosystem before they are reflected in market prices (Werner et al., 2022).

- **Persistent lag of large language models (LLMs):** AI tools such as ChatGPT, Claude, Google Gemini, and DeepSeek remain in the lowest ranks (22nd to 25th) with marginal explanatory significance. Although their contribution slightly improves relative to Bitcoin—possibly due to the linguistic and informational complexity surrounding Ethereum network upgrades—the structural pattern remains unchanged. Generative AI functions as a

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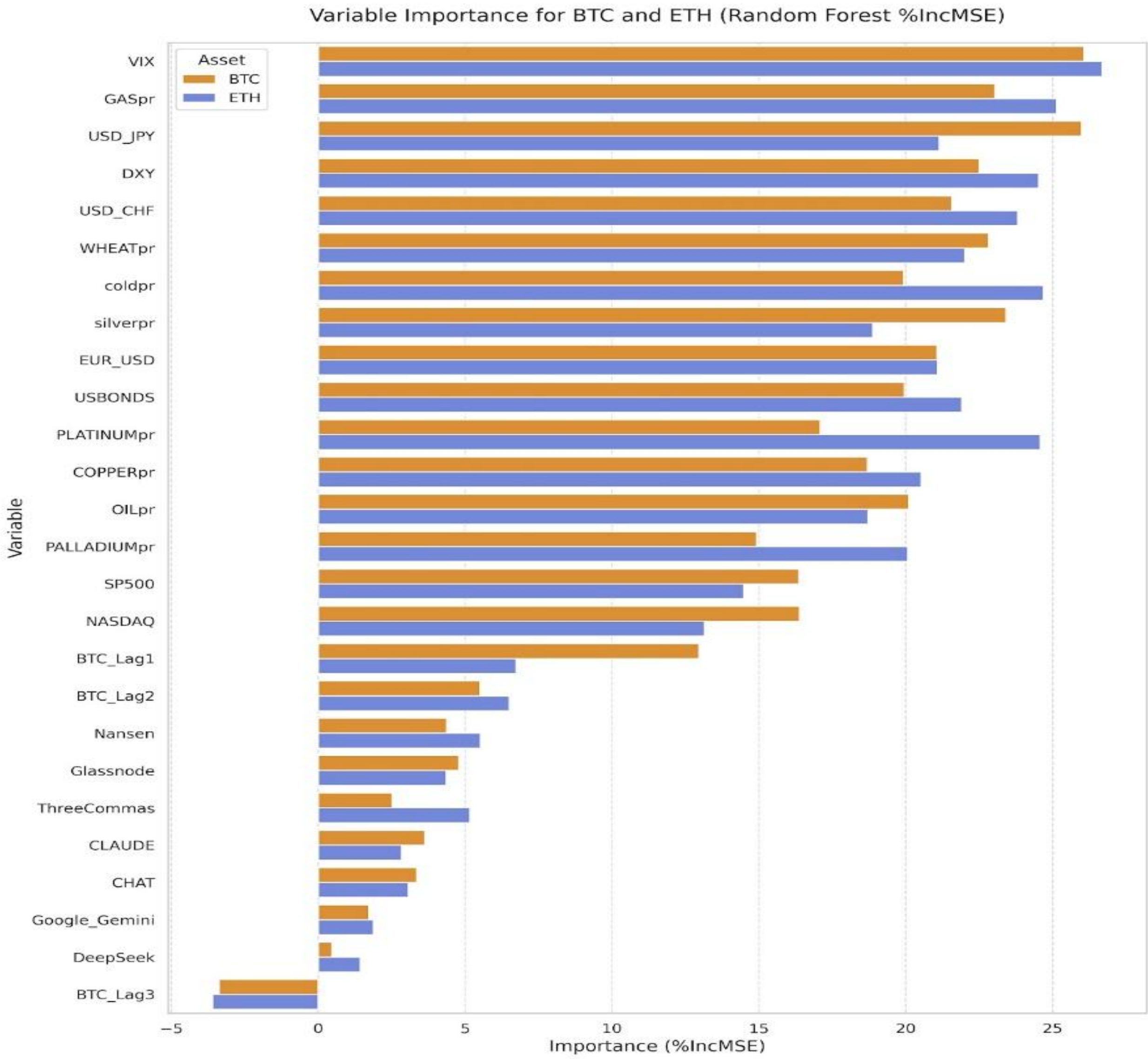
delayed cognitive layer, whereas on-chain analytics and macro-financial variables act as the primary drivers of price shocks and volatility formation.

3. Comparison of Random Forest Results for Bitcoin and Ethereum

The outputs of the Random Forest model reveal a strong structural consistency in the dominance of macroeconomic variables across both assets. However, differences in the ranking of certain variables highlight fundamental divergences in the economic nature and pricing identity of each cryptocurrency.

Figure 3: Comparison of Random Forest Results for Bitcoin and Ethereum



Source: Authors' own elaboration based on R software outputs

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The differences can be highlighted as follows:

3.1. Pricing Identity: Bitcoin as a Speculative Monetary Asset vs. Ethereum as a Digital Industrial Utility

- **Bitcoin:** Its identity as a monetary and speculative asset is reflected in the strong influence of currency pairs (e.g., USD/JPY) and the U.S. Dollar Index (DXY) in the top ranks. This confirms that Bitcoin volatility is primarily driven by an inverse pricing mechanism linked to global liquidity conditions and monetary dynamics (Liu, Tsyvinski, & Wu, 2022).

- **Ethereum:** In contrast, Ethereum behaves more like a technological infrastructure asset. The prominence of gas prices (rank 2) and industrial metals such as platinum (rank 4) indicates that its price dynamics are closely tied to operational costs (notably energy inputs) and real technological production cycles. This supports the interpretation of Ethereum as a functionally oriented digital commodity embedded within the broader technological production system (Corbet, et al, 2020).

3.2. Semantic Shift in Equity Market Sensitivity (S&P 500 vs NASDAQ)

A notable inversion appears in the relative importance of U.S. equity indices across the two assets:

- **Bitcoin:** The NASDAQ index exhibits stronger explanatory and predictive power (rank 14) than the S&P 500 (rank 15), reflecting Bitcoin's tight linkage to technology shocks, artificial intelligence dynamics, and its pricing as a high-risk technology-driven asset.

- **Ethereum:** The S&P 500 (rank 15) slightly outperforms NASDAQ (rank 16). This divergence can be explained by Ethereum's institutional and structural integration into decentralized finance (DeFi) and smart contract ecosystems. Consequently, Ethereum is more exposed to broader macro-financial and real-sector dynamics represented by the S&P 500, rather than being purely driven by technology-sector cycles and speculative innovation waves (Adrian, et al, 2022).

3.3. Information Efficiency and Shock Absorption

Lagged variables exhibit substantially weaker effects in Ethereum compared to Bitcoin. Specifically, **ETH_Lag1** shows a lower impact (6.74%) versus **BTC_Lag1** (12.95%). This statistically confirms that Ethereum markets display higher informational efficiency and a shorter price memory than Bitcoin markets. Information, liquidity shocks, and news are rapidly incorporated into prices with minimal persistence in volatility dynamics (Caporale, et al, 2018).

Economically, this behavior can be explained by several structural considerations that distinguish Ethereum from Bitcoin. Ethereum is not solely viewed as a digital asset for speculation or a store of value; rather, it represents the foundational infrastructure for a vast ecosystem of decentralized applications (dApps), decentralized finance (DeFi), smart contracts, and non-fungible tokens (NFTs). This significant diversity in demand sources and use cases generates a continuous flow of new information related to economic activity within the network itself, making investors more reliant on current developments than on historical price patterns. Consequently, current volatility becomes a reflection of the ongoing technical, operational, and economic developments within the Ethereum ecosystem, rather than merely a mechanical extension of past volatility (Cong, L. W., Li, Y., & Wang, N., 2021).

From another perspective, this disparity may reflect a difference in the nature of the investors themselves. Bitcoin is still largely traded as an independent investment or speculative asset, which allows the effects of behavioral shocks and price momentum to persist for a relatively longer period. Conversely, Ethereum's value is tied to a broad spectrum of economic activities within the network. This makes its valuation more correlated with continuous information flows and fundamental variables associated with the dApps ecosystem, and consequently less dependent on short-term price memory (Baur, D. G., & Dimpfl, T., 2018).

3.4. Information Architecture, Data Platforms, and Generative AI Tools:

- **The Lag of Large Language Models (LLMs):** For both cryptocurrencies, Bitcoin and Ethereum, general generative AI applications such as ChatGPT and Claude ranked at the bottom, confirming their role as a "cognitive layer" that interprets shocks rather than creating them (Makarov, I., & Schoar, A., 2020).

- **Smart Liquidity:** The (Nansen) platform outperformed in Ethereum (ranked 19th) compared to (Glassnode) in Bitcoin. This reflects Ethereum's nature as a centralized hub for decentralized finance (DeFi), where predictive value is concentrated in tracking "smart liquidity" wallets rather than merely measuring general supply and demand (Werner, S. M., Perez, D., Gudgeon, L., Klages-Mundt, A., Harz, D., & Knottenbelt, W. J., 2022).

Ultimately, the results regarding the digital information architecture reveal a clear gradation in the predictive value of data sources within cryptocurrency markets. Specialized platforms dedicated to collecting and analyzing native market data outperform general generative AI applications. Large Language Models (LLMs) such as ChatGPT and Claude, as well as Google Gemini and DeepSeek, were concentrated in the lower ranks regarding explanatory and predictive importance for both Bitcoin and Ethereum. This reflects the nature of their role within the digital financial ecosystem. These models lack direct access to price formation mechanisms or actual liquidity flows; instead, they function primarily as a cognitive layer that aggregates, analyzes, reformulates, and interprets available information.

Therefore, their impact remains indirect, as they inherently rely on economic, financial, and blockchain-extracted data produced by other entities. Consequently, the Random Forest model does not assign them high importance, as it favors variables closer to the source of the economic or financial shock itself. In other words, generative AI models accelerate the comprehension and dissemination of information among investors, but they do not, in themselves, constitute an independent structural factor capable of directly generating or explaining volatility.

Conversely, the results demonstrate that predictive value increases the closer the data source is to real economic activity within the network. This phenomenon is more pronounced in the case of Ethereum, where Nansen achieved a better ranking than similar platforms used for Bitcoin analysis. This can be explained by the distinct economic nature of each network. Bitcoin primarily serves as a store of value and an investment asset (Baur, D. G., Hong, K., & Lee, A. D., 2018); hence, essential information surrounding it is concentrated on circulating supply, large wallet movements, and cross-exchange flows. Ethereum, however, represents an integrated economic infrastructure encompassing decentralized finance (DeFi), smart contracts, lending platforms, staking, liquidity provision, and non-fungible tokens (NFTs) (Makarov, I., & Schoar, A., 2022). This makes tracking the behavior of smart wallets and institutional investors more crucial than merely monitoring the movement of the coins themselves.

From this premise, Nansen's superiority in the case of Ethereum reflects the rise of what can be termed "smart liquidity"—that is, liquidity managed by institutional wallets, professional investors, or advanced financial protocols possessing a greater capacity to rapidly absorb and react to information. The movement of these wallets does not merely represent standard financial transfers; rather, they carry proactive signals regarding investment trends, asset reallocation, and major market players' expectations concerning future risks and returns. Therefore, their data acquires a high predictive value for Ethereum's volatility. In Bitcoin, the importance of data remains more closely tied to macroeconomic supply and demand indicators and capital movements between wallets and exchanges (Makarov, I., & Schoar, A., 2022). This explains the relative importance of network analysis platforms, though they do not reach the predictive level achieved by smart liquidity tracking tools within the Ethereum ecosystem.

These results indicate a fundamental difference between the two cryptocurrencies regarding the nature of information influencing volatility. While Bitcoin relies more heavily on information related to aggregate capital flows and global macroeconomic conditions, Ethereum is far more dependent on information linked to internal economic activity within the network itself (Cong, L. W., Li, Y., & Wang, N., 2021). Therefore, data extracted from the behavior of smart wallets and decentralized applications gains higher importance in explaining Ethereum's volatility compared to Bitcoin. Thus, the results do not merely reflect a discrepancy in the performance of analytical platforms; they also unveil a structural divergence in price formation mechanisms between a digital asset primarily serving a savings and investment function, and a digital platform representing an integrated economic system where multiple financial and productive activities continuously interact.

Ultimately, it can be concluded that investors and hedge funds do not treat Bitcoin and Ethereum as identical assets within their risk profiles. While Bitcoin is utilized as a financial instrument reflecting fluctuations in monetary policy and exchange rates, Ethereum is traded as an "operational asset" whose cost and demand are linked to industrial production and the state of traditional markets. Furthermore, general generative AI does not play a significant role in creating volatility for either cryptocurrency; rather, technological predictive power is concentrated in specialized liquidity-tracking platforms tailored to the technological architecture of each network.

4. Conclusions and Comparison with Previous Empirical Studies:

The empirical estimations of the Random Forest algorithm demonstrated that global economic and financial factors represent the primary determinant of the movements of the studied crypto assets. The Volatility Index (VIX), alongside exchange market and global financial market indices, topped the list of the most important variables for both Bitcoin and Ethereum. This empirically proves that these markets are no longer isolated ecosystems but have fully integrated into global liquidity cycles.

Conversely, the results regarding AI variables such as ChatGPT, Claude, Gemini, and DeepSeek presented a structural paradox, positioning them in relatively lower ranks in terms of importance for predicting the price volatility of the studied cryptocurrencies. This finding indicates that these tools, despite their advancement, possess limited independent explanatory power for price shocks compared to traditional variables during the study period. However, the outperformance of specialized analytical platforms relying on machine learning algorithms—such as Glassnode, Nansen, and 3Commas—over general AI applications confirms a scientific reality: the actual value of AI in financial markets lies not in its ability to read and analyze general news, but in its capacity to process live on-chain data and execute direct algorithmic trading. This underscores the growing role of specialized data in the microstructure of digital asset markets.

The findings of the current study align with the conclusions of (Kim et al., 2016), which affirmed that textual data extracted from user comments and sentiment represents a vital source for enhancing the predictability of cryptocurrency volatility. This supports the importance of employing unstructured data in modern intelligent models.

Furthermore, the study's results are consistent with (Jiang et al., 2017), which demonstrated the effectiveness of deep reinforcement learning models in managing digital portfolios and adapting to rapid changes in crypto markets, reflecting the capability of AI technologies to handle highly volatile financial environments.

These findings also correspond with (McNally et al., 2018), which showed the superiority of Recurrent Neural Networks (RNN) and LSTM models over traditional statistical models in predicting Bitcoin prices, confirming the efficiency of deep learning models in capturing the nonlinear patterns of financial time series.

On the same subject, (Valencia et al., 2019) revealed that integrating sentiment analysis extracted from social media platforms with market data contributes to improving the accuracy of short-term cryptocurrency price trend predictions.

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Similarly, (Chen et al., 2020) confirmed that the effectiveness of machine learning models varies depending on the nature and frequency of the data, as intelligent models achieve better results when dealing with high-frequency data and complex dynamic patterns.

The current study's results also align with (Hamayel and Owda, 2021), which proved the ability of GRU and LSTM models to achieve high levels of accuracy in predicting the prices of Bitcoin, Ethereum, and other cryptocurrencies, with deep models excelling in absorbing severe market fluctuations.

The findings are also in agreement with (Amirzadeh et al., 2022), which concluded that deep and hybrid neural network models outperform traditional statistical models in interpreting nonlinear relationships and predicting cryptocurrency price movements and their volatility.

This result is consistent with (Wang et al., 2023), which proved that deep learning models are more efficient than traditional econometric models in predicting cryptocurrency volatility and managing its associated risks.

(Brini and Lenz, 2024) supported this trend by affirming the capacity of machine learning models to improve estimation and pricing accuracy, as well as handle the high levels of volatility characteristic of digital asset markets.

Finally, the current study's results agree with (Islam et al., 2025), which affirmed that machine learning models continue to achieve good predictive performance in cryptocurrency markets despite their characteristic high noise and volatility, thereby reinforcing the role of artificial intelligence in enhancing forecasting and investment decision-making.

In general, the accumulated empirical evidence in recent literature confirms that deep learning models and artificial neural networks have significantly contributed to improving the accuracy of financial volatility predictions, particularly in cryptocurrency markets characterized by a high degree of instability and dynamism. This is entirely consistent with the findings of the present study.

Conclusion

The estimation results derived from the Random Forest algorithm reveal various complex pricing dynamics within digital asset markets. The findings demonstrate that these assets do not operate in an isolated technological environment; rather, they are an organic extension of the global financial system. Their volatility is heavily dominated by macroeconomic indicators, international liquidity flows, financial panic shocks, and behavioral finance dimensions—specifically through panic, optimism, and herd behavior.

The results focused on tracking, exploring, and identifying the actual role of artificial intelligence tools and financial analysis platforms in price forecasting, which can be summarized in the following conclusions:

- Contrary to hypotheses positioning artificial intelligence as a primary driver of modern markets, the findings proved that Large Language Models (LLMs) such as ChatGPT, Claude, and Gemini did not rank highly in terms of predictive and explanatory power regarding the volatility of the studied cryptocurrencies. Economically, this confirms that these tools function as a cognitive and explanatory layer; they receive economic and financial shocks, analyze them, and accelerate their transmission to investors, but they lack the structural capacity to independently generate pricing shocks apart from macroeconomic fundamentals.

Furthermore, the model demonstrated the relative importance of variables reflecting investors' actual actions—namely, direct execution operations—over those reflecting opinions and analyses. Consequently, algorithmic trading platforms like ThreeCommas and live on-chain data analysis platforms outperformed general AI tools. Algorithms price what is actively occurring within order books and blockchains much faster and more accurately than what is written on news or generative platforms.

The results also revealed a divergence in technological identity and "smart liquidity" tracking between Nansen and Glassnode. This fundamental divergence stems from the nature of the effective platforms for each asset based on its economic identity. In the Ethereum network, which serves as the infrastructure for the Decentralized Finance (DeFi) ecosystem and smart contracts, the **Nansen** platform emerged as a superior predictive tool due to its ability to track smart liquidity and institutional wallets geared toward operational use. Conversely, the **Glassnode** platform retained its importance within the Bitcoin network, which is priced as a "store of value," where analytical significance is concentrated on reading aggregate supply indicators and holding/hoarding movements.

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