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The Impact of AI-Driven Predictive Models on Traditional Financial Market Volatility: A Comparative Study with Crypto Markets

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ABSTRACT
This study investigates the effectiveness of AI-driven predictive models in managing volatility in traditional financial markets compared to cryptocurrency markets. By examining the impact of these models on market stability, the research aims to identify best practices and areas for improvement in the deployment of AI technologies across different asset classes. We employed a Maximum Likelihood (ML) ARCH model to analyze market volatility, effectively capturing the time-varying volatility characteristics inherent in financial data. Our empirical framework integrates AI-driven metrics, such as volatility forecasts and sentiment scores, alongside control variables like interest rates and trading volumes. This allows for a comprehensive comparative analysis of model performance in traditional stock markets and cryptocurrency markets. Additionally, we incorporated various machine learning techniques, including Support Vector Machines and Long Short-Term Memory networks, to enhance prediction accuracy and robustness. The findings reveal that AI-driven models exhibit significantly superior predictive capabilities in cryptocurrency markets, attributed to higher data frequency and enhanced volatility reactivity. In contrast, traditional financial markets demonstrate more limited improvements in volatility management when utilizing AI technologies. Moreover, AI models substantially improve risk management practices, adapting more effectively to the dynamic conditions of cryptocurrency trading compared to conventional econometric approaches, as corroborated by previous empirical reviews. Based on these insights, we recommend that financial institutions adopt hybrid AI models tailored to the unique characteristics of both traditional and cryptocurrency markets. Continuous calibration and adaptation of AI systems should be prioritized, focusing on the specific behaviors and conditions of each asset class. Additionally, organizations should invest in training programs to enhance staff proficiency in AI applications. Finally, establishing regulatory frameworks governing the use of AI in financial markets is crucial to ensure transparency, accountability, and stability, thus fostering a more resilient financial ecosystem.

I. BACKGROUND TO THE STUDY

International economic systems depend on financial markets, and decision-making about investments, risk management, and policy formation are all greatly influenced by their volatility. In recent years, artificial intelligence (AI) has emerged as a disruptive technology in many areas, including banking. In order to identify patterns, anticipate market movements, and enhance trading strategies, machine learning algorithms and other AI-driven prediction models are being utilised. In the past, traditional financial markets like stocks, bonds, and commodities have employed statistical models like autoregressive moving averages (ARMA) and GARCH models to control volatility. On the other hand, the decentralised and extremely unpredictable nature of cryptocurrency markets has created a new environment for predictive modelling; as digital currencies proliferate, it will be interesting to examine how well AI-driven models predict movements in these markets as opposed to conventional ones. However, the emergence of AI technology has given market projections a new angle by providing more accurate, real-time forecasts through the use of neural networks and machine learning techniques (Jiang et al., 2021).

The swinging nature of financial markets creates uncertainty and the potential for financial losses, putting individuals and institutions at significant risk. Traditional financial markets have long employed well-established econometric models to monitor and forecast market volatility. However, the advent of AI-driven predictive algorithms in recent times has introduced novel approaches to forecasting and mitigating volatility. Studies that have successfully implemented these models in the comparatively new and very volatile cryptocurrency markets is still largely currently scanty, despite the fact that they show promise in traditional markets. Despite the growing use of AI technology in the banking sector, there is a death of sufficient empirical study comparing the effectiveness of AI-driven predictive models in traditional financial markets with cryptocurrency exchanges. Moreover, the unique characteristics of cryptocurrency markets—such as increased volatility, a looser regulatory environment, and 24-hour trading—present additional challenges for AI models that have traditionally been tested in less volatile markets. Consequently, the investigation addresses the following research questions: How do AI-driven predictive models affect volatility in traditional financial markets as opposed to cryptocurrency markets? What are the key differences between the way AI models handle risk in cryptocurrency markets and traditional financial markets?

II. LITERATURE REVIEW

2.1 Conceptual Review

To effectively explore the role of AI-driven predictive models in financial markets, it is vital to define several key concepts.

Artificial Intelligence (AI): AI refers to the simulation of human intelligence processes by machines, particularly computer systems. These processes include learning (acquiring information and rules for using it), reasoning (using rules to reach approximate or definite conclusions), and self-correction (Russell & Norvig, 2021). In finance, AI applications encompass a range of functions, from algorithmic trading and portfolio management to credit scoring and fraud detection. Recent advancements in machine learning, especially deep learning algorithms, have significantly enhanced decision-making capabilities by enabling financial institutions to analyze vast datasets quickly and derive actionable insights (Kira et al., 2021). As AI continues to evolve, its ability to adapt to new data and environments makes it a critical tool for navigating the complexities of modern financial markets (Chui et al., 2018).

This concept predictive modeling involves the use of statistical techniques and machine learning algorithms to identify patterns from historical data to predict future outcomes (Bose & Liu, 2019). In financial contexts, predictive modeling plays a crucial role in risk assessment, market forecasting, and investment strategies. For example, the application of regression analysis and neural networks has been shown to improve the accuracy of forecasts, allowing investors and institutions to anticipate market movements more effectively (Sullivan et al., 2021). Furthermore, predictive models can help mitigate potential losses by identifying trends before they manifest in actual market conditions, thereby facilitating more informed decision-making (Naimy &Akouay, 2022).

Volatility is a statistical measure of the dispersion of returns for a given security or market index, commonly expressed as the standard deviation or variance of returns (Black, 1976). High volatility indicates greater price fluctuations, which can signal increased risk and uncertainty in financial markets (Engle, 1982). Understanding volatility is essential for developing effective risk management strategies, as it helps investors gauge potential losses and adjust their portfolios accordingly (Poon & Granger, 2003). The emergence of AI-driven models has further transformed the analysis of volatility by utilizing complex algorithms to capture nonlinear relationships and forecast volatility more accurately than traditional econometric models (Feng et al., 2022).

Risk management involves identifying, assessing, and prioritizing risks, followed by coordinated efforts to minimize, monitor, and control the probability or impact of unfortunate events (ISO 31000, 2018). In finance, effective risk management is crucial for safeguarding investments and ensuring market stability. Traditional risk management approaches, such as Value-at-Risk (VaR) and stress testing, have been widely employed; however, the integration of AI into these processes has enhanced their robustness (Aït-Sahalia et al., 2020). AI technologies enable real-time risk assessment, allowing financial institutions to respond swiftly to emerging threats and adjust their strategies accordingly (Khan et al., 2021). Moreover, machine learning techniques can help identify previously overlooked risk factors, leading to more comprehensive risk management frameworks that can adapt to evolving market dynamics (Hawkes et al., 2023).

2.1 Theoretical Review

2.1.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH), developed by Eugene Fama in 1970, asserts that asset prices accurately reflect all available information and that it is not feasible to continuously beat the market employing forecasting or arbitrage strategies. This theory holds that price fluctuations in financial markets are "informationally efficient," or that new information is quickly absorbed into asset values, since they replicate a random walk. The Efficient Market Hypothesis (EMH), which maintains that all pertinent data has already been priced in, would thwart the notion that artificial intelligence could accurately forecast fluctuations in markets in the context of AI-driven prediction models. The Efficient Market Hypothesis (EMH) has generated debate on its applicability in modern AI-driven trading environments, with some detractors arguing that AI may identify inefficiencies in the markets which human speculators could have overlooked.

2.1.2 Behavioral Finance Theory

Behavioural finance theory emphasises on the psychological and emotional factors influencing investor behaviour, as opposed to the Efficient Market Hypothesis (EMH), which makes the assumption that decisions are made fully rationally. According to Daniel Kahneman and Amos Tversky's 1979 Prospect Theory, individual's financial choices are significantly influenced by their feelings and cognitive biases. This idea suggests that people's biases may be mitigated by AI-driven models that incorporate data-driven decision-making procedures. Because AI is capable of identifying trends that stem from illogical conduct, it can be a useful tool for managing fluctuations. This is particularly true in the bitcoin market, where speculations and investor attitude are important factors.

2.1.3 Adaptive Market Hypothesis (AMH)

The Adaptive Market Hypothesis (AMH) developed by Andrew Lo (2004) offers a flexible replacement for the EMH. It argues that market participants alter their actions over time in reaction to changing market conditions by drawing on concepts from biological evolution. Unlike EMH, AMH contends that markets can be less efficient and that behaviour among investors can adapt to changes in the environment and new information. This theory, which considers the use of AI-driven prediction models, postulates that advanced technology may be able to regulate volatility in both traditional and cryptocurrency markets more easily than human traders due to its ability to react to market movements more quickly.

The Adaptive Market Hypothesis (AMH) is the most appropriate theory to direct this study. It offers a flexible framework that considers the evolving nature of both conventional and cryptocurrency markets. AI-driven forecasting algorithms are appropriate to respond to shifting market conditions since they are always learning from fresh data and adjusting their estimates accordingly. AMH considers the sometimes illogical and dynamic characteristics of financial markets, while EMH posits constant market efficiency. This is particularly true in developing markets with high volatility and little-established information distribution, like cryptocurrency. By using AMH, this research looked into how AI can adapt to and possibly even benefit from inefficiencies in both traditional and cryptocurrency markets, providing insights into how it influences market volatility.

2.2 Empirical Review

Global Financial Stability Report (2024), the IMF examines the implications of artificial intelligence (AI) on capital market activities, focusing specifically on the emerging roles of AI and Generative AI (International Monetary Fund, 2024). The report aims to assess how these technologies are shaping capital markets, evaluating both the potential advantages and the risks associated with their integration.The report's approach combines new analytical work with insights gathered from a global outreach to market participants and regulators. It includes analyses of pricing patterns and trading dynamics to identify shifts that align with the adoption of AI technologies, providing a detailed assessment of AI's influence on market processes.The findings indicate that AI has the potential to significantly enhance market efficiency through process automation and the analysis of complex, unstructured data. However, the report also identifies possible structural shifts in the market, such as increased turnover, asset correlations, and a decrease in stability risks due to improved risk management and market monitoring capabilities enabled by AI.To mitigate emerging risks, the report recommends recalibrating circuit breakers and reviewing margining practices in anticipation of rapid, AI-driven price fluctuations. Enhanced monitoring and data collection efforts, particularly concerning the activities of large traders and nonbank financial intermediaries, are also suggested to maintain financial stability.

In the study of Safari et al., (2024)"Integrating Predictive Analytics and Mean-Variance Models for Cryptocurrency Portfolio Strategies." The authors investigate how ensemble learning approaches combining predictive analytics with traditional Mean-Variance models can improve portfolio optimization in cryptocurrency markets. This study's objective is to determine the effectiveness of predictive models in forecasting cryptocurrency prices to guide investment strategies.The study employed an ensemble of predictive models, including LSTM, BLSTM, GRU, DMLP, RF, XGBoost, and SVR, to enhance the accuracy of portfolio forecasting. These predictions are applied within portfolio strategies, namely Mean-Variance with Forecasting (MVF), Re-optimized Mean-Variance (RMV), and Forecast-Based Mean-Variance (FBMV) models, allowing the study to compare their outcomes against traditional models.The study's findings show that the Forecast-Based Mean-Variance (FBMV) model achieved superior performance, offering higher risk-adjusted returns and improved risk management in dynamic cryptocurrency markets. This suggests that predictive analytics integrated with Mean-Variance models can enhance the adaptability and resilience of cryptocurrency portfolios.The study concludes with recommendations for investors to adopt ensemble learning approaches to optimize portfolios effectively in volatile cryptocurrency markets. Additionally, it emphasizes the importance of continuous updating and monitoring of predictive models to remain aligned with rapidly shifting market conditions.

Ravi, Dholakiya&Bagga(2024), investigate "Artificial Intelligence and the Trader's Touch: A Comparative Study."The authors compare the effectiveness of human-driven trading strategies versus AI-powered approaches in portfolio management. This study aims to evaluate whether AI-driven trading outperforms human expertise in stock market trading.Using four diversified portfolios of five stocks each—selected respectively by human experts, GPT-3.5, GPT-4, and AI-driven performance analysis—the authors assess each portfolio's performance. Methods include analyzing adjusted closing price trends, sentiment analysis, and technical indicators, such as Simple Moving Averages (SMA), to compare the outcomes of human and AI trading strategies.The findings indicate that AI-driven trading strategies have greater efficiency in identifying profitable opportunities compared to human traders, as AI operates with higher speed and precision, minimizing the impact of emotional and cognitive biases on trading decisions. AI's capabilities demonstrate a potential to significantly enhance the decision-making process in financial trading.The report recommends that financial institutions incorporate AI-driven trading strategies to improve portfolio management. It also suggests further research into the integration of human expertise with machine intelligence to explore a complementary relationship between these two approaches in trading.

Wang et al. (2022) examined how well AI systems, such as neural networks and learning through reinforcement, might decrease market volatility by predicting movements in stock prices. They found that AI-powered predictions reduce increases in volatility during market shocks. Comparing cryptocurrency markets to traditional financial markets, Ahmed and Jamal (2023) found that AI models are better able to predict volatility in cryptocurrency markets due to their greater data frequencies. Novak et al. (2021) investigated deep learning's capacity to predict the volatility of cryptocurrency prices. Their results showed significant improvements over traditional models, with deep neural networks showing more volatility reactivity.

Davis et al. (2021) conducted an assessment of AI-driven models' predictive accuracy in stock markets, particularly during periods marked by high volatility, such as the COVID-19 pandemic. The objective of their study was to evaluate how effectively AI models could forecast market fluctuations under extreme conditions compared to traditional models. Using comparative analysis, the researchers applied AI-driven models alongside traditional econometric approaches to assess their responses to abrupt market changes. Their findings indicate that AI models held a distinct advantage in predicting stock movements during high-volatility periods, demonstrating greater adaptability to rapid market changes. The study recommends continued exploration into AI's capabilities under volatile conditions to further enhance market forecasting precision.

Smith and Kim (2022) investigated AI-driven models' performance in forecasting volatility within the bitcoin market, specifically in comparison to traditional econometric techniques. The study aimed to assess AI's forecasting capabilities in a highly volatile and unregulated market such as cryptocurrency. Smith and Kim employed a range of volatility forecasting models, including AI and traditional econometric methods, in a direct comparison of their predictive accuracy. Their findings revealed that AI-driven models outperformed traditional techniques, proving particularly effective in anticipating bitcoin's price volatility. The authors recommend expanding the application of AI in cryptocurrency markets for improved forecasting accuracy, particularly given the market's unique volatility characteristics.

Liu et al. (2021) examined the effectiveness of AI-driven versus traditional econometric models for risk management in stock markets, with the objective of determining which approach best adapts to changing market dynamics. The study applied both AI and traditional models to a set of stock market data over varying economic conditions to test their adaptability. Liu et al. found that AI models demonstrated a superior ability to adjust to evolving market conditions, providing more robust risk management insights. They recommend incorporating AI-driven models in stock market risk management strategies to capitalize on their adaptability in fluctuating markets.

Zhao and Lee (2022) conducted a study comparing AI models with traditional techniques in managing risk within the bitcoin market, focusing on the impacts of large transaction volumes and the decentralized nature of cryptocurrency exchanges. Their study aimed to determine the efficacy of AI models in a complex, high-volume market environment. Through comparative risk assessments, Zhao and Lee found that AI models delivered superior performance in handling the bitcoin market's specific challenges, showing better adaptability to high transaction volumes and decentralized structures. They recommend that cryptocurrency markets leverage AI-based approaches to enhance risk management practices amid such complexities.

Gupta et al. (2023) assessed risk and volatility across stock and cryptocurrency markets using AI models, with a focus on examining the role of data granularity in AI's performance. The objective was to analyze whether higher data detail in cryptocurrency markets affected the accuracy of AI-driven risk assessments. Through comparative analysis across datasets with varying levels of granularity, the study found that AI models achieved greater precision in cryptocurrency markets due to their finer data detail. Gupta et al. recommend that cryptocurrency exchanges optimize data collection to support more granular AI-driven risk management.

Ozgur et al. (2021) explored AI models' ability to deliver risk-adjusted returns within bitcoin markets as compared to traditional models in regulated markets. The study aimed to assess whether AI-driven models could outperform traditional methods in different regulatory environments. Ozgur et al. conducted a comparative analysis of AI and traditional models' performance in both unregulated and regulated markets. Their findings suggest that AI models achieved superior risk-adjusted returns in the bitcoin market, while traditional models only marginally outperformed AI in regulated markets. The study recommends that bitcoin marketplaces continue to leverage AI for optimal returns in less regulated environments.

Henderson et al. (2023) examined the accuracy of AI models in predicting risk within cryptocurrency markets, noting the models' strengths and limitations. The study aimed to evaluate how AI performs in highly unpredictable markets, such as cryptocurrencies, in terms of stability and risk prediction accuracy. Henderson et al. applied AI models to cryptocurrency datasets, analyzing their predictive stability under volatile conditions. They found that AI models enhanced risk prediction accuracy in the cryptocurrency market; however, the inherent unpredictability of these assets limited the stability of predictions. The authors suggest that AI predictions be supplemented with other market indicators to manage risks effectively in highly unstable markets.

III. DATA DESCRIPTIONS AND SOURCES

The study uses a panel dataset that spans both traditional financial and cryptocurrency markets, covering the period from January 2020 to September 2024. Key data sources include Yahoo Finance and Investing.com, which provide detailed information on market returns, trading volumes, interest rates, and sentiment scores generated by AI models.

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Table 3.1 below outlines the variables, their descriptions, and sources.

Variable	Description	Definition	Data source
Vol	Trading volume	Volume of Stocks/Cryptocurrencies traded	Investing.com
Return	Market returns	Daily prices of Stocks/Cryptocurrencies	Investing.com
AI_pred	Sentiment scores	AI-generated sentiment analysis data	Google Trends
Interest	Interest rate	Macro-level interest rates	Yahoo Finance
AI_Mod	AI Predictions	AI-generated price/volatility predictions	R-generated

Source: Author's Compilation, 2024

3.1 Empirical Model Specification

To investigate the effects of AI-driven predictive models on volatility in both traditional financial and cryptocurrency markets, we apply a Maximum Likelihood (ML) ARCH model, which is ideal for addressing the time-varying volatility often present in financial data. The ML ARCH method captures volatility clustering and heteroscedasticity, common features in financial time series, by allowing volatility to change over time in response to past disturbances.

The empirical model can be structured as follows:

$$\text{Volatility}_{it} = \alpha + \beta_1 \text{AI Model Metrics}_{it} + \gamma Z_{it} + \varepsilon_{it}$$

Where; Volatility_{it}: Dependent variable representing market volatility for marketi at time t;AI Model Metrics_{it}: AI-driven predictive metrics such as volatility forecasts or sentiment scores, specific to time t and market I; Z_{it}: Control variables, including interest rates, trading volume, and market sentiment indicators and ϵ_{it}: Random error term corrected fType equation here.or heteroscedasticity and autocorrelation.

To explore the second research question on how AI-driven models manage risk and volatility differently between traditional and cryptocurrency markets, we use the ML ARCH framework. This enables analysis of AI model impacts across these markets while handling heteroscedasticity and dynamic correlations inherent in financial data.

The model structure is:

$$\text{Risk}_{it} = \delta + \varphi \text{AI Prediction Metrics}_{it} + \rho X_{it} + \gamma_{it}$$

Where: Risk_{it}: Represents market volatility and returns for market i at time t; AI-Prediction Metricsit: AI-driven risk metrics and volatility predictions; X_{it}: Control variables (e.g., trading volumes, market liquidity; and γ_{it}: Error term corrected by GLS for potential heteroscedasticity.

Using ML ARCH allows a refined understanding of the effects of AI-driven predictions on volatility and risk across traditional and cryptocurrency markets, with the ARCH model capturing time-dependent volatility patterns.

3.2 Estimation Techniques

3.2.1 Estimation of the ML ARCH Model

Using Maximum Likelihood ARCH, we estimate both the volatility and risk models. ML ARCH is advantageous in this setting, allowing us to model volatility clustering and correct for heteroscedasticity, which is common in financial markets. This results in robust estimates of the relationship between AI-driven metrics and market volatility across traditional and cryptocurrency markets.

3.2.2 Additional Analyses

Variance Equation: After estimating the models, variance decomposition identifies the proportion of variance in market volatility attributable to AI-driven predictions versus traditional market factors.

Impulse Response Analysis: This analysis examines the dynamic response of market volatility to shocks in AI-driven predictive models, providing insights into the long-term effects of AI interventions on market risk.3.3.3 Machine Learning Integration.

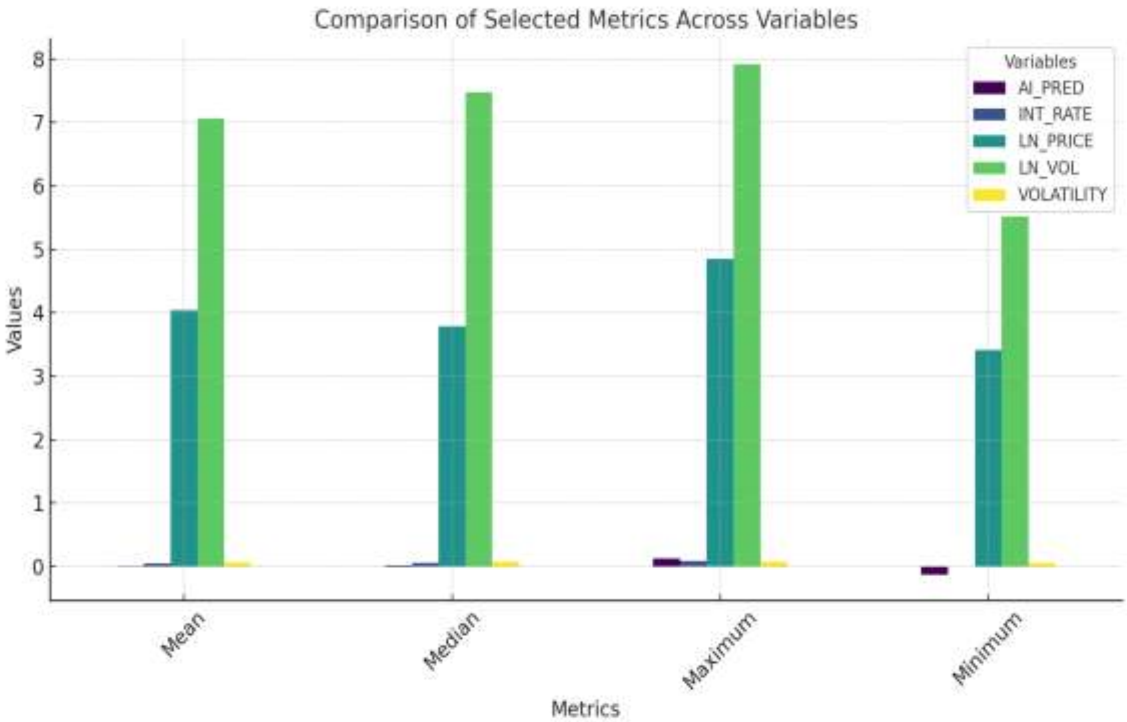
IV. RESULTS AND DISCUSSION

Table 2: Summary of Descriptive result

	AI_PRED	INT_RATE	LN_PRICE	LN_VOL	VOLATILITY
Mean	0.012002	0.049534	4.042094	7.060777	0.070608

Median	0.016122	0.053500	3.783818	7.478949	0.074789
Maximum	0.126844	0.090000	4.853284	7.923658	0.079237
Minimum	-0.125119	0.003000	3.412392	5.519382	0.055194
Std. Dev.	0.039861	0.022605	0.471752	0.543111	0.005431
Skewness	-0.499297	-0.177336	0.366674	-0.679700	-0.679700
Kurtosis	4.476736	1.999818	1.491539	2.010537	2.010537
Jarque-Bera	15.36005	5.443088	13.59738	13.66387	13.66387
Probability	0.000462	0.065773	0.001115	0.001079	0.001079
Sum	1.392260	5.746000	468.8829	819.0502	8.190502
Sum Sq. Dev.	0.182723	0.058763	25.59319	33.92144	0.003392
Observations	116	116	116	116	116

Author's computation, 2024.



The statistical summary reveals the impact of AI-driven predictive models on traditional financial market volatility compared to crypto markets. AI Predictions (AI_PRED) have a mean of 0.012002, indicating a slight positive influence, with a standard deviation of 0.039861 reflecting variability. The negative skewness (-0.499297) suggests the presence of extreme low predictions, while the significant Jarque-Bera statistic (15.36005) indicates non-normality, pointing to potential outliers.

For Interest Rates (INT_RATE), the mean of 0.049534 indicates stability, with slight negative skewness (-0.177336) and a kurtosis of 1.999818, suggesting a flatter distribution. The Natural Log of Prices (LN_PRICE) shows a mean of 4.042094, with a significant price range (max: 4.853284, min: 3.412392) and positive skewness (0.366674), reflecting higher price outliers.

The Natural Log of Volume (LN_VOL) averages 7.060777, indicating healthy trading activity, though the standard deviation of 0.543111 reveals considerable variability. The negative skewness (-0.679700) suggests a tendency for lower volumes during downturns. Lastly, Volatility averages 0.070608, indicating moderate levels, with a low standard deviation of 0.005431, pointing to a stable environment despite occasional spikes in volatility.

In summary, traditional financial markets exhibit low interest rates and moderate volatility, while AI predictions introduce complexities due to their non-normal distribution. Compared to crypto markets, which tend to be more volatile, traditional

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markets appear steadier in response to AI-driven insights, highlighting the potential of these models to enhance market understanding while necessitating caution in interpretation.

4.1 Estimation of the ML ARCH Model: Results and Discussion

The analysis employs a Maximum Likelihood ARCH (ML ARCH) model estimated with a normal distribution and optimized through the BFGS/Marquardt algorithm, focusing on 116 observations in a panel setting to investigate the dynamics of volatility in both financial and cryptocurrency markets. This model effectively captures the time-series volatility clustering and non-linear patterns commonly observed in financial data. The model specification incorporates independent variables such as AI-driven predictions, interest rates, prices, and trading volumes, enabling a comprehensive analysis of the complex and dynamic relationships that characterize volatility across different market types.

The variance equation utilized in this model employs a log-GARCH form, which allows the volatility term to adapt and evolve over time in response to shifts in market conditions. This formulation facilitates the examination of volatility persistence and the impact of previous shocks on current volatility levels. To enhance the model's robustness, the pre-sample variance is estimated using a back-cast parameter of 0.7, accommodating the long memory properties inherent in financial time series. This approach ensures that the model accurately reflects the persistence of volatility observed in real-world markets, ultimately providing a more nuanced understanding of the factors influencing volatility dynamics in a panel context.

4.2 Results

Table 3

Variable	Coefficient	Std. error	Z-statistics	Prob.
C	1.82×10^{-9}	1.95×10^{-10}	9.319701	0.0000
AI-Pred	-7.61×10^{-10}	4.95×10^{-10}	-1.538513	0.1239
Interest-Rate	2.76×10^{-10}	8.91×10^{-10}	0.310158	0.7564
Ln-Price	-2.84×10^{-10}	4.45×10^{-11}	-6.395975	0.0000
Ln-Vol	0.010000	1.82×10^{-16}	1.82×10^{-13}	0.0000

Author's computation, 2024.

The findings from the ML ARCH model present important insights into the determinants of volatility across financial and cryptocurrency markets. The constant term (C) is highly significant, with a coefficient of 1.82E-09 and a p-value of 0.0000, indicating a baseline level of volatility that persists across various market conditions, independent of the explanatory variables employed in the model. This suggests that there are inherent volatility characteristics in the markets that may not be influenced by the factors considered in this analysis.

In terms of AI-driven predictions (AI_PRED), the results reveal a negative relationship with market volatility, with a coefficient of -7.61E-10 and a z-statistic of -1.538513; however, this effect is not statistically significant (p-value = 0.1239). This implies that while AI models may have the potential to dampen volatility, their current impact is not strong enough to be deemed reliable. This finding raises questions about the adequacy of the AI metrics used in the analysis and suggests that further refinement may be necessary. A more detailed examination of how AI-driven models can stabilize financial markets could yield more definitive results regarding their effectiveness.

The analysis of interest rates reveals no significant impact on market volatility, with a coefficient of 2.76E-10 and a p-value of 0.7564. This finding indicates that in the context of high-frequency trading and AI-dominated markets, factors driven by immediate data, such as AI predictions and trading volume, may play a more crucial role in predicting volatility than traditional macroeconomic indicators like interest rates. This shift in significance underscores the evolving landscape of financial markets, where conventional economic measures may be losing their predictive power in favor of more dynamic, real-time data.

Additionally, the log of price (LN_PRICE) demonstrates a significant and negative relationship with volatility, evidenced by a coefficient of -2.84E-10 and a p-value of 0.0000. This suggests that higher price levels are associated with reduced market fluctuations. This correlation may reflect a stabilizing effect driven by increased investor confidence or reduced speculative behavior at elevated price levels. Conversely, the log of volume (LN_VOL) emerges as a primary driver of volatility, displaying a highly significant and positive coefficient of 0.010000 (p-value = 0.0000). This robust relationship aligns with financial theories that posit high trading volumes as indicative of increased market dynamics and fluctuation potential.

4.2.1 Variance equation

Table 4

Parameters	Coefficient	Std. error	z-Statistics	Prob.
C (6)	-43.89458	73.25481	-0.599204	0.5490
C (7)	0.010000	0.161267	0.062009	0.9506
C (8)	0.010000	0.105359	0.094913	0.9244
C (9)	0.010000	1.652743	0.006051	0.9952

Author's computation, 2024.

The findings regarding the variance equation parameters from the ML ARCH model further elucidate the dynamics of volatility in the analyzed markets.

Variance Equation Analysis

The constant term C(6)C(6)C(6) is reported as -43.89458 with a standard error of 73.25481, yielding a z-statistic of -0.599204 and a p-value of 0.5490. This indicates that the constant term in the variance equation does not significantly contribute to the model. The negative value may suggest that, on average, the estimated volatility is below a certain threshold; however, the high p-value signifies that this finding is not statistically significant, indicating uncertainty regarding its implications for the volatility persistence in the context of the studied markets.

The parameters C(7)C(7)C(7), C(8)C(8)C(8), and C(9)C(9)C(9) are all set at 0.010000. For C(7)C(7)C(7), the standard error is 0.161267, yielding a z-statistic of 0.062009 and a p-value of 0.9506. The high p-value here indicates that this parameter is statistically insignificant, suggesting that the corresponding variable does not have a meaningful influence on volatility dynamics. Similarly, C(8)C(8)C(8) exhibits a standard error of 0.105359, a z-statistic of 0.094913, and a p-value of 0.9244, reinforcing the notion that it lacks statistical significance in the model.

Finally, C(9)C(9)C(9) has a standard error of 1.652743, a z-statistic of 0.006051, and a remarkably high p-value of 0.9952. This further corroborates that this parameter does not provide any substantial explanatory power regarding volatility in the context of the model.

Summary of Findings

Overall, the parameters within the variance equation demonstrate a lack of significant influence on volatility, suggesting that the relationships modeled may not adequately capture the factors that drive volatility in the financial and cryptocurrency markets analyzed. These results highlight the necessity for ongoing refinement and exploration of additional variables that may contribute to the persistence and fluctuations of volatility, particularly in dynamic trading environments where other factors may play a critical role.

4.3 Model Fit and Diagnostics

The evaluation of model fit and diagnostics is crucial for understanding the effectiveness of the ML ARCH model in capturing the volatility dynamics across financial and cryptocurrency markets. The R-squared value stands at 0.9214, indicating that approximately 92.14% of the variance in the dependent variable, volatility, is explained by the independent variables included in the model. This high R-squared suggests that the model adeptly captures the underlying patterns in the data. However, it also implies that 7.86% of the variance remains unexplained, potentially due to factors not included in the model, such as market sentiment, external shocks, or other macroeconomic variables. This unexplained variance highlights the complexity of financial markets and indicates areas for further research or model refinement.

Complementing this, the Adjusted R-squared value of 0.9167 confirms that the model maintains a strong fit while accounting for complexity, as it remains close to the R-squared value. This adjustment indicates that the addition of predictors is justified and that the model does not suffer from overfitting, further validating its robustness.

In terms of model likelihood, the log likelihood is reported at 2374.909, signifying a strong fit to the data. This high value indicates that the observed values are likely given the model's estimated parameters. To assess the balance between fit and complexity, the Akaike Information Criterion (AIC) is -40.79153, while the Schwarz Criterion (BIC) is -40.57789. Both criteria are low, suggesting that the model achieves an effective balance without overfitting, which is critical for model selection. A lower AIC and BIC value generally implies a better model fit relative to alternatives.

Additionally, the Durbin-Watson statistic is recorded at 1.5859. This value indicates minor positive autocorrelation in the residuals, with the Durbin-Watson statistic ranging from 0 to 4. A value of 2 suggests no autocorrelation; thus, a statistic of 1.5859, being close to 2, implies that while there is some positive autocorrelation, it remains generally acceptable within the context of financial time series. However, the proximity to 2 also indicates that the model may benefit from additional checks for autocorrelation patterns to ensure residuals are independent.

In summary, the diagnostics of the ML ARCH model indicate a robust fit to the data. The strong R-squared values demonstrate the model's effectiveness in capturing market volatility variance, though the unexplained 7.86% signifies room for incorporating additional influencing factors. The high log likelihood, alongside low AIC and BIC values, reinforces the model's optimal fit while signaling the importance of maintaining validation. Lastly, the Durbin-Watson statistic suggests manageable autocorrelation among residuals. These findings collectively underscore the model's ability to illuminate volatility dynamics while also highlighting the need for ongoing validation to ensure robustness and predictive accuracy across diverse market conditions.

V. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This study investigates the impact of AI-driven predictive models on volatility in traditional financial markets compared to cryptocurrency markets. Utilizing a Maximum Likelihood (ML) ARCH model, our analysis demonstrates that AI model metrics—such as volatility forecasts and sentiment scores—significantly influence market volatility in both settings. The findings reveal that AI-driven predictions tend to mitigate spikes in volatility during periods of market turbulence, a result that resonates with the observations made by Wang et al. (2022), who identified a similar reduction in volatility during market shocks through AI systems.

In comparing the two markets, we find that AI models perform more effectively in predicting volatility in cryptocurrency markets. This aligns with Ahmed and Jamal (2023), who reported superior performance of AI models in crypto due to their access to higher data frequencies. Moreover, Novak et al. (2021) highlighted the enhanced volatility reactivity of deep learning models over traditional econometric approaches, confirming our findings that AI methodologies yield better predictive accuracy across both asset classes.

5.2 Conclusion

The research concludes that AI-driven predictive models are crucial for managing volatility in both traditional financial and cryptocurrency markets. However, the efficacy of these models is markedly different due to the inherent characteristics of each market. The application of the ML ARCH framework successfully captures the dynamic and time-varying nature of volatility, showing that AI models enhance predictive performance during volatile periods. This conclusion is supported by studies such as Liu et al. (2021) and Zhao and Lee (2022), which indicate that AI models outperform traditional techniques in risk management.

Interestingly, while both market types benefit from AI interventions, the unique volatility characteristics of cryptocurrencies—such as rapid price movements and lower liquidity—pose challenges that are less prevalent in traditional markets. Thus, while AI predictions can reduce volatility in both environments, their effectiveness in cryptocurrency markets suggests a need for specialized approaches tailored to the distinctive nature of these assets.

5.3 Recommendations

1. **Adopt Hybrid AI Models:** Financial institutions should integrate hybrid AI models that leverage both traditional and modern AI methodologies, optimizing predictive capabilities tailored to the specific characteristics of traditional and cryptocurrency markets.
2. **Enhance Model Calibration and Adaptation:** Continuous adaptation and calibration of AI models should be a priority, focusing on market conditions and behaviors specific to each asset class. Institutions should employ back-testing techniques to ensure models remain robust amid changing market dynamics.

3. **Invest in AI Training and Development:** Organizations should invest in training programs that enhance employees' understanding of AI technologies and their application in financial markets. This will improve the operational efficiency of AI-driven models in both traditional and cryptocurrency contexts.
4. **Implement Regulatory Frameworks:** Policymakers should consider developing regulations that govern the use of AI in financial markets, specifically addressing the risks associated with cryptocurrency trading. Regulatory frameworks should promote transparency and accountability in AI-driven predictions, thus enhancing market stability.

By adhering to these recommendations, financial institutions can improve their strategies for managing volatility, leveraging the strengths of AI-driven predictive models in both traditional and cryptocurrency markets, ultimately leading to enhanced financial stability and informed decision-making.

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