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Portfolio Diversification and Financial Investment Opportunity: Exploring Portfolio Management Through the Dynamic Dependence of Cryptocurrencies

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ABSTRACT

This study explores the dynamics of portfolio diversification and financial investment opportunities through cryptocurrency assets. The rapid rise of digital currencies in the global financial landscape has raised crucial questions about their relationships with traditional assets and their potential role in effective portfolio management. The primary goal of this research is to assess the interdependence and co-movement of various cryptocurrencies and their suitability for inclusion in traditional investment portfolios. To achieve this, the study employs advanced econometric methods, including the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, to analyze the volatility and dependency structures among cryptocurrencies, traditional financial assets, and crude oil prices. The research hypothesizes that cryptocurrencies offer diversification benefits due to their distinct return characteristics and weak correlations with traditional asset classes. Empirical results confirm that cryptocurrencies exhibit varying degrees of dependence under different market conditions, influenced by factors such as investor sentiment and macroeconomic shocks. The findings suggest that while some cryptocurrencies function effectively as standalone investments, others enhance the risk-return profiles of diversified portfolios. Notably, the study identifies significant interactions between cryptocurrency returns, traditional financial indices, and crude oil prices, underscoring the interconnected nature of modern financial markets. This research contributes to the discourse on modern portfolio theory by providing new insights into the integration of digital assets in investment strategies. The findings emphasize the importance of timing and market conditions when incorporating cryptocurrencies into portfolios. Ultimately, this study highlights the dual role of cryptocurrencies as both diversification tools and high-risk, high-

reward assets, offering valuable implications for investors and policymakers navigating the complexities of digital finance.

INTRODUCTION

Portfolio management in contemporary financial markets faces new challenges and opportunities with the emergence of cryptocurrencies. These digital assets, secured by cryptography and leveraging blockchain technology, have captured the interest of investors, regulators and the general public (Manjula et al., 2022). Their decentralized nature and promise of secure, intermediary-free transactions have reshaped the financial landscape, offering new prospects for investment and portfolio diversification.

While cryptocurrencies have grown in popularity since the creation of Bitcoin in 2009, their complex dynamics and relationship with traditional financial markets raise important questions (Aliyev, 2022). Investors seek to understand how the evolution of cryptocurrencies is influenced by global economic events, particularly financial crises, and how they interact with traditional assets in constructing diversified portfolios.

This study aims to explore in depth this complex relationship between cryptocurrencies and traditional assets, focusing on the dynamic dependence between these two financial universes. Through an in-depth literature review and hypothesis development, we will analyze how emerging characteristics of cryptocurrencies, such as volatility and risk, relate to traditional financial markets (Wang et al., 2022). Additionally, a methodological approach based on the ARCH model will be used to illuminate the underlying dynamics and implications for portfolio management.

This exploration aims to fill existing knowledge gaps and open new research perspectives on the mechanisms governing the relationship between cryptocurrencies and traditional investment portfolios (Joseph et al., 2024). By better understanding this complex interaction, investors will be able to make more informed decisions to optimize their portfolios in an ever-changing financial environment.

This document is structured as follows: Section 2 provides a review of the literature. In Section 3, we detail the research methodology. The results and discussions are presented in Section 4. Finally, in Section 5, we present the conclusion.

1. LITERATURE REVIEW

The dynamic relationship between cryptocurrencies and traditional assets has been a growing area of research due to the unique characteristics of cryptocurrencies, such as high volatility and extreme price movements. Several studies have highlighted the diversification benefits that cryptocurrencies provide. For instance, Corbett et al. (2018) demonstrated the relative isolation of cryptocurrencies like Bitcoin, Ripple, and Litecoin from traditional assets, offering significant diversification opportunities, particularly for short-term investors. Similarly, Baumöhl (2019) found near-zero correlations between cryptocurrencies and forex market currencies, further emphasizing their potential for portfolio diversification. Other studies, such as those by Kostika and Laopodis (2019) and Charfeddine et al. (2019), revealed weak long-term interdependence between cryptocurrencies and traditional assets, which vary depending on market conditions and temporal contexts.

Beyond diversification, cryptocurrencies also demonstrate hedging and safe-haven potential. Dyhrberg (2016) showed that Bitcoin acts as a short-term hedge against fluctuations in FTSE indices and the US dollar, underscoring its utility in financial risk management. Bouri et al. (2017a) concluded that Bitcoin is a weak hedge and more suitable for diversification, with time-varying properties that depend on specific market conditions. In a similar vein, Tufan et al. (2022) found a significant relationship between Bitcoin and gold, suggesting that Bitcoin can serve as a hedge, though its link to crude oil is weaker or negligible.

Several studies have also focused on the interdependence and causal relationships between cryptocurrencies and traditional assets. Yavuz et al. (2022) discovered bidirectional causality between cryptocurrencies and bond markets, highlighting their predictive value for traditional assets. Furthermore, Detthamrong et al. (2024) identified causal interdependence between major cryptocurrencies (e.g., Tether and USD Coin) and global economic assets such as gold, bonds, and equity indices.

Volatility and shock transmission are other critical aspects of the relationship between cryptocurrencies and traditional assets. Kurka (2019) and Ji et al. (2018) found weak unconditional connections between cryptocurrencies and traditional assets but noted significant transmission of shocks during periods of market turbulence. Guesmi et al. (2019) showed that Bitcoin's volatility significantly influences other assets, acting as a hedge during downturns. Bhuiyan et al. (2021), using wavelet analysis, highlighted Bitcoin's leader-follower relationships with gold and the US dollar, showing limited integration with the global financial system.

The temporal and structural dynamics of cryptocurrency relationships with traditional assets have also been studied extensively. Bouri et al. (2017b) demonstrated that Bitcoin's hedging properties depend on time horizons and market conditions, with significant changes observed following the December 2013 crash. Maghyereh and Abdoh (2021) examined the long-term bidirectional dependence between Bitcoin and global stock indices, while Wu (2021) emphasized Bitcoin's unique and complex relationship with gold compared to other assets.

During financial crises, cryptocurrencies exhibit heightened volatility and varying interactions with traditional markets. Doumenis et al. (2021) observed higher volatility in Bitcoin compared to traditional assets, particularly during the COVID-19 period, underscoring its speculative nature. Elsayed et al. (2022) highlighted unidirectional volatility spillovers from Bitcoin to traditional assets, indicating its influence during periods of financial uncertainty.

Overall, the literature suggests that cryptocurrencies provide significant diversification benefits, with limited integration into traditional financial systems. Their hedging capabilities and shock transmission dynamics, however, vary depending on market conditions and temporal factors. These insights provide the foundation for this study, which aims to further explore the complex relationships between cryptocurrencies and traditional assets using advanced econometric techniques.

2. RESEARCH METHODOLOGY

In this subsection, we present the sample data that forms the basis of our study on the dynamic relationship between cryptocurrencies and traditional assets. We focus our attention on a select set of five cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Tether (USDT), alongside three major traditional assets such as the S&P 500 Index, the Dow Jones Industrial Average (DJIA) and the price of crude oil (WTI). This selection of daily chronological data, covering a significant period from January 1, 2016 to December 12, 2023, was carried out to ensure adequate representativeness of temporal variations.

To study the dynamic relationship between cryptocurrencies and traditional assets, empirical analysis is stronger than theoretical literature. This is supported by a variety of studies.

The model therefore looks like this:

$$\boldsymbol{BTC = \alpha_0 + \beta_1\, ETH + \beta_2\, XRP + \beta_3\, USDT + \beta_4\, SP500 + \beta_5\, DJIA + \beta_6\, WTI + \varepsilon_i} \qquad (1)$$

With;

BTC: Represents the independent variable and indicates the virtual currency Bitcoin,
ETH: Represents a dependent variable and indicates the virtual currencyEthereum,
XRP: Represents a dependent variable and indicates the virtual currency Ripple,
USDT: Represents a dependent variable and indicates the virtual currency Tether,
S&P500: Represents a dependent variable and indicates the stock market index S&P 500,

DJIA: Represents a dependent variable and indicates the stock market index Dow Jones Industrial Average,

WTI: Represents a dependent variable and indicatesthe price of crude oil,
β: Represents the estimated coefficients of the study variables.
$\boldsymbol{\alpha_0}$: Is a constant term, the ordinate at the origin of the regression line?
$\boldsymbol{\varepsilon_i}$: The error term verifying the assumptions of the OLS method.

Autoregressive (AR) and moving (MA) models can be effectively combined to form a general and useful class of time series models, known as ARMA models.(Box, 2013).According to the correlogram of the residuals, our ARMA model is well represented by an order (p, q) equal to (2, 0).

In order to empirically test this structural regression model, equation 1 is transformed into a reduced form of the ARCH model as follows:

the associated ARCH model is characterized by an order p equal to 2, i.e. an ARCH (2) model. So, our ARCH (2) model is written in the following form:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 (2)$$

With:

σ_t^2: The conditional variance at time t;
ω: The model constant;
α_i : The ARCH coefficients for the delays i;
ε_{t-i} : The residuals of past observations.

3. RESULTS AND DISCUSSIONS

3.1 Descriptive statistics

Descriptive statistics provides a comprehensive and accessible approach to data analysis by combining numerical and graphical methods. By combining these approaches, descriptive statistics provides a robust framework for exploring, analyzing, and effectively communicating the characteristics of datasets, regardless of the application domain. These charts provide an intuitive overview of the data, making it easier to interpret.

3.1.1 Graphical analysis

The chart above illustrates the daily price movement of cryptocurrencies and traditional assets from 2016 to the end of 2023. During this period, cryptocurrencies experienced significant fluctuations, notably Bitcoin (BTC) which reached an all-time high near $20,000 in December 2017, then fell in 2018 before experiencing significant increases in 2020 and 2021, surpassing $60,000 in May and November 2021. Ethereum (ETH) and XRP also saw notable swings.

In contrast, Tether (USDT) has maintained remarkable stability, with a current price of around $1.11, which sets it apart from other cryptocurrencies.

When it comes to traditional assets, the S&P 500 and the Dow Jones Industrial Average have seen steady growth with minor fluctuations during the mentioned period. In contrast, the price of crude oil (WTI) has been subject to significant fluctuations, mainly influenced by factors such as production, global demand and geopolitical tensions.

In short, all the series represented in the graph show an absence of stability over time, with the notable exception of Tether (USDT) among cryptocurrencies.

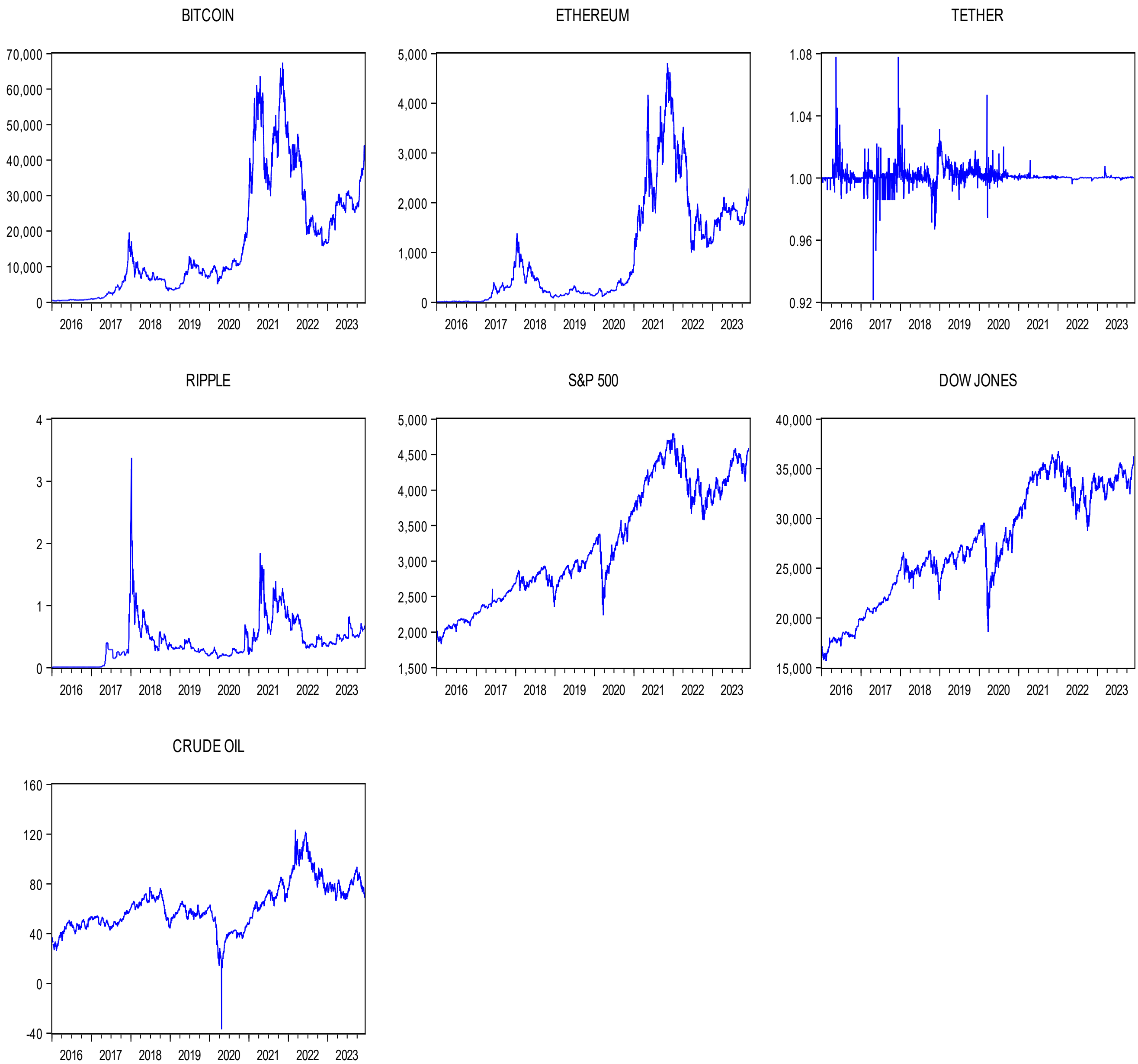

Figure 1. Historical evolution of the prices of cryptocurrencies and traditional assets
Source: Developed by the author

3.1.2 Digital analysis

The Table 1 below provides descriptive statistics for different cryptocurrencies (BTC, ETH, USDT, XRP) as well as some traditional assets (DJIA, S&P 500, WTI).

Table 1. Descriptive statistics

	BTC	*ETH*	*USDT*	*XRP*	*DJIA*	*S&P500*	*WTI*
Mean	16710.98	961.7673	1.001082	0.417025	27317.90	3249.449	61.87059
Median	9598.995	378.3050	1.000300	0.342685	26651.77	3002.735	59.21000
Maximum	67510.06	4805.950	1.077880	3.377810	36799.65	4796.560	123.6400
Minimum	357.5300	0.921000	0.921300	0.004500	15660.18	1829.080	-36.98000
Std. Dev.	16235.29	1094.861	0.006094	0.355134	5725.967	827.0814	19.03534
Skewness	1.076654	1.277704	1.003104	2.033012	-0.15524	0.199057	0.457248
Kurtosis	3.177121	3.876728	40.69028	11.62303	1.874156	1.680127	3.512146
Jarque-Bera	564.4525	882.5418	172255.7	10990.01	164.9218	229.8093	132.8385

Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Comments	2902	2902	2902	2902	2902	2902	2902

Source: Developed by the author

Table 1 presents the descriptive statistics for different variables, all based on a set of 2902 observations. The BTC series displays significant volatility, with a high standard deviation of 16235.29 and significant spikes in the price, suggesting a skewed distribution towards higher values. The ETH variable shows less volatility than BTC, but a slightly asymmetric distribution, with a standard deviation of 1094.861 and a positive skewness of 1.277704. USDT shows stability around parity with the dollar, but a distribution with heavier tails than normal, indicated by a high kurtosis of 40.69028. The XRP variable has a very low mean and a very skewed distribution with a high skewness of 2.033012. The DJIA and SP 500 show positive averages, with slightly skewed distributions. The WTI variable has a positive mean with an asymmetric distribution. Jarque-Bera tests show that not all series follow a normal distribution.

3.2 The correlation matrix between the variables

Table 2 indicates a more commonly used correlation test to assess multi-collinearity between two variables is the Pearson correlation coefficient.

Table 2. Correlation matrix results

	BTC	*ETH*	*XRP*	*USDT*	*S&P500*	*DJIA*	*WTI*
BTC	1						
ETH	0.938358	1					
XRP	0.669668	0.695801	1				
USDT	-0.064068	-0.080000	-0.001848	1			
S&P500	0.885523	0.869100	0.569280	-0.079256	1		
DJIA	0.850621	0.823838	0.602825	-0.058534	0.982941	1	
WTI	0.576151	0.656148	0.451389	-0.098584	0.693995	0.705942	1

Source: Developed by the author

The negative correlation of Tether (USDT) with all other variables suggests that the price movements of Tether are inverse compared to the other financial assets mentioned.

Cryptocurrencies have high positive correlations with each other, suggesting a tendency to move in the same direction.

There are high positive correlations between cryptocurrencies and stock indices, indicating some synchronization in their performance, likely influenced by macroeconomic factors or general market trends.

The positive correlations between oil (WTI) and cryptocurrencies could indicate a similarity in how these assets react to overall economic factors.

The strong positive correlation between S&P500 and DJIA suggests that they tend to move very similarly, often mirroring the overall performance of the US stock market.

3.3 Estimation methods and interpretation of results

3.3.1 Unit root test

The KPSS test depends on the calculated test statistic and the associated decision rule. If the test statistic is greater than the critical value (defined at a certain level of significance), we reject the null hypothesis in favor of the alternative hypothesis, indicating non-stationarity.

Table 3. KPSS unit root test results

Variable	BTC	ETH	XRP	USDT	S&P500	DJIA	WTI
LM-Stat	4.226	3,915	1.606	0.209***	6,277	6.172	3.168

Note: *** 1% (0.739).
Source: Developed by the author

This table indicates that all variables are not stationary, except the Tether series (USDT), since its LM test statistic value (0.209) is less than the critical value (0.739) at the 1% significance level.

3.3.2 Ordinary Least Squares Estimation

By considering the continuous nature of price variations of cryptocurrencies and traditional assets, OLS makes it possible to explicitly model the quantitative impact of one on the other. Additionally, OLS provides residual diagnostic tools, facilitating model validation and ensuring compliance with basic assumptions.

Some researchers have used the OLS method to estimate the parameters of their models,Rai and Kumari (2021) demonstrated the relevance of this technique in assessing the impact of global pandemic announcements on cryptocurrency returns and volatility. Moreover, Allen (2022) took a comprehensive approach using both parametric (OLS) and non-parametric methods (non-linear correlation measures, GMC, and non-parametric copula estimates) to estimate the parameters of their models and assess the relationships between cryptocurrencies and the S&P500 index. Table 4 below presentsthe estimate ofordinary least squares (OLS) method.

Table 4. OLS estimation results

Dependent variable: BTC				
Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
VS	-19569.28	14776.30	-1.324370	0.1855
ETH	10.37174	0.237888	43.59921	0.0000
XRP	1986.507	423.1789	4.694249	0.0000
USDT	9226.353	14754.32	0.625332	0.5318
DJIA	0.269704	0.112147	2.404927	0.0162
S&P500	5.237490	0.870815	6.014469	0.0000
WTI	-131.6685	6.847286	-19.22930	0.0000
R-squared	0.913442	Akaike info criterion		19.78530
F-statistic	5091.775	Hannan-Quinn critic.		19.79050
Prob(F-statistic)	0.000000	Durbin-Watson stat		0.019911

Source: Developed by the author

The results of Table 4 aboveof a multiple regression where the dependent variable (the variable predicted) is the price of Bitcoin (BTC) are as follows: This model suggests significant and positive relationships between the price of Bitcoin (BTC) and the prices of Ethereum (ETH), Ripple (XRP), Dow Jones (DJIA) and the S&P500 index. That is, it measures the proportion of the total variance of the dependent variable (BTC). However, the F-test statistic value is high (5,091.775) with very low probability (0.0000), indicating that the model is overall statistically significant. The Durbin-Watson test presents a value very close to zero (0.019911), this suggests a possibility of autocorrelation of the residuals.

3.3.3 Autocorrelation test

The Breusch-Godfrey autocorrelation test, also called the Lagrange Multiplier (LM) test for serial autocorrelation, is a statistical method used to detect the presence of autocorrelation in the residuals of a regression model (Breusch, 1978). The LM statistic follows a chi-square distribution under the null hypothesis.

Null hypothesis (H0): There is no autocorrelation in the model residuals.

Table 5 below presents the Breusch-Godfrey autocorrelation test.

Table 5. Results of the Breusch-Godfrey autocorrelation test

Breusch-Godfrey Serial Correlation LM Test			
F-statistic	72978.95	Prob. F(2.2893)	0.0000
Obs*R-squared	2845.598	Prob. Chi-Square(2)	0.0000

Source: Developed by the author

The F statistic is extremely high (72978.95) and the associated probability (Prob. F (2, 2893)) is very close to zero (0.0000). This suggests that the model is overall significant and that it is unlikely that the coefficients are all equal to zero. Obs*R-squared (Observations multiplied by R-squared) is a measure of the extent of autocorrelation in the model residuals. In summary, the results strongly suggest the presence of autocorrelation in the model residuals. Therefore, it may be necessary to adjust the model to account for autocorrelation in the residuals.

3.3.4 Heteroskedasticity test

The heteroskedasticity test aims to determine whether the error variance of a regression model remains constant across all values of the independent variable. If the p-value associated with the test is below a significance threshold, generally 5%, we reject the null hypothesis of absence of heteroscedasticity, indicating that the variance of the errors is not constant. The most commonly used tests include the Breusch-Pagan test, which is widely recognized in the literature.

Table 6 below shows the Breusch-Pagan-Godfrey heteroskedasticity test.

Table 6. Results of the Breusch-Pagan-Godfrey Heteroskedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	47.53968	Prob. F(6.2895)	0.0000
Obs*R-squared	260.2827	Prob. Chi-Square(6)	0.0000
Scaled explained SS	1862.552	Prob. Chi-Square(6)	0.0000

Source: Developed by the author

The Breusch-Pagan-Godfrey test confirms previous graphical observations by rejecting the null hypothesis of homoscedasticity (constancy of the variance of the residuals) in favor of the alternative hypothesis of heteroskedasticity. This means that the residuals exhibit an inconstant variation in their variance. Therefore, it is appropriate to explore and apply an ARCH or GARCH model to better model the conditional volatility of variables.

3.3.5 Estimation of the ARCH (Autoregressive Conditional Heteroskedasticity) model

The literature offers a considerable variety of ARCH model specifications that studied to detail the characteristics of financial markets. Various proposed ARCH processes are covered in several studies such as:Bera and Higgins (1993); Bollerslev el al. (1992); Gouriéroux (1997); Li et al. (2002).

3.3.5.1 Model result and interpretation

The results of Table 7 of estimation of the ARCH regression model (2) for the dependent variable "Bitcoin (BTC)" with different explanatory variables are as follows:

Table 7. Estimation results of the ARCH model (2)

Dependent Variable: BITCOIN				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
VS	-9687.396	1157.375	-8.370142	0.0000***
ETH	9.747150	0.016451	592.4982	0.0000***
USDT	1615.038	1157.711	1.395026	0.1630
XRP	538.1208	26.85593	20.03732	0.0000***
S&P500	6.307206	0.069199	91.14610	0.0000***
DJIA	-0.086242	0.009018	-9.563017	0.0000***
WTI	-73.51175	0.373221	-196.9657	0.0000***
Variance Equation				
VS	13978.53	2008.618	6.959276	0.0000***
RESID(-1)^2	0.796630	0.054397	14.64488	0.0000***
RESID(-2)^2	0.367130	0.034923	10.51249	0.0000***
R-squared	0.894381	Akaike info criterion		17.09054
Log likelihood	-24796.92	Schwarz criterion		17.11112
Durbin-Watson stat	0.013530	Hannan-Quinn critic.		17.09795

(***) Indicate respectively the significance of the coefficients at the 1% threshold.
Source: Developed by the author

The R-squared is high (0.894381), indicating that the model explains a large portion of the variance in the dependent variable. In other words, approximately 89.44% of the variance in Bitcoin's price is explained by the explanatory variables included in the model. Thus, the DW statistic is close to zero (0.013530). This indicates a strong positive autocorrelation in the residuals suggesting that the errors are not independent over time. The quality indicator of the AIC model is 17.09054.

The coefficient of the constant is significant at the 95% confidence level, meaning that the model has a statistically significant fit. A negative value of -9687.396 indicates that when all independent variables are equal to zero, the estimated price of Bitcoin is negative.

The cryptocurrencies Ethereum (ETH) and Ripple (XRP) have a positive and statistically significant relationship with Bitcoin. A one-unit increase in the price of Ethereum is associated with an increase of approximately 9.75 units in the price of Bitcoin, while a one-unit increase in the price of Ripple is associated with an increase of approximately 538.12 units in the price of Bitcoin. This suggests a positive impact of the price action of Ethereum and Ripple on the price of Bitcoin.

Regarding the stablecoin Tether (USDT), although the coefficient is high, the high p-value (0.1630) indicates that its effect is not statistically significant at the 5% level. However, considering the coefficient alone, there appears to be a potentially positive impact of Tether on Bitcoin.

For DJIA and WTI, the estimation shows a negative and statistically significant relationship with Bitcoin. An increase of one unit in the price of the Dow Jones is associated with a decrease of approximately 0.086 units in the price of Bitcoin, while an increase of one unit in the price of crude oil is associated with a decrease of approximately 73.51 units in the price of Bitcoin. This indicates a negative impact of Dow Jones and crude oil prices on Bitcoin.

In contrast, for the S&P500, a one-unit increase in the S&P500 index is associated with an increase of approximately 6.31 units in the price of Bitcoin. This suggests a positive impact of the S&P500 on Bitcoin, implying a possible correlation between the general stock market (represented by the S&P500) and the price of Bitcoin.

In summary, the results suggest that cryptocurrencies, notably Ethereum (ETH) and Ripple (XRP), appear to exert a positive influence on the price of Bitcoin. This trend could indicate a positive correlation between the developments of these cryptocurrencies and the behavior of the Bitcoin market. Conversely, the stablecoin Tether (USDT) presents a neutral relationship despite their coefficient being positive. Whereas, some traditional assets, such as the Dow Jones Industrial Average (DJIA) and the price of crude oil (WTI), appear to be associated with a negative impact on the price of Bitcoin. This observation suggests that variations in Tether and some traditional assets may be linked to downward fluctuations in the Bitcoin market. Furthermore, the S&P500 index shows a positive relationship with the price of Bitcoin, suggesting that movements in the overall market can positively influence the price of Bitcoin.

3.3.5.2 Discussions and implications

The empirical results of this study reveal complex and interconnected dynamics between cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), stablecoin Tether (USDT) and conventional assets such as stock indices (S&P500, DJIA), the price of crude oil (WTI). There is a strong positive correlation between cryptocurrencies including BTC, ETH and XRP, which has major economic implications.

In addition, the high correlations between cryptocurrencies and stock indices (the S&P500 index) highlight a possible convergence of behavior between traditional markets and cryptocurrencies. This synchronization could arise from common macroeconomic factors (which influence the general investment climate) or from a general shift in market sentiment. For investors, this means they need to consider overall market dynamics when evaluating the performance of cryptocurrencies.

The conclusions obtained reinforce the validity of our fourth hypothesis, affirming a significant relationship between Bitcoin and the stock index (S&P500). Our results are consistent with the conclusions of other previous research, notably those of Wang et al. (2022) And Elsayed et al. (2022). This convergence reinforces the robustness of our findings and suggests consistency in the positive relationship between cryptocurrencies and traditional assets, as highlighted by previous research.

Changes in certain traditional assets may be associated with downward fluctuations in the Bitcoin market. In particular, the complexity of the relationships between cryptocurrencies and traditional assets, illustrated by the negative impact of Crude Oil and the Dow Jones on Bitcoin, underlines the interconnection of markets. Investors must take these interactions into account to anticipate market movements. Our findings support the validity of our fifth hypothesis, which posits a mixed relationship between Bitcoin and traditional assets. These results are consistent with the conclusions of pre-existing studies, such as those stated by Doumenis et al. (2021) And Tufan et al. (2022).

CONCLUSIONS AND RECOMMENDATIONS

In conclusion, this study highlights the growing importance of cryptocurrencies as diversification assets in investment portfolios. Investors are encouraged to reassess their approach to these assets, considering their impact on overall portfolio stability and performance. Proactive risk management and a thorough understanding of the interactions between cryptocurrencies and traditional markets are essential for informed investment decisions.

The empirical results highlight the relevance of the selected data sample, covering a significant period and revealing complex interactions between digital and traditional assets, as well as the price of crude oil. Using the ARCH model helped capture temporal variations in volatility, providing crucial information for adjusting investment strategies.

These results suggest that cryptocurrencies can play a significant role in investment portfolios. Investors are encouraged to reconsider the place of these assets in their strategies, carefully evaluating their impact on stability and overall performance.

In considering avenues for future research, it would be interesting to explore how the growing adoption of cryptocurrencies influences investors' decision-making patterns, portfolio management strategies, and attitudes toward traditional assets.

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