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ANALYSIS OF THE RELATIONSHIP BETWEEN RETURNS OF NASDAQ COMPOSITE AND BITCOIN

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ABSTRACT

Purpose: The article aims to investigate the relationship between the returns of the NASDAQ Composite stock index and the Bitcoin cryptocurrency.

Theoretical framework: According to the literature, it is obvious that cryptocurrencies are very volatile, especially during the economic instability period. There is a belief that when uncertainty is in the economy, investors prefer alternative investment opportunities. There is a need to prove that.

Design/Methodology/Approach: The study employs two different models, the ARMAX and the GARCH, to analyze the data from March 2018 to March 2023. The results of the analysis suggest a significant relationship between the returns of the NASDAQ Composite and Bitcoin. These results have important implications for investors and policymakers.

Findings: The findings suggest that investors need to be aware of the potential risks and benefits associated with investing in both assets, particularly in times of economic uncertainty. Policymakers may also need to consider the impact of traditional stock markets and the overall economy on cryptocurrencies.

Research, Practical & Social implications: The research suggests that investors should be careful with cryptocurrencies.

Originality/Value: The results are based on the time series analysis that makes the research original. Because there are few examples of time series and volatility analysis of cryptocurrencies.

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ANÁLISE DA RELAÇÃO ENTRE RETORNOS DO NASDAQ COMPOSITE E BITCOIN

RESUMO

Objetivo: O artigo tem como objetivo investigar a relação entre os retornos do índice de ações NASDAQ Composite e a criptomoeda Bitcoin.

Enquadramento teórico: De acordo com a literatura, é óbvio que as criptomoedas são muito voláteis, especialmente durante o período de instabilidade económica. Existe a crença de que quando há incerteza na economia, os investidores preferem oportunidades alternativas de investimento. É necessário provar isso.

Desenho/Metodologia/Abordagem: O estudo emprega dois modelos diferentes, o ARMAX e o GARCH, para analisar os dados de março de 2018 a março de 2023. Os resultados da análise sugerem uma relação significativa entre os retornos do NASDAQ Composite e do Bitcoin. Estes resultados têm implicações importantes para investidores e decisores políticos.

Constatações: As conclusões sugerem que os investidores precisam de estar conscientes dos potenciais riscos e benefícios associados ao investimento em ambos os activos, especialmente em tempos de incerteza económica. Os decisores políticos também poderão ter de considerar o impacto dos mercados de ações tradicionais e da economia em geral sobre as criptomoedas.

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Implicações de pesquisa, Práticas e Sociais: A pesquisa sugere que os investidores devem ter cuidado com as criptomoedas.
Originalidade/Valor: Os resultados são baseados na análise de séries temporais que tornam a pesquisa original. Porque existem poucos exemplos de séries temporais e análises de volatilidade de criptomoedas.

Palavras-chave: NASDAQ Composite, Bitcoin, Criptomoeda, GARCH, ARMAX, Decisão de Investimento.

ANÁLISIS DE LA RELACIÓN ENTRE LOS RENDIMIENTOS DEL NASDAQ COMPOSITE Y BITCOIN

RESUMEN
Propósito: El artículo tiene como objetivo investigar la relación entre los rendimientos del índice bursátil NASDAQ Composite y la criptomoneda Bitcoin.
Marco teórico: Según la literatura, es obvio que las criptomonedas son muy volátiles, especialmente durante el período de inestabilidad económica. Existe la creencia de que cuando hay incertidumbre en la economía, los inversores prefieren oportunidades de inversión alternativas. Es necesario demostrarlo.
Diseño/Metodología/Enfoque: El estudio emplea dos modelos diferentes, ARMAX y GARCH, para analizar los datos desde marzo de 2018 hasta marzo de 2023. Los resultados del análisis sugieren una relación significativa entre los rendimientos del NASDAQ Composite y Bitcoin. Estos resultados tienen implicaciones importantes para los inversores y los responsables de la formulación de políticas.
Hallazgos: Los hallazgos sugieren que los inversionistas deben ser conscientes de los riesgos y beneficios potenciales asociados con la inversión en ambos activos, particularmente en tiempos de incertidumbre económica. Es posible que las autoridades también deban considerar el impacto de los mercados bursátiles tradicionales y la economía en general sobre las criptomonedas.
Investigación, Implicaciones prácticas y Sociales: la investigación sugiere que los inversores deben tener cuidado con las criptomonedas.
Originalidad/Valor: Los resultados se basan en el análisis de series de tiempo que hace que la investigación sea original. Porque existen pocos ejemplos de series temporales y análisis de volatilidad de criptomonedas.

Palabras clave: NASDAQ Composite, Bitcoin, Criptomoneda, GARCH, ARMAX, Decisión de Inversión.

INTRODUCTION

Currently, we observe fluctuations (volatility) in the US economy (The Economist, 2023). Also, it is obvious that cryptocurrencies are very volatile, especially during the economic instability period. There is a belief that investors prefer alternative investment opportunities when there is uncertainty in the economy. One of these alternatives is Bitcoin. As Silicon Valley Bank (SVB) got bankrupt, some speculators expected price increases in Bitcoin. Thus, it is important to check whether there is scientific proof to believe that economic and financial instability leads to the price increase in Bitcoin. Here, the NASDAQ composite index is used as an exogenous variable and Bitcoin price as a dependent variable. In addition, different dummy variables are included in the model.

To model the relationship between Bitcoin returns and the NASDAQ composite index as an exogenous variable, we employ two popular time series models, ARMAX and GARCH. The ARMAX and GARCH models are widely used in financial econometrics to analyze time series data. ARMAX models are used for forecasting and control, while GARCH models are used to model and estimate conditional variances in financial time series (Box et al., 2008; Engle, 1982; Tsay, 2010).

The NASDAQ composite index is one of the most widely followed stock market indices and is often used as a benchmark for the performance of the technology sector. It includes the stock prices of more than 3,000 companies, primarily in the technology and biotech industries, and is widely used by investors and analysts to track the performance of the technology sector (Yahoo Finance, 2023). However, as it includes the stocks of all Nasdaq-traded companies, we can use it as a benchmark for the entire US stock market.

Understanding the factors that influence Bitcoin returns, including the impact of external variables such as the NASDAQ composite index, can help investors and speculators to make informed decisions about their portfolios. Furthermore, our findings may have broader implications for the relationship between traditional financial markets and cryptocurrencies, highlighting the potential for cross-market interactions and spillover effects.

THEORETICAL OVERVIEW

Recently many researchers studied the impact of cryptocurrencies on the economy, and they are increasing each year. In 2019, 252 new scientific articles are published about the cryptocurrency, while in 2022 this number doubled and became 553. Most of these articles are published in the USA. This process shows the increasing interest in the relationship between cryptocurrencies and the economy (Detthamrong & Chansanam, 2023). This article is one of the articles that is devoted to describing the effect of the cryptocurrency on national economy.

There are many studies that assert that gold prices increase while uncertainty exists in the economy. Because investors do not want to risk their money in uncertain markets, they start to invest the biggest portion of their money in traditional assets, in other words, in precious metals. Gold is the most popular of them (Triki & Ben Maatoug, 2021). In emerging and developing countries we can face the same situation. In these countries, gold can be a good tool for investors to avoid market uncertainty and recession risks (Gürgün & Ünalmış, 2014). There are some claims about the “gold” effect of Bitcoin in the case of a market recession. Some investors believe that demand for Bitcoin (and other cryptocurrencies) becomes higher when the market faces recession or uncertainty (Haq et al., 2021).

GARCH family models are typically employed in order to model the volatility. The study of S. Sharma is one example of this. In his study, he concludes that GARCH(1,1) is a suitable model to model the returns of the Indian market indices (Sharma, 2023). This model is also important to model the volatility of cryptocurrencies.

DATA AND METHODOLOGY

Data is taken from Yahoo Finance. It is daily data that covers 5 years:

- 23.03.2018-22.03.2023 for BTC-USD
- 23.03.2018-21.03.2023 for the NASDAQ Composite index

However, the data points of Bitcoin are more than the data points of the NASDAQ Composite, because Bitcoin is traded the whole week including weekends, while NASDAQ Composite is traded only during business days. It is only considered the days when the price for both variables is available. Also, outliers are included as dummy variables in some candidate ARMAX models. Thus, in my models there are the following variables:

a. BTC-USD returns and its lagged variables as endogenous variables.

b. NASDAQ Composite index returns as an exogenous variable.

c. Outliers of both BTC-USD and NASDAQ Composite index return as an exogenous variable.

There are several outliers in both cases, and it is needed to be modeled to capture the whole picture of the economic situation and Bitcoin relationship.

Generally, the modeling is based on the ARMAX model. But it is not enough for the whole picture because Bitcoin prices and its returns are very volatile. We use the residuals based on the selected ARMAX model to model volatility using the GARCH model. All modeling processes, descriptive statistics, graphs, and hypothesis tests are generated with the help of MATLAB.

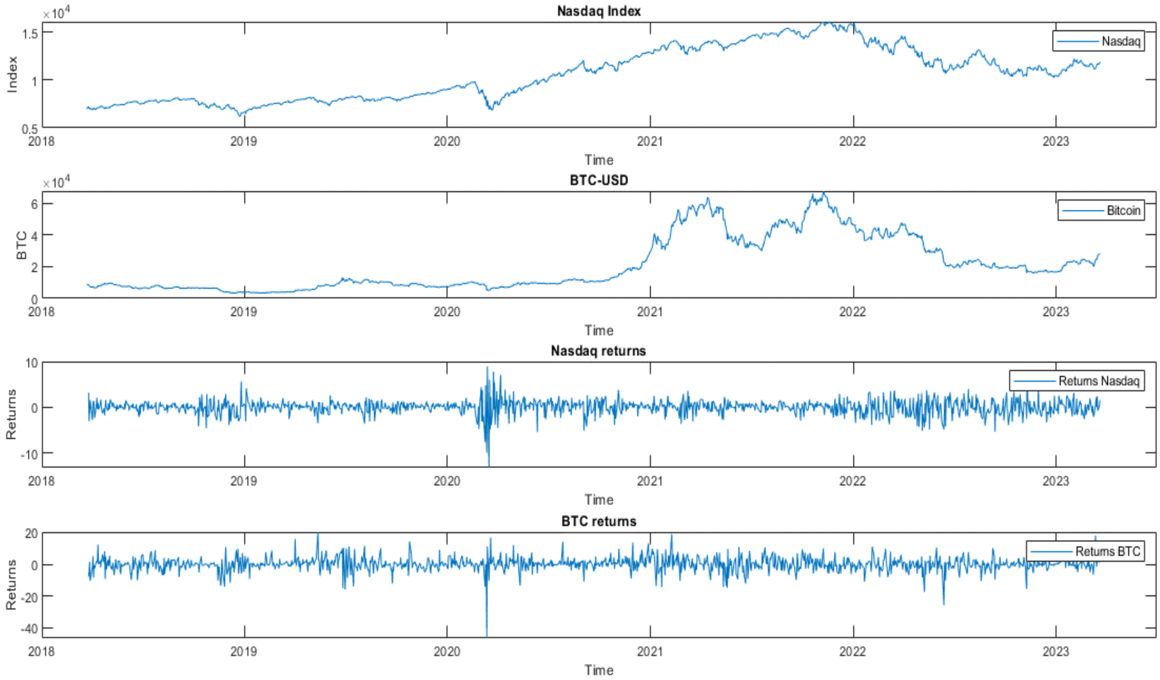
RESULTS AND DISCUSSION

Returns and Descriptive Statistics

As it is mentioned above the volatility of Bitcoin and the NASDAQ Composite is different. It is visible that (*figure 1*) both Bitcoin prices and returns are more volatile than the prices and returns of the NASDAQ Composite. Some correlation between the two variables is also possible.

From this point, it is important to use the returns of both variables for analysis and modeling purposes. Because in the figure below we can see that prices are not stationary, and they contain stochastic trend. Nonstationary data may create a spurious regression (Enders, 2015). Taking this into account, Augmented Dickey-Fuller and Phillips-Perron unit root tests are conducted on both data. According to both statistics, the return of Bitcoin and NASDAQ Composite are stationary.

Figure 1. The prices and returns of the NASDAQ Composite Index and Bitcoin



Source: Generated using MATLAB based on the data taken from Yahoo Finance (2023)

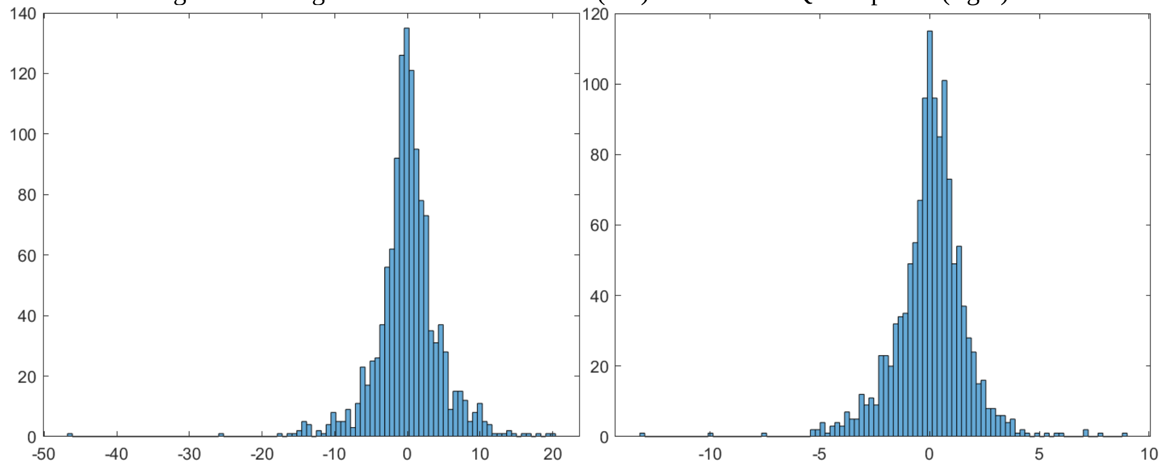
The descriptive statistics prove that the return of Bitcoin is much more volatile than the return of the NASDAQ Composite. Because its variance is about 10 times bigger than the variance of NASDAQ returns. Higher kurtosis gives us information about heavier tails. The difference between the 25th and 75th quantile also shows that the return of Bitcoin is more volatile. Histogram, Boxplot, and QQ plot will give us a broader picture.

Table 1. Descriptive Statistics

	Returns of Bitcoin	**Returns of NASDAQ Composite**
mean:	0.0919	0.0421
variance	20.2402	2.6545
skewness	-0.9842	-0.5951
kurtosis	14.5729	9.6678
q25	-1.7435	-0.6965
q75	2.1051	0.8906
median	0.0909	0.1169

Source: Author's computations based on the data taken from Yahoo Finance (2023)

Figure 2. Histogram of returns of Bitcoin (left) and NASDAQ Composite (right).

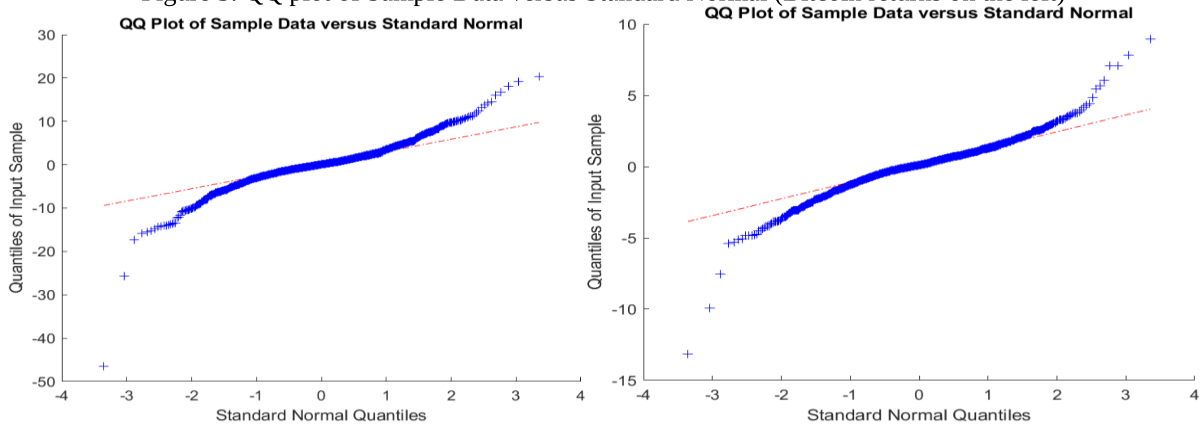


Source: Generated using MATLAB based on the data taken from Yahoo Finance (2023)

On the left, we can see the histogram of Bitcoin returns (*figure 2*). Its standard deviation is more than the standard deviation of Nasdaq and tails are heavier. There is skewness in both variables. These are proof that data is not normally distributed.

The left side QQ plot shows Bitcoin returns are not normally distributed and have heavy tails and outliers (*figure 3*). NASDAQ Composite returns are a bit closer to the normal distribution (right side QQ plot). Jarque-Bera test also rejects the null hypothesis in the case of both variables. Thus, these variables are not normally distributed. However, we have enough long-time period data to claim that they are asymptotically normally distributed. The analysis is conducted for 1256 data points.

Figure 3. QQ plot of Sample Data versus Standard Normal (Bitcoin returns on the left)

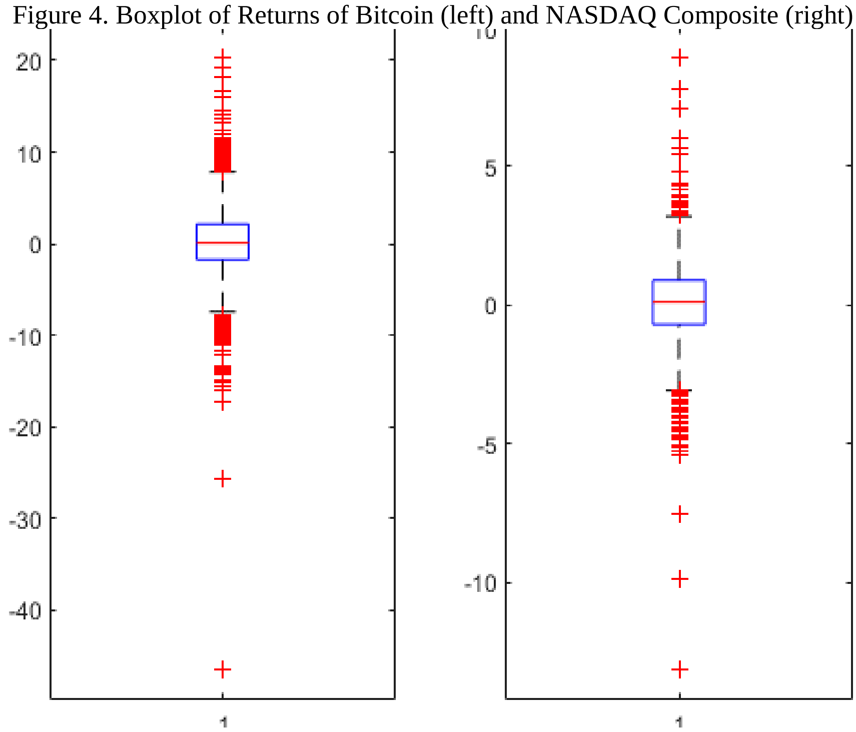


Source: Generated using MATLAB based on the data taken from Yahoo Finance (2023)

Outliers

Again, the left side shows the Bitcoin return boxplot, the right side shows NASDAQ Composite return boxplot (*figure 4*). According to the conservative approach of the boxplot, we can see that there are many outliers in Bitcoin returns. But it would be incorrect to consider all of them as outliers. NASDAQ Composite returns show many outliers (red plus) too. It is decided to consider a return an outlier if it is above and below the +-3 standard deviation away from the mean.

Figure 4. Boxplot of Returns of Bitcoin (left) and NASDAQ Composite (right)



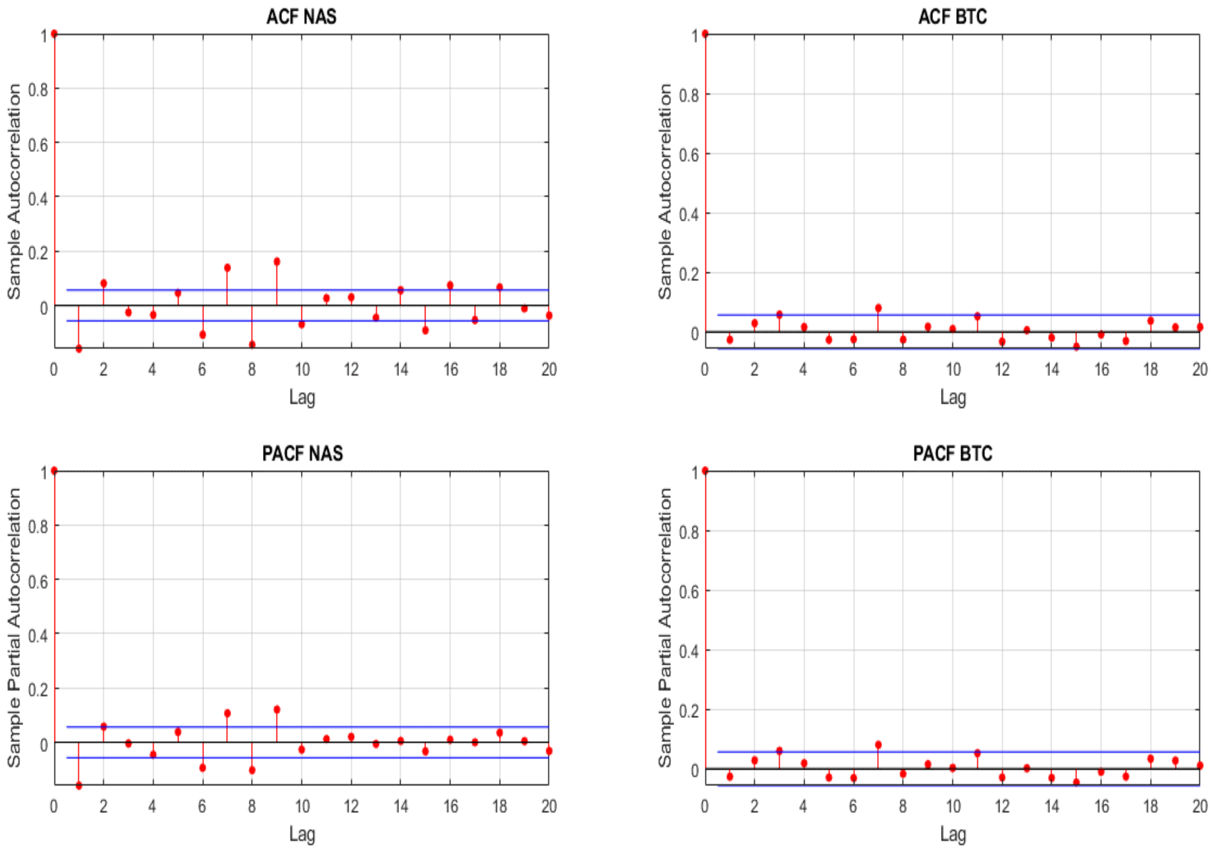
Source: Generated using MATLAB based on the data taken from Yahoo Finance (2023)

According to this method, we have 24 Bitcoin outliers, and 14 NASDAQ Composite outliers. NASDAQ's main outliers belong to the pandemic period. Although, Bitcoin return shows outliers for different years.

Autocorrelation and Partial Autocorrelation

Autocorrelation is tested using Ljung-Box Q-test. The test rejects the null hypothesis that there is no autocorrelation. Thus, both Bitcoin and NASDAQ returns have autocorrelation with their lagged values. In the case of the Ljung-Box test of squared returns, Bitcoin doesn't show autocorrelation of squared returns. But NASDAQ's squared returns are autocorrelated. A squared return's autocorrelation is important to decide whether there is a clustering of volatility or not. If yes, then ARCH-GARCH model should be considered. But Bitcoin's returns are volatile, and we will need GARCH model.

Figure 5. ACF and PACF plot of Returns of NASDAQ Composite and Returns of Bitcoin



Source: Generated using MATLAB based on the data taken from Yahoo Finance (2023)

There is no special pattern for specific ARMA(p, q) model selection. But in the case of Bitcoin returns, decreasing ACF and PACF after lag 7 is visible. It is considered in the ARMAX model.

Econometric Model

There are 4 ARMAX models that are considered. All of them are compared based on the Akaike and Bayesian Information Criterions. First of all, ARMA(3,1)X(1) model is checked. Formula is as follows:

$$rt_{Bit_t} = \alpha + \beta_1 * rt_{Bit_{t-1}} + \beta_2 * rt_{Bit_{t-2}} + \beta_3 * rt_{Bit_{t-3}} + \delta_1 * rt_{Nas_{t-1}} + \epsilon_t + \theta_1 * \epsilon_{t-1}$$
(1)

Here, rt_{Bit_t} and $rt_{Nas_{t-1}}$ are returns of Bitcoin and NASDAQ Composite at time t, respectively. α is intercept term. ϵ_t shows error term at time t, while β, δ and θ are coefficients for lagged values of Bitcoin return, NASDAQ Composite return and error term respectively.

According to the Ljung-Box Q-test there is no serial correlation in residuals. So, model fits well.

The second model is ARMA(2,2)X(1):

$$rt_{Bit_t} = \alpha + \beta_1 * rt_{Bit_{t-1}} + \beta_2 * rt_{Bit_{t-2}} + \delta_1 * rt_{Nas_{t-1}} + \epsilon_t + \theta_1 * \epsilon_{t-1} + \theta_2 * \epsilon_{t-2} \quad (2)$$

As in previous model, residuals are not serially correlated and model fits well.

In the third model it is taken into account that PACF decreases after lag 7. Also, outliers are added to the model as 2 dummy variables. One for outliers of Bitcoin return and one for outliers of NASDAQ Composite return. So, ARMA(7,1)X(2) model is used:

$$rt_{Bit_t} = \alpha + \beta_1 * rt_{Bit_{t-1}} + \beta_2 * rt_{Bit_{t-2}} + \beta_3 * rt_{Bit_{t-3}} + \cdots + \beta_7 * rt_{Bit_{t-7}} + \delta_1 * rt_{Nas_{t-1}} + \delta_2 * rt_{Nas_{t-2}} + \gamma_1 * X_{Bit} + \gamma_2 * X_{Nas} + \epsilon_t + \theta_1 * \epsilon_{t-1} \quad (3)$$

Here X_{Bit} and X_{Nas} are outliers of Bitcoin and NASDAQ returns, while γ_1 and γ_2 are respective coefficients. The modeling of outliers should give us a better model.

At the last model more MA term is added to the previous model. ARMA(7,3)X(2) model:

$$rt_{Bit_t} = \alpha + \beta_1 * rt_{Bit_{t-1}} + \beta_2 * rt_{Bit_{t-2}} + \beta_3 * rt_{Bit_{t-3}} + \cdots + \beta_7 * rt_{Bit_{t-7}} + \delta_1 * rt_{Nas_{t-1}} + \delta_2 * rt_{Nas_{t-2}} + \gamma_1 * X_{Bit} + \gamma_2 * X_{Nas} + \epsilon_t + \theta_1 * \epsilon_{t-1} + \theta_2 * \epsilon_{t-2} + \theta_3 * \epsilon_{t-3} \quad (4)$$

Residuals are not serially correlated and the model fits well.

In all models there is no serial correlation of residuals. We need to compare them based on the AIC and BIC values. The table 2 compares the AIC and BIC values.

Table 2. AIC and BIC values of considered ARMAX models.

MODEL	AIC	BIC
ARMA22X1	3.0107	3.0352
ARMA31X1	3.0039	3.0285
ARMA71X2	**2.5720**	**2.7726**
ARMA73X2	2.5742	2.7830

Source: Author's computations based on the data taken from Yahoo Finance (2023)

Both AIC and BIC values are smaller in ARMA(7,1)X(2) model. As mentioned before, including outliers to the model makes it better. We should continue with residuals of ARMA(7,1)X(2) for GARCH model.

Parameters and their significance show that lagged values of Bitcoin returns are not significant for future values of Bitcoin returns. However, 1st lag of NASDAQ Composite return has positive significant effect on Bitcoin return. There are 38 parameters for dummy variables. 31 of them is significant. Negative outliers of NASDAQ and Bitcoin returns decreases the returns of Bitcoin. While positive outliers of NASDAQ have both negative and positive effect on bitcoin return. It shows that shocks in economy have impact on Bitcoin. But we cannot claim that it always has positive effect on Bitcoin returns.

Volatility model

GARCH(1,1) model a volatility model. The GARCH model allows for the variance to be a function of not only the past squared errors, but also past variances. It is in the following form:

$$y_t = \mu_t + \epsilon_t$$

$$\epsilon_t = \sigma_t * z_t \tag{5}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where:

y_t is the observed time series data at time t.
μ_t is the conditional mean of y_t at time t.
ϵ_t is the error term (i.e., the deviation of y_t from its mean) at time t.
σ_t is the conditional standard deviation of ϵ_t at time t.

z_t is a standardized normal random variable with mean zero and variance one.
ω is a constant, representing the long-term average level of the variance of the error term.
α_i and β_j are the parameters of the model, where α_i is the weight given to the squared error at time $t-i$, and β_j is the weight given to the past variance at time $t-j$.

In our model the GARCH formula is as follows:

$$\sigma_t^2 = 0.3191 + 0.0494\epsilon_{t-1}^2 + 0.9242\sigma_{t-1}^2 \tag{6}$$

Thus, the long-term average level of the variance of the error term of Bitcoin returns is 0.31 which is very high and there is strong impact of 1st lag of variance on variance of error term.

Moreover, all coefficients are statistically significant:

Table 3. Parameter estimate of GARCH(1,1) model

	Estimate	**Standard Error**	**P-value**
$\boldsymbol{\omega}$	0.3191	0.1315	0.0152
$\boldsymbol{\alpha_i}$	0.0494	0.0116	0
$\boldsymbol{\beta_j}$	0.9242	0.0164	0

Source: Author's computations based on the data taken from Yahoo Finance (2023)

CONCLUSION

In conclusion, the findings of the ARMAX and GARCH(1,1) models suggest that shocks in the economy, as represented by the NASDAQ index, can have an impact on the returns of Bitcoin. Specifically, negative outliers in NASDAQ returns were found to decrease Bitcoin returns, while positive outliers had both negative and positive effects. This suggests that the relationship between Bitcoin and traditional financial markets is complex and may be affected by a variety of factors.

Moreover, the estimated values of omega, alpha, and beta in the GARCH(1,1) model for Bitcoin returns suggest that the long-term average level of the variance of the error term is relatively high, with past variance having a strong impact on current variance. This indicates that Bitcoin returns are characterized by volatility persistence, which has important implications for risk management and investment decisions.

Overall, these findings highlight the need for further research and analysis of the dynamics between Bitcoin and traditional financial markets. While it is clear that shocks in the economy can impact Bitcoin returns, the exact nature and direction of these effects may be influenced by a variety of factors that require further investigation.

REFERENCES

Box, G. E., Jenkins, G. M., & Reinsel, G. C. (2008), *Time series analysis: forecasting and control.* John Wiley & Sons.

Brooks, C. (2019), *MATLAB for finance: An introduction to financial engineering with MATLAB.* Cambridge University Press.

Detthamrong, U., & Chansanam, W. (2023), Trend and Knowledge Structure of Cryptocurrency Research in the Scopus Database. *International Journal of Professional Business Review*, *8*(4), e01640–e01640. https://doi.org/10.26668/businessreview/2023.v8i4.1640

Enders, W. (2015), *Applied Econometric Time Series, 4th ed.* John Wiley & Sons.

Engle, R. F. (1982), "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation", *Econometrica: Journal of the Econometric Society*, 50(4), pp. 987-1008.

Gürgün, G., & Ünalmış, İ. (2014). Is gold a safe haven against equity market investment in emerging and developing countries? *Finance Research Letters*, 11(4), 341–348. https://doi.org/10.1016/j.frl.2014.07.003

Haq, I. U., Maneengam, A., Chupradit, S., Suksatan, W., & Huo, C. (2021). Economic Policy Uncertainty and Cryptocurrency Market as a Risk Management Avenue: A Systematic Review. *Risks*, 9(9), Article 9. https://doi.org/10.3390/risks9090163

Sharma, S. (2023). Modelling Volatility of Size Indices Through Garch and Tgarch Models: Evidence from India. *International Journal of Professional Business Review*, 8(4), e01639–e01639. https://doi.org/10.26668/businessreview/2023.v8i4.1639

The Economist (2023), *For markets Silicon Valley Bank's demise signals a painful new phase,* https://www.economist.com/finance-and-economics/2023/03/14/for-markets-silicon-valley-banks-demise-signals-a-painful-new-phase, [Accessed 24.04.2023]

Triki, M. B., & Ben Maatoug, A. (2021), The GOLD market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. *Resources Policy*, 70, 101872. https://doi.org/10.1016/j.resourpol.2020.101872

Tsay, R. S. (2010), *Analysis of financial time series*. John Wiley & Sons.

Yahoo Finance (2023), *Nasdaq Composite (^IXIC) Historical Data*, https://finance.yahoo.com/quote/%5EIXIC/history/, [Accessed 24.04.2023]

Yahoo Finance (2023), *Bitcoin USD (BTC-USD) Historical Data*, https://finance.yahoo.com/quote/BTC-USD/history/, [Accessed 24.04.2023]

APPENDIX

Table 1. Coefficient estimates, standard errors, and p-values of ARMA(7,1)X(2) model.

Variables	Estimated coefficients	Standard errors	P-values
Intercept	0.2063	0.1057	0.0509
$rt_{Bit_{t-1}}$	-0.027	0.0622	0.6636
$rt_{Bit_{t-2}}$	-0.0012	0.0016	0.4488
$rt_{Bit_{t-3}}$	0.0406	0.026	0.1184
$rt_{Bit_{t-4}}$	0.0105	0.0235	0.6548
$rt_{Bit_{t-5}}$	0.0253	0.0282	0.3696
$rt_{Bit_{t-6}}$	-0.0317	0.0237	0.181
$rt_{Bit_{t-7}}$	0.0377	0.0281	0.1785
$rt_{Nas_{t-1}}$	0.6179	0.0706	0
$rt_{Nas_{t-2}}$	0.0177	0.0841	0.8338
$X_{bit} - positive$	15.5077	0.3267	0
$X_{bit} - positive$	22.1318	0.4174	0
$X_{bit} - positive$	13.7869	0.5638	0
$X_{bit} - positive$	16.5214	1.5519	0
$X_{bit} - positive$	12.908	0.4363	0
$X_{bit} - positive$	13.5662	0.6734	0
$X_{bit} - positive$	17.8	0.365	0
$X_{bit} - positive$	17.5321	0.3439	0
$X_{bit} - negative$	-11.0247	1.0683	0
$X_{bit} - negative$	-14.545	0.4637	0
$X_{bit} - negative$	-16.5495	1.0578	0
$X_{bit} - negative$	-17.4769	0.4898	0
$X_{bit} - negative$	-12.8607	0.5368	0
$X_{bit} - negative$	0.0725	0.7284	0.9207
$X_{bit} - negative$	-0.0064	0.0732	0.9307
$X_{bit} - negative$	-14.1979	0.2322	0
$X_{bit} - negative$	-13.739	0.8343	0
$X_{bit} - negative$	-14.6734	0.8305	0
$X_{bit} - negative$	-13.2922	0.3547	0
$X_{bit} - negative$	-12.7158	0.5753	0
$X_{bit} - negative$	-14.8205	1.0414	0
$X_{bit} - negative$	-15.2415	0.3853	0
$X_{bit} - negative$	-23.0548	0.5644	0
$X_{bit} - negative$	-14.1538	0.5046	0
$X_{Nas} - positive$	-9.25	0.7981	0
$X_{Nas} - positive$	4.7302	3.1211	0.1296
$X_{Nas} - positive$	1.4362	2.0969	0.4934
$X_{Nas} - positive$	-1.8311	1.2793	0.1523
$X_{Nas} - positive$	-3.7002	0.8439	0
$X_{Nas} - positive$	2.9452	1.4631	0.0441
$X_{Nas} - positive$	5.3849	1.4485	0.0002
$X_{Nas} - negative$	-9.6144	1.3159	0
$X_{Nas} - negative$	-40.0667	0.9575	0
$X_{Nas} - negative$	-2.1481	2.1804	0.3245
$X_{Nas} - negative$	-2.3725	0.8351	0.0045
$X_{Nas} - negative$	-7.7572	0.4875	0
$X_{Nas} - negative$	-4.9045	0.487	0
$X_{Nas} - negative$	-6.5381	0.9496	0
Error term	0.0377	0.0758	0.6187

Source: Authors' computations based on the data taken from Yahoo Finance (2023)