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Examining the impact of bitcoin and other cryptocurrencies' prices on public finance variables

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ABSTRACT

This study examines the impact of Bitcoin and other cryptocurrency price fluctuations on key indicators of public finance. From a classification perspective, the research is applied in nature and employs a quasi-experimental, ex post facto methodology. To evaluate the magnitude and effects of shocks on public finance variables, the ARCH-GARCH model was utilized. Prior to this analysis, the variables were subjected to descriptive statistics, and the research hypotheses were tested using regression methods. The results confirmed that all variables were stationary. However, multicollinearity analysis revealed a collinearity issue between the inflation rate and gross domestic product (GDP), prompting the construction of two separate models to address this. Diagnostic tests indicated that neither autocorrelation nor non-normality of residuals posed any problems for either model, thereby affirming the robustness of the regression outcomes. The findings indicated that investor sentiment, government expenditure, and financial leverage significantly influenced cryptocurrency returns at the 5% level ($p < 0.05$). In contrast, GDP and firm size did not demonstrate statistically significant effects within this threshold. At a 95% confidence level, investor sentiment was shown to exert a direct influence on returns, suggesting that variations in emotionally driven investor behavior are closely tied to shifts in cryptocurrency market performance.

Keywords: Bitcoin, Cryptocurrencies, Public finance, Validation

Introduction

Cryptocurrencies represent a newly emerging class of financial assets that have witnessed rapid expansion, largely due to their capacity to enable secure, transparent, and decentralized blockchain-based electronic transactions across international borders. Bitcoin, introduced in 2009 by the pseudonymous developer Satoshi Nakamoto, was the first decentralized digital currency and has since played a foundational role in the development of the cryptocurrency ecosystem. A growing body of empirical research has focused on the price volatility of cryptocurrencies. One study analyzing 45 digital currencies found that, during the COVID-19 pandemic, their price fluctuations were more pronounced and unstable compared to traditional global stock markets [1].

Recent financial literature has increasingly explored the effects of the COVID-19 pandemic on cryptocurrencies, particularly their potential role in hedging investment portfolios during periods of market turmoil. Research in [2-4] suggests that cryptocurrencies may function as safe-haven assets in times of financial crisis, providing protective benefits in stock, commodity, and foreign exchange markets. Notably, empirical findings indicate that Ethereum may offer stronger safe-haven characteristics than Bitcoin during such periods [2, 3].

Similarly, findings from EGARCH modeling indicate that the leverage effect is statistically significant for cryptocurrencies such as Litecoin, Ripple, and Ethereum, but not for Bitcoin [5]. Furthermore, Bitcoin's volatility is considerably higher during speculative market phases compared to more stable periods [6], [7]. The influence of news on return volatility in the cryptocurrency market during the COVID-19 pandemic has also been examined using the GARCH-MIDAS framework. Results suggest that cryptocurrencies experienced elevated volatility and risk levels throughout the pandemic period [8]. Bitcoin's volatility is known to affect the pricing of other cryptocurrencies. For investors, accurately gauging market direction is essential. Ethereum, one of the most prominent cryptocurrencies, has demonstrated periods of strong price correlation with Bitcoin.

An analysis of correlation coefficients between Bitcoin and Ethereum shows that the two assets have often moved in close alignment under specific market conditions.Despite growing interest and advanced modeling techniques, forecasting cryptocurrency price movements remains a complex challenge. According to the Efficient Market Hypothesis (EMH) and the Random Walk Theory [9, 10], cryptocurrency prices reflect all publicly available information at any given time and follow an unpredictable path, leaving little scope for accurate prediction. However, several scholars argue that EMH fails to account for certain irregularities, such as sudden short-term price spikes [11]. They maintain that many financial markets—particularly in developing economies—are not fully efficient, thereby enabling investors to exploit unpriced or delayed information to anticipate price trends. Moreover, behavioral finance theories posit that investor sentiment holds substantial predictive value for asset returns [12, 13].

Although seemingly minor, it is a well-established fact in financial markets that news and disclosures related to investor behavior and sentiment can exert a substantial influence on cryptocurrency prices and may serve as useful indicators for predicting stock market trends. Prior research on stock price forecasting has primarily concentrated on traditional financial indicators [14-16]. However, existing studies on cryptocurrency price prediction exhibit several notable limitations. While some employ data from multiple sources to enhance predictive accuracy compared to single-source models, they often neglect qualitative variables—such as textual information and behavioral indicators. Furthermore, current research generally fails to differentiate between highly active cryptocurrencies and less-traded or inactive digital assets. This omission suggests that differing activity levels may produce distinct price prediction dynamics. To address these gaps, the present study seeks to investigate the influence of Bitcoin and other major cryptocurrencies on public finance variables, thereby contributing to a more nuanced understanding of their broader economic impact.

The role of cryptocurrencies in different economic sectors

Materials and Methods

From a classification perspective, this study is applied in terms of its purpose, quasi-experimental in design, and ex post facto in nature. Methodologically, it follows a correlational approach, while its data collection is descriptive–analytical. The statistical population encompasses the Tehran Stock Exchange. The data analyzed consist of time series reflecting changes and cumulative variations in the cryptocurrency index and Iran's macroeconomic indicators over the period from 2011 to 2021 (corresponding to 1390–1400 in the Iranian calendar).

The role of cryptocurrencies in different economic sectors

Analyses and studies by economists in developing countries suggest that cryptocurrencies hold considerable potential to accelerate economic development. The growth of internet infrastructure in these regions has often been the result of timely opportunities to connect with the global digital network. This connectivity has enabled users not only to access information but also to participate in global trade through cryptocurrencies. The rising adoption of the internet has further promoted the exchange of ideas, technologies, and financial innovations between developing and developed nations.

Babazadeh *et al*. (2021) proposed a conceptual framework titled A Conceptual Model of Facilitating Indicators for the Use of Cryptocurrencies in International Transactions under Sanctions. In this study, six categories of key indicators were identified and prioritized. These included cryptocurrency regulation, the development of software and hardware infrastructure, the issuance of national cryptocurrencies, the promotion of cryptocurrency adoption, and support for cryptocurrency mining activities [17]. Similarly, Aghamohammadi *et al*. (2020), in their study Estimating Investment Risk in a Cryptocurrency Portfolio and Its Optimization Using the Value-at-Risk Method, focused on constructing a portfolio of cryptocurrencies with the highest trading volume and liquidity. Using the Value-at-Risk (VaR) approach, they measured the risk and return of the portfolio and proposed an optimal investment strategy [18]. Dehghan Khavari *et al*. (2020) explored the theme of Cryptocurrency and Its Role in Economic Development**.** Their findings suggest that cryptocurrencies have sparked a transformation in economic transactions, challenging the dominance of traditional fiat currencies. The study highlights Bitcoin's potential to empower startups in Iran and argues that cryptocurrencies could serve as effective tools for fostering national economic growth [19]. In another relevant study, Ahmet *et al*. (2022) examined China's Transition to a Digital Dollar and Foreign Trade. This paper provides an in-depth overview of China's efforts to introduce a central bank digital currency (CBDC) and its potential implications for international trade [20].

To evaluate market shocks and impulses from competing sectors and to forecast potential instability or crashes within the cryptocurrency market, this section analyzes several key variables: inflation, Brent crude oil prices, gold prices (specifically based on the traditional Bahar Azadi gold coin design), liquidity, and the USD to IRR exchange rate. The dataset comprises monthly observations from 2019 to 2022. Data on inflation, liquidity, exchange rates, and Bahar Azadi coin prices were collected from the World Bank and the *Economic Indicators* journal, while Brent crude oil prices were obtained from the U.S. Energy Information Administration (EIA).

In the initial stage, following seasonal adjustment of each variable, the KPSS test was employed to assess unit roots and determine the stationarity of the variables. Subsequently, the volatility of the cryptocurrency market price index, along with the individual economic variables related to competing markets, was modeled. The analysis then focused on evaluating the impact of dummy variables and the volatility of competing markets on the fluctuations in the cryptocurrency market index. To examine the behavior of the dummy variables, the relevant index was derived using two methods: first, by constructing a composite index through Principal Component Analysis (PCA), and second, by calculating the index using the EMSI formula. In the final step, the index was categorized into two sentiment-based effects: optimistic and pessimistic.

To measure the effects of optimism and pessimism on the volatility of cryptocurrency prices, the Ordinary Least Squares (OLS) or Weighted Least Squares (WLS) methods were employed. The volatility and uncertainty variables of competing markets were added to the models as control variables. The general structure of the model includes the following equation:

Predict VIX = F(Fi, M, Inf, GDP, Pn, Pa, Ps, Pr, DUM, S, Ro, Val, Lv, Man)

Where the factors are defined as:

Fi = Financial volatility

M = Money supply

Inf = Inflation rate

GDP = Gross Domestic Product

Pn = Oil price

Pa = Exchange rate

Pt = Gold price

Ps = Price index in the cryptocurrency market

Pr = Interest rate

DUM = Dummy variable (international and political relations)

S = Firm size

Ro = Profitability

Val = Firm value

Lv = Financial leverage

Man = Type of ownership

In this study, to examine the effect of the COVID-19 pandemic on the return-volatility relationship, the EGARCH-M model is applied, while the average return is estimated using the Autoregressive Moving Average (ARMA) model [21]. The EGARCH(1,1) formula used in this study's mean equation is as follows:

$$r_t = c + \sum_p \varphi_p r_{t-p} + \sum_q \theta_q \varepsilon_{t-q} + \lambda \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t, and \ \mathrm{In}\,(\sigma_t^2) = \omega + \alpha_1 \big(|z_{t-1}| - E(|z_{t-1}|)\big) + \alpha_2 z_t + \beta \ \mathrm{In}(\sigma_{t-1}^2) \tag{1}$$

Based on this, in the present study, the dependent variable is the returns in cryptocurrency markets, and the explanatory variables include COVID-19 conditions, cryptocurrency prices, oil and gold market prices, inflation rate, national income, and the amount of investments made in the cryptocurrency sector.

The implementation of tests, identification, estimation, and evaluation of the models—as well as static and dynamic forecasting and the assessment of their accuracy—were carried out using EViews version 9.

Results and Discussion

First, the descriptive statistics of the companies used in the study were analyzed **(Table 1)**.

Table 1. Descriptive Statistics of Research Data

	LOG(P)	LOG (VS)	VS	LOG(VO)	LOG(VF)	LOG (SF)	LOG (NINFE)	LOG (NC)	LOG (NAC)	LOG (CPI)	LOG (LIQ)	LOG (man)	LOG (PGOLDOLD)	PGOLDOLD	S	POILB
Mean	10.110	-0.797	0.469	-1.739	-4.184	3.912	0.016	-5.011	-4.763	5.125	15.558	10.207	9.103	9311.804	4.393	87.287
Median	10.210	-0.774	0.461	-1.554	-4.194	3.942	0.140	-5.150	-4.773	5.218	15.550	10.398	9.153	9444.683	4.644	103.947
Maximum	10.647	-0.203	0.816	-0.957	-2.991	4.144	2.984	-2.713	-4.047	5.523	16.274	10.519	9.520	13633.440	4.846	127.195
Minimum	9.588	-1.687	0.185	-3.102	-5.210	3.712	-2.412	-7.061	-5.435	4.531	14.896	9.319	8.280	3944.078	3.503	33.210
Standard Deviation	0.306	0.293	0.126	0.598	0.485	0.108	1.194	0.921	0.350	0.321	0.421	0.374	0.285	2323.036	0.416	30.455
Skewness	-0.152	-0.710	0.039	-0.632	0.169	-0.248	0.112	0.526	-0.055	-0.550	0.075	-1.296	-1.075	-0.363	-0.717	-0.517

Kurtosis	1.784	3.443	2.666	2.069	2.847	2.017	2.404	3.065	1.961	1.868	1.765	3.120	3.866	2.827	1.874	1.581
Jarque-Bera	4.455	6.272	0.334	6.979	0.392	3.435	1.149	3.152	3.091	7.055	4.384	19.068	15.232	1.575	9.412	8.733
Probability	0.108	0.043	0.846	0.031	0.822	0.180	0.563	0.207	0.213	0.029	0.112	0.000	0.000	0.455	0.009	0.013
Sum	687.46	-54.20	31.88	-118.25	-284.49	266	1.097	-340.76	-323.89	348.50	1057.95	694.09	618.994	6.332E+05	298.7	5935.55
Sum of Squared Deviations	6.280	5.750	1.069	23.992	15.788	0.780	95.592	56.774	8.206	6.923	11.854	9.367	5.437	3.620E+08	11.59	62144.1

, ** , * indicate significance at the 1%, 5%, and 10% probability levels, respectively.**

The cryptocurrency price index data were analyzed on a monthly basis from 2019 to 2022. Initially, the KPSS test was applied to assess the stationarity of the time series. Results confirmed that the series is stationary at both the 1% and 5% significance levels. Subsequently, to capture the volatility dynamics and forecast potential crashes in the cryptocurrency price index, the optimal conditional mean equation was estimated. This process involved identifying and selecting the appropriate ARMA model order, which was achieved using the Box-Jenkins methodology.

Table 2. ARIMA Modeling for the Logarithmic Forecast of the Cryptocurrency Price Index

SIGMASQ	MA(2)	MA(1)	AR(1)	C	Variable
0/0018*	0/1505	0/4979*	0/966*	10/0662*	Coefficient
0/0002	0/1341	0/1509	0/0329	0/2143	Standard Error
7/4812	1/1228	3/2988	29/399	46/9697	t-Statistic

, ** , * denote significance at the 1%, 5%, and 10% probability levels, respectively.**

As shown in **Table 2**, the optimal model selected is ARMA(1,2), which combines an autoregressive term of order 1 (AR(1)) with a moving average term of order 2 (MA(2)). While all model coefficients are statistically significant at the 1% level, the coefficient for MA(2) is not significant; however, due to its t-statistic exceeding one, it remains included in the model and is not excluded. Subsequently, to capture conditional heteroskedasticity and model the volatility of the cryptocurrency price index, the EGARCH model was employed to estimate price turbulence.

Table 3. Estimation Results of the Volatility Model and Crash Prediction of the Cryptocurrency Price Index

Conditional Mean Equation of Log(P_sa)					
Variable	$_0\alpha$	AR(1)	MA(1)	MA(2)	@Trend
Coefficient	9/5925*	0/9676*	0/5834*	0/1996*	0/0121*
Standard Error	0/000000067	0/02222	0/03224	0/05363	0/00122
Conditional Variance Equation $\log(\sigma_t^2)$					
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$	
Coefficient	*-1.1464	*-0.8899	*0.2003	*0.7098	
Standard Error	0.0031	0.0200	0.0697	0.0005	

Table 3 presents two equations: the upper equation corresponds to the conditional mean, while the lower one represents the conditional variance. The term C(6) denotes the constant (β_0), and C(7), C(8), and C(9) correspond to the coefficients α, γ, and β, respectively, as outlined in the EGARCH model specification detailed in Chapter 3. All estimated coefficients in the EGARCH model are statistically significant. Notably, the positive value of γ indicates that positive shocks to the price index increase volatility and market uncertainty, whereas negative shocks tend to decrease volatility in the cryptocurrency market.

Table 4. Estimation Results of Inflation Volatility Model Due to Cryptocurrency Market Instability

Conditional Mean Equation of Inflation Log(CPI_SA)				
Variable	α_0	AR(1)	AR(2)	MA(1)
Coefficient	6/8607	1/7721*	-0/7738*	-0/4163*
Standard Error	0/2090	0/000	0/000	0/0773
Conditional Variance Equation $\log(\sigma_t^2)$				
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$
Coefficient	-1/6616	4984**-0/	*57320/	0/8066*
Standard Error	68960/	19590/	14490/	0/0637

, ** , * indicate significance at the 1%, 5%, and 10% levels, respectively.**

Estimation results of the exchange rate volatility model influenced by instability in the cryptocurrency market

Conditional Mean Equation of Exchange Rate Log(EXR_SA)				
Variable	α_0	AR(1)	MA(1)	
Coefficient	10/8077*	0/98050*	0/3716**	
Standard Error	0/4332	0/0056	0/1472	
Conditional Variance Equation $\log(\sigma_t^2)$				
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$
Coefficient	-1/9439	0/7229**	28020/	0/7841*
Standard Error	40430/	36170/	17990/	0/0577

, ** , * indicate significance at the 1%, 5%, and 10% levels, respectively.**

The coefficient γ related to the variable $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is not significant even at the 10% level, indicating that exchange rate shocks are symmetric.

Estimation Results of Gold Price Volatility Due to Cryptocurrency Market Instability

Conditional Mean Equation of Gold Price Log(PGOLDOLD_SA)				
Variable	α_0	@Trend	AR(1)	MA(1)
Coefficient	8/5088	0/0124*	0/9670*	0/2302**
Standard Error	0/0679	0/0018	0/0251	0/1004
Conditional Variance Equation $\log(\sigma_t^2)$				
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$
Coefficient	0/0351	3412*-0/	1953***0/	0/9643*
Standard Error	0.1101	0.0072	10430/	0/000

, ** , * respectively indicate significance at the 1%, 5%, and 10% probability levels.**

Estimation results of the liquidity volatility model due to the instability of the cryptocurrency market.

The conditional mean equation of inflation Log(LIQ_SA)				
Variable	α_0	@Trend	AR(1)	MA(1)
Coefficient	14/8489	0.0211	0/8659*	0.1569
Standard Error	0/0020	0/0018	0/0246	0.00467
The conditional variance equation $\log(\sigma_t^2)$				
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$
Coefficient	-2.1625	-0/5875***	-0/6317*	0.08380*
Standard Error	0.9412	0.3325	0.1832	0.1078

, ** , * respectively indicate statistical significance at the 1%, 5%, and 10% probability levels.**

Estimation results of the oil price volatility model due to the instability of the cryptocurrency market.

The conditional mean equation of oil price Log(POILB_SA)				
Variable	α_0	AR(1)	AR(2)	MA(1)
Coefficient	4/4689	0/1564*	0/7854*	0/9857*
Standard Error	0/1965	0/0344	0/0252	0/0045
The conditional variance equation $\log(\sigma_t^2)$				
Variable	$_0\beta$	$\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\|$	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	$\log(\sigma_{t-1}^2)$
Coefficient	-3/2349	5565**-0/	-1/2478*	0/3669*
Standard Error	62720/	26190/	18490/	0/1369

, ** , * respectively indicate statistical significance at the 1%, 5%, and 10% significance levels.**

In **Table 4**, the first equation represents the conditional mean equation for the logarithm of inflation, followed by the conditional variance equation beneath it. As observed in the table, all coefficients of the EGARCH model are statistically significant at the reported significance levels.

Table 4 presents the results of the EGARCH modeling for inflation shocks. As observed in the conditional variance equation, all EGARCH model coefficients except for the γ coefficient are significant at the 5% level. The insignificance of the γ coefficient indicates that exchange rate shocks are symmetric.

Table 4 presents the results of the EGARCH modeling for shocks in the gold market. As seen in the conditional variance equation, the coefficients α and β in the EGARCH model are significant at the 1% level, and the coefficient γ is significant at the 10% level.

The results of **Table 4** show that the coefficients γ and β in the EGARCH equation are statistically significant at the 1% level, while the coefficient α is significant at the 10% level.

Table 4 also indicates that in the conditional variance equation of oil price, the coefficients γ and β are statistically significant at the 1% level, and the coefficient α is significant at the 5% level. In the following section, after modeling the volatility of the cryptocurrency market price index as well as each economic variable related to competing markets, the effect of dummy variables and the volatility of competing markets on the fluctuations (volatility) of the cryptocurrency market price index is evaluated.

Table 5. Estimation results of volatility predictors for the cryptocurrency price index using the GARCH-MIDAS method.

Variable	CC (Intercept)	OPTNEW	GCPI	GLIQ	GP (-1)
Coefficient	0/0003	-0/00022*	5/2448*	0/8437*	0/6166*
Standard Error	0/00003	0/00003	0/3295	0/1272	0/0440
t-Statistic	9/3317	-6/5588	15/9168	6/6315	14/0012

, ** , and * respectively indicate significance at the 1%, 5%, and 10% probability levels.**

Weighted model	R² coefficient	0/887	Unweighted model	R² coefficient	0/406
	Durbin-Watson	1/91		Durbin-Watson	2/04

Table 10. Estimation results of volatility predictors for the cryptocurrency price index using the GARCH-MIDAS method.

Variable	CC (Intercept)	PESSNEW	GCPI	GLIQ	GP (-1)
Coefficient	0/0003	0/00016*	5/7937*	0/7216**	0/6273*
Standard Error	0/00004	0/00004	0/6511	0/3469	0/0471
t-Statistic	7/3371	3/9621	8/8982	2/0799	13/3112

, ** , and * respectively indicate significance at the 1%, 5%, and 10% probability levels.**

Weighted model	R² coefficient	0/8612	Unweighted model	R² coefficient	0/403
	Durbin-Watson	2/04		Durbin-Watson	2/01

Estimation results of volatility predictors for the cryptocurrency price index using the GARCH-MIDAS method.

Variable	CC (Intercept)	SENTNEW	GCPI	GLIQ	GPOILB	GP(-1)
Coefficient	0/00031	0/000096**	6/005*	0/7833**	-0/0067	0/5822*
Standard Error	0/00005	0/000036	0/6683	0/3232	0/0055	0/0452
t-Statistic	6/3040	2/6356	8/9859	2/4235	-1/2157	12/8797
, ** , and *** respectively indicate significance at the 1%, 5%, and 10% probability levels.						
Weighted model	R^2 coefficient	0/8535	Unweighted model		R^2 coefficient	0/3765
	Durbin-Watson	1/88			Durbin-Watson	1/94

Estimation results of volatility predictors for the cryptocurrency price index using the GARCH-MIDAS method.

Variable	CC (Intercept)	OPTEM	GCPI	GGOLDOLD	GP(-1)
Coefficient	0/0004	-0/0002*	3/2646*	0/0763*	0/5633*
Standard Error	0/00004	0/00003	0/7049	0/0139	0/0269
t-Statistic	9/4448	-7/7208	4/6311	5/4950	20/9366
, ** , and *** respectively indicate significance at the 1%, 5%, and 10% probability levels.					
Weighted model	R^2 coefficient	0/92	Unweighted model	R^2 coefficient	0/44
	Durbin-Watson	1/83		Durbin-Watson	1/98

Table 5 reveals that the pessimistic effects—derived from the composite index—have a positive and statistically significant impact on the volatility of the predicted cryptocurrency price index. This implies that an increase in pessimistic sentiment corresponds to heightened market volatility, although the relatively small coefficient indicates the effect's magnitude is limited. Moreover, uncertainty, as well as the volatility of inflation and liquidity, exert positive and significant influences on fluctuations within the cryptocurrency market. The coefficient sizes suggest that the cryptocurrency market is considerably more sensitive to inflation and liquidity volatility and uncertainty than to other factors, including pessimistic sentiment.

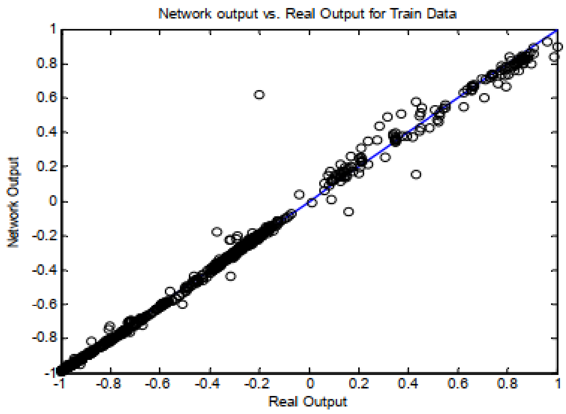
Table 5 investigates the influence of optimistic sentiment and emotions—derived from the EMSI index—alongside the volatility of competing markets on fluctuations within the cryptocurrency market. The findings reveal that optimistic sentiment exerts a negative and statistically significant effect on cryptocurrency market volatility, indicating that heightened optimism reduces market uncertainty and turbulence. However, the relatively small coefficient suggests this effect's magnitude is limited. Additionally, the volatility of inflation and gold prices significantly and positively impacts cryptocurrency market fluctuations. The coefficients for inflation and gold price volatility (3.2646 and 0.0763, respectively) underscore their substantial role, with their effects surpassing those of optimistic sentiment and emotions in shaping market volatility.

Table 5 presents the effects of political risk—extracted from the EMSI index—and gold price uncertainty on cryptocurrency market volatility. The results indicate that pessimistic sentiment and emotion have a positive and statistically significant impact on market volatility and fluctuations. However, the relatively small coefficient values (0.0002 and 0.00019) suggest that the intensity of this effect is limited. Furthermore, gold market volatility also exerts a positive and significant influence on the volatility of the cryptocurrency market.

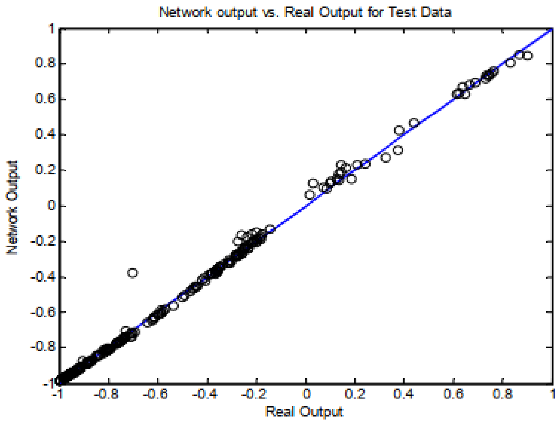
Table 6. Estimation results of volatility predictors for the cryptocurrency price index using the Hawkes method.

Variable	CC (Intercept)	PESSEM	PESSEM(-1)	GGOLDOLD	GP(-1)
Coefficient	0/0005	0/0002**	0/00019	0/0987***	0/5592*
Standard Error	0/00014	0/000096	0/00013	0/05455	0/1031
t-Statistic	3/8783	2/3114	1/4988	1/8109	5/4195
, ** , and *** respectively indicate significance at the 1%, 5%, and 10% probability levels.					
R^2 coefficient	0/44				
Durbin-Watson	1/97				

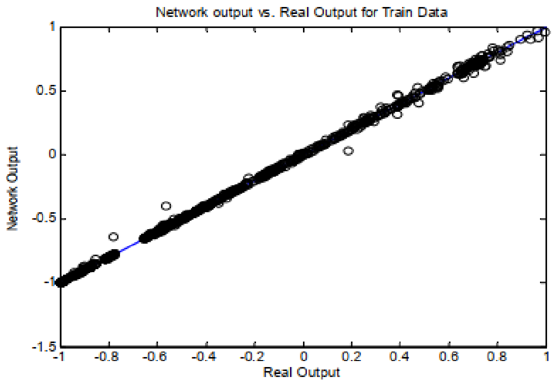
In this section of the study, the validity of the estimated models is evaluated and analyzed. One of the most common methods for training neural networks is the use of the backpropagation training method with the Marquardt-Levenberg algorithm.



a: Model Validation in the Cryptocurrency Market



b: Validation in Modeling the Volatility of the Cryptocurrency Market



c: Model Validation in Modeling the Spread of the COVID-19 Pandemic

figure 1- Model Validation

Based on the results obtained from data analysis, the disruption components exhibit a heterogeneous trend, and the estimated model is able to predict the type of fluctuations in cryptocurrency market volatility due to the COVID-19 pandemic with minimal error.

Conclusion

This study aimed to investigate the impact of Bitcoin and other cryptocurrencies on key public financial variables. The findings reveal that the COVID-19 pandemic had a significantly negative effect on the relationship between return volume and return volatility in cryptocurrency markets, particularly in the context of identifying price bubbles. The pandemic's adverse effects manifested in the form of widespread negative sentiment, reduced trading activity, and a decline in the overall volume of cryptocurrency transactions in financial markets. Consequently, the increased market volatility during the COVID-19 period negatively influenced broader public financial indicators.

The results further indicate that the global spread of COVID-19 contributed to heightened inflation, declining domestic production, and rising exchange rates. While all countries were affected by the pandemic, underdeveloped and less-developed nations faced more pronounced consequences due to structural inefficiencies in their financial systems.

Among the economic variables identified as contributing to instability in the cryptocurrency market during the pandemic were exchange rates, gross domestic product (GDP), inflation, and the volume of issued liquidity. These factors were found to negatively influence the return volume and volatility dynamics of parallel markets, such as gold and crude oil. Specifically, cryptocurrency price fluctuations exerted a destabilizing influence on these markets during the pandemic.

The analysis confirmed that price volatility in cryptocurrency markets led to a decline in returns across financial markets during the pandemic. Notably, price bubbles in the digital asset market occurred concurrently with similar phenomena in the gold and crude oil markets. This simultaneous behavior is attributed to speculative gains and the rapid expansion of the cryptocurrency sector. The findings suggest that digital asset markets often grow rapidly during periods of negative shocks in traditional commodity markets, reflecting speculative behavior rather than fundamental value shifts.

Based on these results, it is recommended that policymakers and regulatory bodies develop and implement a clear set of regulations and executive guidelines to identify and address instances of market manipulation and insider trading. Furthermore, a supervisory framework should be established that integrates quantitative models and expert oversight to detect, monitor, and control such activities effectively.

One limitation of this study lies in the availability of data, as information related to cryptocurrencies was obtained solely through MetaTrader platforms, which provide historical data for a limited number of years. This constraint restricts the scope of long-term analysis. Additionally, since the research is confined to a specific time frame, its findings should be generalized to future periods with caution.

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References

1. Kurihara Y, Fukushima A. The market efficiency of Bitcoin: A weekly anomaly perspective. J Appl Finance Bank. 2017;7(3):57-64. Physica A. 2018;503:257-62.
2. Bouclyour J, Selmi R. Ether: Bitcoin's competitor or ally? 2017.
3. Available from: https://arxiv.org/pdf/1707.07977.pdf
4. Caporale GM, Gil-Alana L, Plastun A. Persistence in the cryptocurrency market. Res Int Bus Finance. 2018;46:141-8.

5. Lahmiri S, Bekiros S, Salvi A. Long-range memory, distributional variation and randomness of Bitcoin volatility. Chaos Solitons Fractals. 2018;107:43-8.
6. Lamoureux CG, Lastrapes WD. Persistence in variance, structural change, and the GARCH model. J Bus Econ Stat. 1990;8(2):225-34.
7. Latif SR, Mohd MA, Amin MN, Mohamad AL. Testing the weak form of efficient market in cryptocurrency. J Eng Appl Sci. 2017;12(9):2285-8.
8. Lee DKC, Guo L, Wang Y. Cryptocurrency: A new investment opportunity? J Altern Invest. 2018;20(3):16-40.
9. Fama EF. Efficient capital markets: A review of theory and empirical work. J Finance. 1970;25(2):383-417.
10. Cheah ET, Mishra T, Parhi M, Zhang Z. Long memory interdependency and inefficiency in Bitcoin markets. Econ Lett. 2018;167:18-25.
11. Wang JC. A simple macroeconomic model of bitcoin. Bitquant Res Lab Work Pap. 2014;(1).
12. Ong B, Lee TM, Guo L, Lee DKC. Evaluating the potential of alternative cryptocurrencies. In: Lee DKC, editor. Handbook of digital currency. San Diego: Elsevier; 2015. p. 81-135.
13. Jiang Y, Nie H, Run W. Time-varying long-term memory in Bitcoin market. Finance Res Lett. 2018;25:280-4.
14. Cho H, Hong IB. The impact of consumer trust on attitudinal loyalty and purchase intentions in B2C e-marketplaces: intermediary trust vs seller trust. Int J Inf Manag. 2011;31(5):469-79.
15. Hu Y, Valera HGA, Oxley L. Market efficiency of the top market-cap cryptocurrencies: Further evidence from a panel framework. Finance Res Lett. 2019;31:138-45.
16. Zhang W, Wang P, Li X, Shen D. The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. Physica A. 2018;510:658-70.
17. Babazadeh Y, Faghihi Farahmand N, Pasbani M, Alavi Matin Y. A conceptual model of the facilitating indicators for the use of cryptocurrencies in international transactions under sanction conditions. Int Bus Manag J. 2021;4(1):167-88. doi:10.22034/jiba.2021.43301.1592
18. Aghamohammadi A, Vahhadi F, Sighali M, Bani Mahd M. Estimating investment risk in a cryptocurrency portfolio and its optimization using the Value at Risk method. Financial Stud. 2020;13(47):17-31. Available from: https://www.sid.ir/fa/journal/ViewPaper.aspx?id=580355
19. Dehghan Khavari S, Soltani M, Mirzababai FS, Khajeh-ha A. Cryptocurrency and its role in economic development. In: 5th National Conference on Economics, Management, and Accounting; 2020; Ahvaz, Iran. Available from: https://civilica.com/doc/1234689
20. Aysan AF, Kayani FN. China's transition to a digital currency: Does it threaten dollarization? Asia Glob Econ. 2022;2(1):100023. doi:10.1016/j.aglobe.2021.100023
21. Van Hout MC, Bingham T. "Silk Road", the virtual drug marketplace: A single case study of user experiences. Int J Drug Policy. 2013;24(5):385-91.