

Article

Cryptocurrency, Gold, and Stock Exchange Market Performance Correlation: Empirical Evidence

Kanellos Toudas ¹, Démétrios Pafos ², Paraskevi Boufounou ^{3,*} and Athanasios Raptis ⁴¹ Department of Agricultural Business Administration & Supply Systems Management, Agricultural University of Athens, 118 55 Athens, Greece; kstoudas@aua.gr² School of Social Sciences, Hellenic Open University, 263 35 Patras, Greece³ Department of Economics, National and Kapodistrian University of Athens, 106 79 Athens, Greece⁴ National School of Public Administration, Piraeus 211 Ave, 177 78 Athens, Greece; raptisathanasios@gmail.com

* Correspondence: pboufounou@econ.uoa.gr

Abstract: This paper examines the correlation between three prospective investing options: the Bitcoin cryptocurrency price, gold, and the Dow Jones stock index. The main research question is whether there is a causal effect of gold and the DWJ on Bitcoin and how this effect varies over time. The study begins with a background analysis that explains the definitions and operation of cryptocurrencies, followed by a brief overview of gold and its derivatives. In addition, a historical review of stock markets is provided, with a focus on the Dow Jones index. Then, a literature review follows. Daily data from three separate periods are used, each spanning four years. The first period, running from October 2014 to September 2018, provides an overview of the introduction of official cryptocurrency price data. The second period, running from Oct 2018 to Sept 2022, captures more recent trends preceding COVID-19. The third period, from January 2020 to December 2023, is the whole COVID-19 period with the initiation, embedded, and terminal phases. Classical inductive statistical methods (descriptive, correlations, multiple linear regression) as well as time series analysis methods (autocorrelation, cross-correlation, Granger causality tests, and ARIMA modeling) are used to analyze the data. Rigorous testing for autocorrelation, multicollinearity, and homoskedasticity is performed on the estimated models. The results show a correlation of Bitcoin with gold and the DWJ. This correlation varies over time, as in the first period the correlation mainly concerns the DWJ and in the second it mainly concerns gold. By using ARIMA models, it was possible to make a forecast in a time horizon of a few days. In addition, the structure of the forecasting mechanism of gold and DWJ on Bitcoin seems to have changed during the COVID-19 crisis. The findings suggest that future research should encompass a broader dataset, facilitating comprehensive comparisons and enhancing the reliability of the conclusions drawn.

Keywords: cryptocurrencies; bitcoin; gold; DWJ**JEL Classification:** E52; E31; J23

Citation: Toudas, K.; Pafos, D.; Boufounou, P.; Raptis, A. Cryptocurrency, Gold, and Stock Exchange Market Performance Correlation: Empirical Evidence. *FinTech* **2024**, *3*, 324–336. <https://doi.org/10.3390/fintech3020018>

Academic Editor: David Roubaud

Received: 15 April 2024

Revised: 2 June 2024

Accepted: 11 June 2024

Published: 18 June 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Gold and stock exchange have always been pivotal for investors. Cryptocurrency has also attracted the attention of investors (and researchers too) as an alternative investment. This paper aims to compare three different investment options: the Bitcoin cryptocurrency price, the gold price, and the Dow Jones stock index level examining three periods. The first period, from October 2014 to September 2018, marked the initiation of the official cryptocurrency price data. The second period, from October 2018 to May 2022, aimed to capture more recent trends before the effects of COVID-19 were fully embedded, and the third period, from January 2020 to December 2023, is the whole COVID-19 period with the initiation, embedded, and terminal phases.

Ref. [1] used cryptographic proof to solve the double-spending issue when he introduced modern blockchain technology. Nakamoto's creative application, as noted by [2,3] sets the stage for an electronic payment system based on cryptographic proof rather than trust, allowing decentralized transactions without the need for a middleman. Cryptographic techniques are used by cryptocurrencies, a subset of digital currencies, to achieve consensus [4]. They are classified as non-legal tender by the World Bank, European Banking Authority (EBA), and European Securities and Markets Authority (ESMA), but are legal tender in El Salvador [4]. Cryptocurrency is defined by the FATF as a digital representation of value that serves as a store of value, an accounting unit, and a medium of exchange but does not have the legal standing of a national currency [4].

By providing a thorough understanding of the complex world of cryptocurrencies, this multifaceted exploration aims to set the stage for future research. Electronic money is different from digital currency in that it is a digital form of legal tender, whereas digital or virtual currency is a more general term that includes electronic money to some degree [5]. Digital currencies were defined as forms of digital money without a specific legal status by the European Central Bank (ECB) in 2012 as part of a comprehensive report aimed at classifying and regulating them (ECB, 2015). The International Monetary Fund (IMF) further classified cryptocurrencies as a subset of digital currencies, which include Bitcoin and other cryptocurrencies as well as simpler IOUs and those linked to physical assets, like gold [4]. Digital currencies or digital debt systems are what the Committee on Payments and Market Infrastructures (CPMI), a division of the Bank for International Settlements (BIS), refers to as cryptocurrencies. Even though the Bretton Woods agreement was abandoned in 1973, gold has become less important in the global monetary system. The IMF is one of the world's biggest official holders of gold [6]. Over time, the legal status of gold ownership in the United States has changed. President Roosevelt outlawed it in 1933, and President Ford reversed the decision in 1974. An important turning point was the removal of barriers and discrimination against private ownership of gold with the liberalization of global markets, especially in China in 2005 and in India in 1991 [7].

A variety of products and services are available for investing in gold, including gold coins, bars, mutual funds, tradable securities, gold derivatives, gold accounts, and shares in gold mining firms. Sovereigns and Krugerrands are examples of physical gold coins that have inherent value. Gold bars are larger quantities of pure gold that are usually kept for investment purposes. They are usually cast or minted. Exchange-traded funds (ETFs) and bonds backed by gold are examples of tradable gold securities that give investors exposure to gold without requiring physical possession. Gold mutual funds invest in a diverse portfolio of gold-related assets by pooling the contributions of several investors. Like futures contracts, gold derivatives let investors make predictions about gold prices in the future. Banks and other financial institutions can provide gold accounts that let people buy and sell gold electronically. Finally, purchasing stock in gold mining firms gives investors a tangential exposure to gold, as the dynamics of the gold market impact the performance of these stocks [8,9]. Every type of gold investment has advantages and disadvantages of its own, enabling investors to customize their portfolios according to their risk tolerance and financial objectives.

The historical demands associated with economic advancement that have changed over time on a global scale are the foundation for the creation of stock exchanges. Technology led to a global economic boom in the middle of the 20th century and the emergence of contemporary stock exchange operating frameworks. The earliest exchanges were encouraged by early economies and agrarian societies in Europe, while resource-rich nations like Africa and Canada witnessed an increase in exchanges due to the mineral trade. The market began in the 17th century, and the Industrial Revolution in the 19th century proved to be crucial. Early 18th-century government bond markets gave rise to stock exchanges, which saw a turning point in 1773 when London traders formalized their domain. The New York Stock Exchange, established in 1792, was impacted by innovations in technology, such as the telegraph, and was instrumental in the post-Civil War era. The transatlantic cable

link established in 1866 and the electronic market established by Nasdaq in 1971 both had revolutionary effects. The London Stock Exchange leads in issuers and variety, while the New York Stock Exchange currently holds the title of the largest in the world. The London Stock Exchange, Euronext, Norex, Nasdaq, Easdaq, and Nasdaq represent the evolution of global markets. Since 1885, the Dow Jones Industrial Average has evaluated the stock performance of thirty major American companies. Because of its small size, some people view it as an incomplete representation when compared to indices like the S&P 500. The index, calculated using a divisor of approximately 0.1474, is 6.7843 times greater than the total of the component values.

The paper is organized as follows. First, a review of the relevant literature is provided. An analysis of the data used follows. Then, the statistical methods (descriptive, correlations, multiple linear regression) as well as the time series analysis methods (autocorrelation, cross correlation, granger causality tests, ARIMA modeling) used to analyze the data and the relative results are presented and analyzed. Following this, the main conclusions drawn are evaluated and the study's practical implications are highlighted. Finally, the main limitations of the study are discussed, and potential future research is indicated.

2. Literature Review

A thorough examination of several factors is included in research on cryptocurrencies and their economic ramifications, which sheds light on their intricate dynamics and wider economic consequences. Using statistical methods based on rescaled range analysis, Ref. [10] investigate the spread and fractal structure of the dynamic relationship between gold and silver prices. In comparison to straightforward wait-and-see and moving average strategies, this analysis shows the efficacy of trading rules over a range of holding periods. By utilizing an asymmetric GARCH methodology, Ref. [11] evaluate Bitcoin's risk-hedging capabilities against gold, highlighting the cryptocurrency's potential as a short-term hedge against stocks. Similarly to this, Ref. [12] fits parametric distributions to examine the statistical characteristics of popular cryptocurrencies. To identify cryptocurrencies with lower risk, Ref. [13] focuses on the tail behavior of returns in five major cryptocurrencies. It does this by estimating risk measures and applying extreme value analysis. Blockchains as distributed ledgers in peer-to-peer networks are examined in detail in [14], which models the blockchain proof-of-work protocol as a stochastic game and examines the equilibrium strategies of rational miners. Ref. [15] have developed a new research avenue in which they thoroughly examine transaction histories within the cryptocurrency complex. They achieve this by using an empirically oriented approach that aims to explain the mechanics of cryptocurrencies and suggest possible avenues for future research. The economic characteristics of digital assets are evaluated by [16], who propose that because cryptocurrencies have weak cross-correlations with traditional assets, they are appropriate for economic diversification. Angerer and colleagues (2021) underscore the significance of consolidating understanding in reaction to swiftly accumulating empirical data regarding cryptocurrencies. Through a thorough meta-analysis, Ref. [17] fills in knowledge gaps regarding the factors influencing cryptocurrency usage intention. To investigate correlations in cryptocurrency contexts, Ref. [18] presents a dual-stage analysis methodology that combines artificial neural networks (ANN) and partial least squares structural equation modeling (PLS-SEM). Ref. [19] make a second contribution in which they conduct a systematic literature analysis and identify three areas of promising future research: non-standardized financial risks, the adoption of innovative cryptocurrencies, and subjective risk perception. Ref. [20] criticize the narrow focus of fintech research and offer a framework that supports a more expansive understanding of user needs in cryptocurrency research. In their analysis of the intricacies of a dual economy, Refs. [21,22] highlight the importance of equivalent nominal interest rates and a risk-adjusted martingale exchange rate in the context of international cryptocurrencies.

The relationship between global energy commodities and the stock markets of China, India, South Africa, and Brazil was investigated by [23]. They analyzed this relationship

using wavelet techniques and discovered that positive co-movements become stronger over time. They also found that this relationship is significantly impacted by volatilities, especially those derived from the US Volatility Index. The authors concluded that investors looking to manage portfolio risks in energy commodities and the stock markets of the nations can benefit from these insights. Using an asymmetric approach, Ref. [24] investigated how susceptible sustainable Islamic stock returns were to implied market volatilities. They discovered that most volatilities had an impact on these returns that is inversely related. The writers stressed how crucial it is to build portfolios using appropriate volatility indices to efficiently manage risk in a variety of market scenarios. Ref. [25] carried out a study within the framework of the COVID-19 pandemic. They looked at the connection between gold and different cryptocurrencies using frequency-dependent asymmetric and causality analysis technologies. According to the research, gold primarily serves as a diversifier and safe haven for most cryptocurrencies over a range of investment horizons. Significant short- and medium-term hedging benefits for Dogecoin, Ripple, and Bitcoin were also found in the study. Ref. [26] examined the short- and long-term relationships between three cryptocurrencies and twenty-one stock exchanges using the VAR/VEC Model. These variables showed cointegration, short-term relationships, and causality, according to their analysis. The Stock Exchange series showed signs of cryptocurrency influence as well, with an average impact of 16, 15, and 16 periods for Bitcoin, Litecoin, and Ripple, respectively. Ref. [27] used the reduction method in a different research project to determine important factors that influence Bitcoin returns and volatility. After conducting an analysis, they concluded that the reduced set of explanatory variables influencing Bitcoin returns includes market capitalization, Bitcoin mining difficulty, gold return, Euro/USD exchange rate return, US Nasdaq stock exchange index return, and Twitter-based economic uncertainty. The authors also discovered that the volume of the cryptocurrency and the lag terms of the ARCH effect have the biggest effects on Bitcoin volatility. Ref. [28] investigated the interactions between Bitcoin to euro, gold, and STOXX50 during the period of COVID-19 and showed that the COVID-19 cases and gold hurt the exchange rate of Bitcoin to euro, while there was great volatility regarding the response of Bitcoin to a shock of STOXX50. Ref. [29] examined the existence of interdependencies between specific stock market indices (namely RTSI, Eurostoxx, and S&P 500), exchange rates (EUR/USD and RUB/USD) and crude oil for the period January 2021 to July 2022 with daily data, applying a wavelet coherence approach, and revealed the existence of strong correlations between all variables, during different time periods and for different frequencies during the period reviewed.

3. Data Analysis

Three time periods comprise the research period: October 2014–September 2018, October 2019–September 2022, and January 2020–December 2023. The availability of data had a significant impact on the choice of the study period. The sub-periods we have chosen have a duration of four years. The first studied period was chosen to represent the time leading up to the Greek economy's recovery from the severe financial crisis that began in 2010. The second period is continuous with the first period. The third period has a period of overlap with the second. The third period is the period from the appearance until the complete disappearance of the pandemic crisis COVID-19. The data available are the closing prices of gold, the DWJ index, and Bitcoin. These data are examined for the abovementioned three different periods, to compare whether the influencing mechanisms between the time series are kept unchanged over time. Time series data are daily values. The key descriptive statistics of Bitcoin, gold, and the DWJ for each period are presented in Table 1 below.

The key research question is whether there is a causal effect of gold and DWJ on Bitcoin. Furthermore, an additional research question is if there are changes over time to the possible causal effects found in the research question. R-language v.4.3.2 and IBM SPSS v.24.0 software were used to analyze the data and to provide the answer to the research question. We applied time series analysis techniques along with traditional descriptive and

inductive statistics techniques. Time plots, multiple scatter dot plot matrices, autocorrelation functions, Granger causality tests, the Pearson's R correlation coefficient, ordinary multiple regression analysis, and cross-correlation time series analysis were specifically used. In particular, initially the simple descriptive indicators for the three time series for each period were calculated, such as the mean, median, standard deviation, skewness, kurtosis, K'S normality, and stationarity tests. Then, the time plot graphs were constructed, which give us a visual overview of the dependence of the three time series. Pearson's correlation coefficient was then implemented for a rough overview of correlation and the corresponding multiple scatter dot plot matrices were produced. Multiple linear regression (non-time series approximation) was applied for an initial estimate of the weighted effects of gold and the DWJ on Bitcoin. Then, all the necessary transformations were implemented such as time lags, time differences, log transformations etc. Next, the autocorrelation and partial autocorrelation functions and relevant graphs were implemented, from which, among other things, the time lag depth of the dependencies is derived. Finally, time series regression models (ARIMA, etc.) were implemented to accurately capture the impact mechanisms of gold and DTC on Bitcoin.

Table 1. Descriptives of the data for each period.

Statistic	Period 1 (Oct 2014 to Sept 2018, n = 994)			Period 2 (Oct 2018 to Sept 2022, n = 989)			Period 3 (Jan 2020 to Dec 2023, n = 986)		
	Bitcoin	Gold	DWJ	Bitcoin	Gold	DWJ	Bitcoin	Gold	DWJ
Mean	2740.36	1231.87	20,072.03	22,620.76	1659.98	29,542.47	28,796.27	1828.74	31,945.63
Median	656.14	1235.73	18,440.33	11,784.14	1743.70	28,722.85	27,272.52	1826.38	33,191.18
Std. Deviation	3714.15	71.78	3069.05	18,062.03	227.95	4007.89	15,143.34	113.08	3518.51
Skewness	1.69	−0.39	0.65	0.74	−0.61	0.08	0.42	−0.37	−1.12
Skewness SE *	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Kurtosis	2.47	−0.45	−1.00	−0.87	−0.94	−1.17	−0.70	−0.14	0.73
Kurtosis S.E.	0.15	0.15	0.15	0.16	0.16	0.16	0.16	0.16	0.16
Normality **	0.299/0.000	0.045/0.000	0.216/0.000	0.234/0.000	0.170/0.000	0.109/0.000	0.070/0.000	0.047/0.000	0.165/0.000

* SE: Standard Error; **: Kolmogorov–Smirnov test (K-S Statistic/*p*-value).

4. Results

Figure 1 below shows time plot graphs for gold, the DWJ, and Bitcoin over three time periods. The overview of the time plot shows that there is a weak visual co-variation in the three sets of times series.

The Pearson's R correlation coefficient was then calculated between the three time series and for the three merged periods (thus, the Pearson coefficient applied to the whole period from 2014 to 2023), resulting in a statistically significant strong positive correlation between all three time series: $R_{\text{Bitcoin \& Gold}} = 0.779$, $p < 0.001$; $R_{\text{Bitcoin \& DWJ}} = 0.863$, $p < 0.001$ and $R_{\text{Gold \& DWJ}} = 0.875$, $p < 0.001$. It is worth noting that there was no significant correlation between gold and the DWJ during the first data period. Figure 2 below depicts a multiple scatter dot matrix that shows a strong positive correlation.

Following the analysis, a multiple linear regression analysis was applied with the price of Bitcoin as the dependent variable; the predictive variables were the prices of gold and the DWJ, with the "enter" method. This analysis—like the previous ones—is applied as an initial and descriptive exploration of the relationship between the three variables. The regression results are presented in Table 2 below. The regression results show a statistically significant effect ($p < 0.05$) of gold and the DWJ on Bitcoin. The data in this regression cover the whole time period, since this regression analyses only simultaneous values without taking time lags into account.

Then, the partial autocorrelation function (PACF) and cross-correlation function (CCF) was estimated for the three time series for the three periods. From the results of the CCF, it follows that there is an effect of the first time order lag on gold and bitcoin, while there is more complicated structure of lag influence to the DWJ, which consists of lags with orders of 1, 2, 3, and 8. Furthermore, a time series cross correlation analysis was performed. The

visual results of the cross-correlation coefficients are presented in Figure 3 below, from which it is evident that the existing influence over Bitcoin is stronger in the case of gold than in the case of DWJ. In Figure 3, there are presenting only some indicative graphs, due to the large number of all possible variable and period combinations. Furthermore, it seems that the structure of these influences is differentiated between the three periods studied.

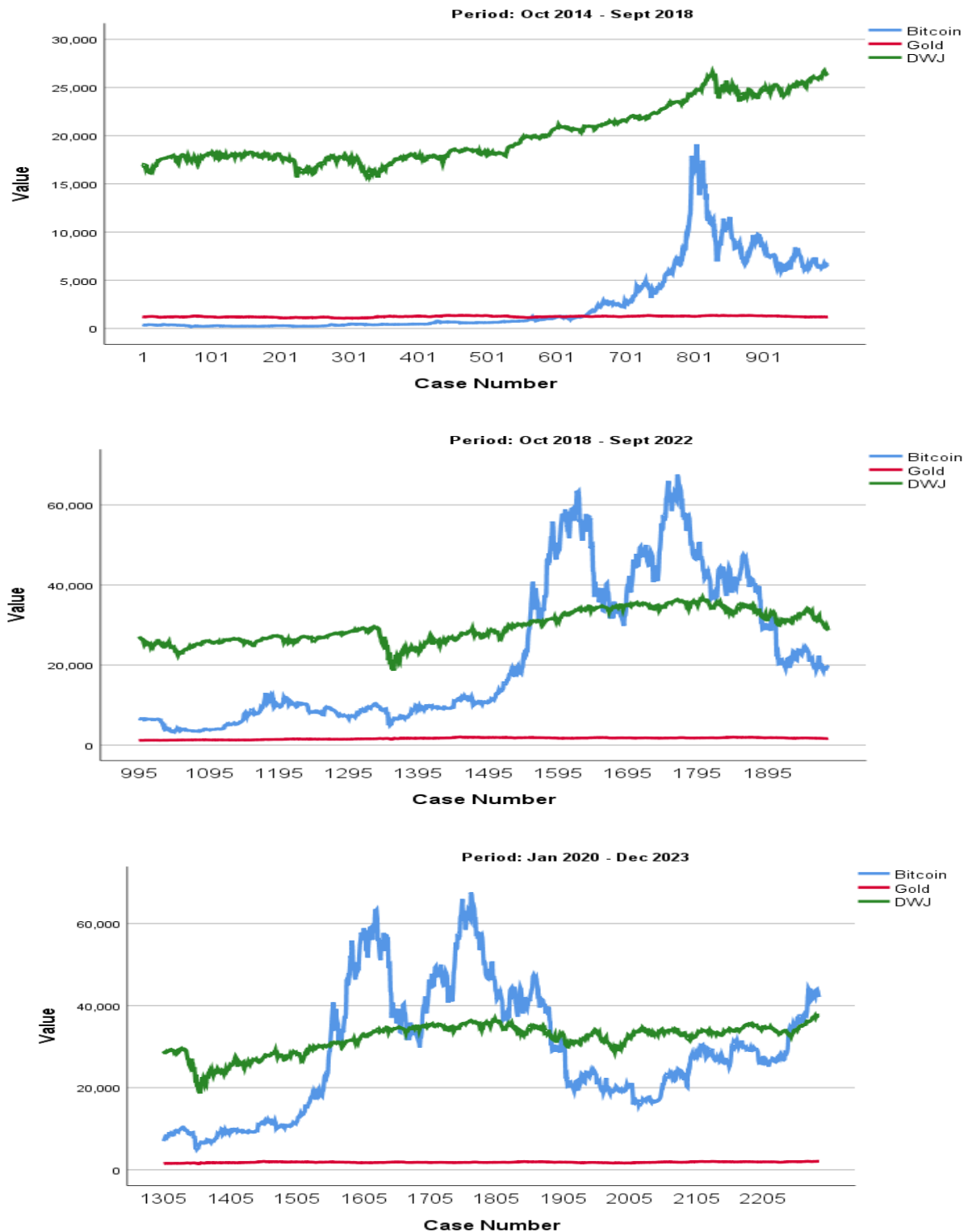


Figure 1. Time plots for three periods for the three sets of time series (Bitcoin, gold, DWJ).

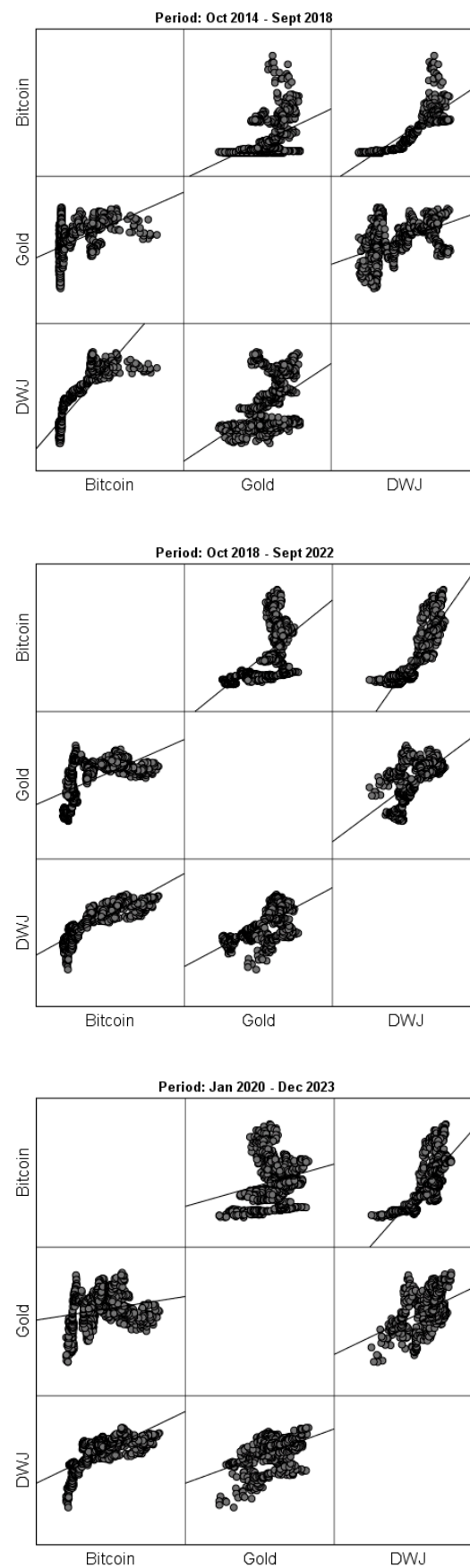


Figure 2. Multiple scatter dot matrix for both periods for Bitcoin, gold, and the DWJ.

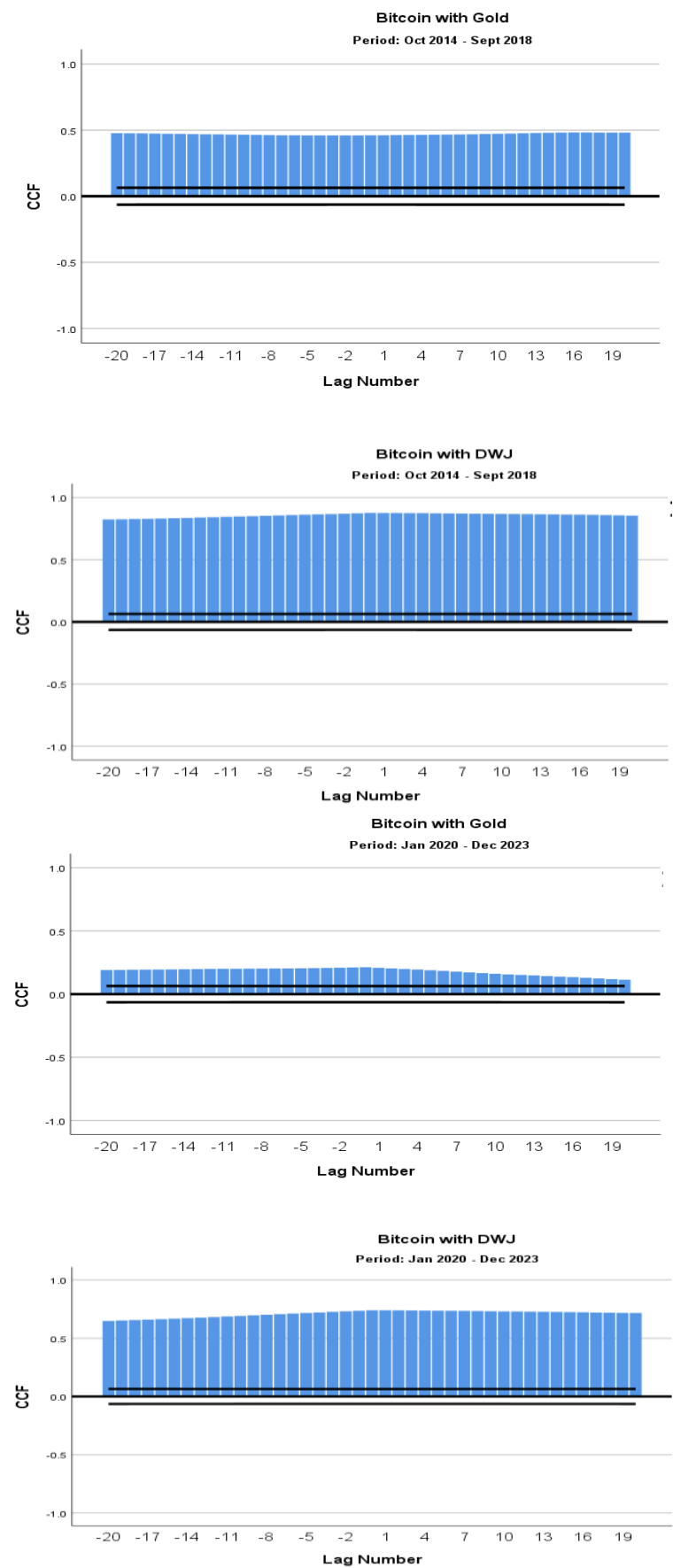


Figure 3. Time series cross correlation analysis for three periods.

Table 2. Results from the multiple regression analysis with the dependent variable (Bitcoin) and the predictors (Gold and DWJ).

Model	Unstandardized Coefficients		Standardized Coefficients		t	p-Value	Collinearity Statistics	
	B	Std. Error	Beta				Tolerance	VIF
(Constant)	−45,128.384	877.68			−51.41	0.000		
Gold	5.53	1.17	0.10		4.71	0.000	0.23	4.27
DWJ	1.97	0.05	0.77		35.58	0.000	0.23	4.27

Given the information obtained from the above analyses, several ARIMA models were performed to test the forecasting ability of gold and DWJ over Bitcoin. We selected the optimum model based on the goodness of fit tests, and the results are presented in Table 3 below, from which it is evident that a different ARIMA model fits each of the three periods best; in particular, the model is differentiated between the COVID-19 period (third period) versus the pre-COVID periods.

Table 3. Results of ARIMA modeling over three periods, with the target variable (Bitcoin) and the predictors (Gold and DWJ).

Fit Statistic	2014–18 ARIMA (0,1,0)	2018–22 ARIMA (0,1,0)	2020–23 ARIMA (0,1,5)
Stationary R-squared	0.001	0.080	0.056
R-squared	0.993	0.995	0.992
RMSE	308.588	1271.314	1347.911
MAPE	3.008	3.038	3.054
MaxAPE	26.482	46.665	37.117
MAE	114.186	728.570	849.275
MaxAE	3572.981	7693.051	7783.377
Normalized BIC	11.471	14.303	14.427

The comparisons between the predicted and observed values are given in Figure 4 below and it seems to be slightly satisfactory. The distribution of the residuals was tested with the KS test and marginally found to be in compliance with the normal distribution ($p = 0.048$).

Finally, a Granger causality test was performed to examine if a cause–effect relationship exists between Bitcoin (effect) and Gold and the DWJ. To perform this, we constructed the LAG time series and the difference time series for gold and the DWJ. The definitions of the two functions are as follows:

$$\text{LAG}(X(t), k) = X(t - k) \text{ and}$$

$$\text{DIFF}(X(t), 1) = X(t) - X(t - 1), \text{DIFF}(X(t), 2) = \text{DIFF}(X(t), 1) - \text{DIFF}(X(t - 1), 1).$$

After constructing these variables, a multiple linear regression was applied with Bitcoin as the dependent variable and all the first to fourth order LAGS and DIFF functions of Gold and DWJ were used as predictors. Because of the large number of predictors, we applied a backward stepwise method of regression, which automatically test–retested and rejected predictors based on their explanatory contribution. The results are given in Table 4 below, from which it is evident that a Granger causality exists. This means that gold and DWJ can in fact predict the values of the Bitcoin, although a set of more complex interactions between the three variables may exist, described by many other variables that are not used in the model.

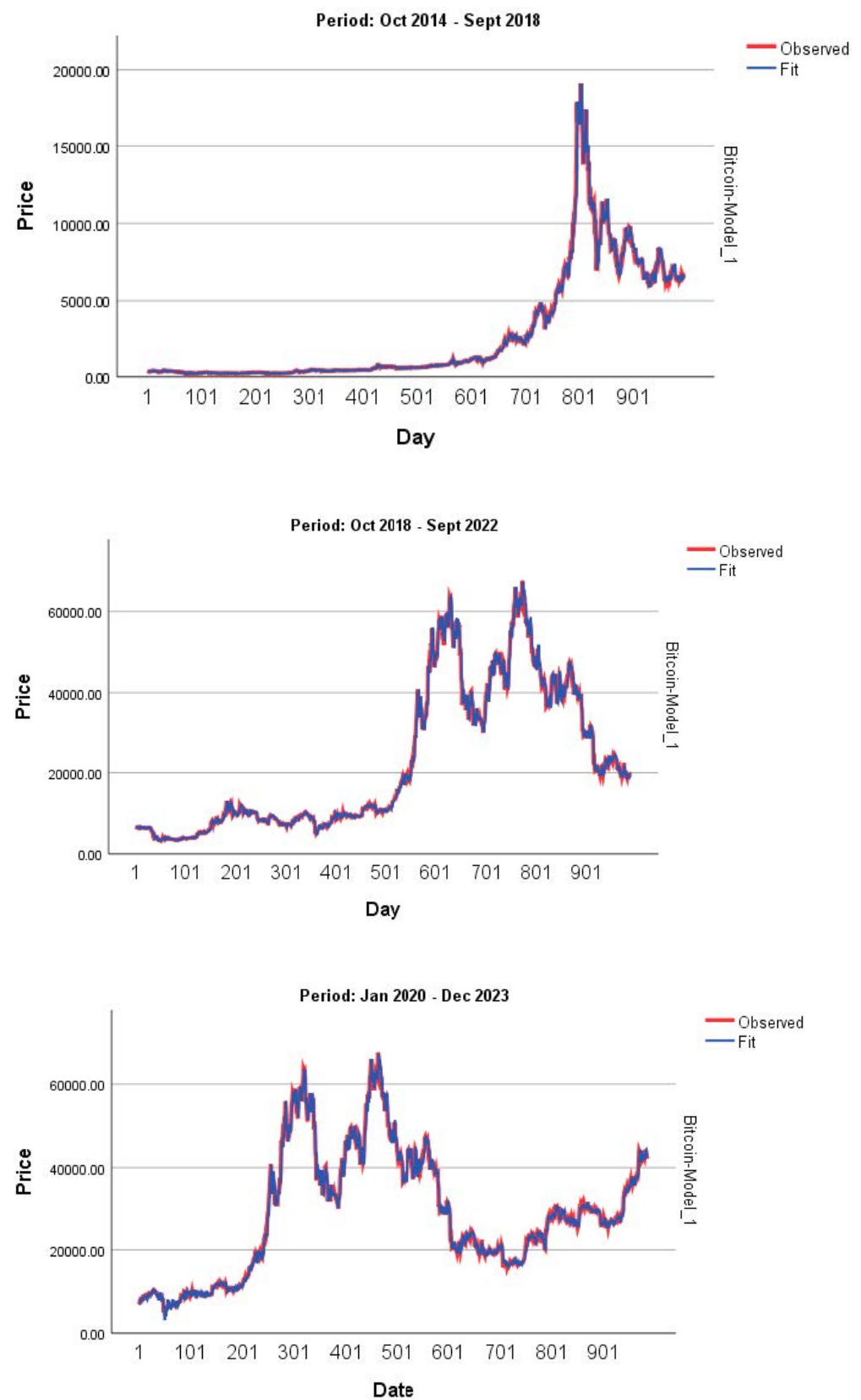


Figure 4. Comparisons from ARIMA modeling for the three periods; observed vs. predicted values.

Table 4. Results of the Granger causality tests over Bitcoin for the three periods.

Period	Model	Unstandardized Coefficients		Standardized Coefficients	t	p-Value	
		B	Std. Error	Beta			
Oct 2014– Sept 2018		(Constant)	−20,524.03	998.99		−20.55	0.000
	Iterations: 6 R ² _{adjusted} = 0.770 ANOVA: F _{7,981;0.05} = 472.63; p-value = 0.000	LAGS (DWJ,3)	1.05	0.02	0.86	48.65	0.000
		LAGS (Gold,1)	8.52	2.80	0.17	3.04	0.002
		LAGS (Gold,5)	−6.67	2.84	−0.13	−2.35	0.019
		DIFF (DWJ,1)	2.71	0.64	0.12	4.25	0.000
		DIFF (DWJ,2)	−2.73	0.80	−0.17	−3.41	0.001
		DIFF (DWJ,3)	0.91	0.36	0.10	2.56	0.011
		DIFF (Gold,1)	9.21	5.50	0.03	1.67	0.094
Oct 2018– Sept 2022		(Constant)	−84,859.26	5574.01		−15.22	0.000
	Iterations: 10 R ² _{adjusted} = 0.794 ANOVA: F _{3,985;0.05} = 1270.01; p-value = 0.000	LAGS (DWJ,5)	−1.62	0.41	−0.35	−4.01	0.000
		LAGS (Gold,5)	24.12	6.63	0.38	3.64	0.000
		Gold	19.18	6.74	0.30	2.84	0.005
		DWJ	2.49	0.41	0.52	6.15	0.000
Jan 2020– Dec 2023		(Constant)	−50,993.98	5262.02		−9.69	0.000
	Iterations: 10 R ² _{adjusted} = 0.559 ANOVA: F _{3,982;0.05} = 416.41; p-value = 0.000	Gold	−15.82	3.12	−0.12	−5.07	0.000
		DIFF (DWJ,1)	2.77	0.83	0.07	3.36	0.001
		LAGS (DWJ,1)	3.40	0.10	0.79	33.87	0.000

5. Discussion and Conclusions

In this study, three alternative investment options were compared: Bitcoin cryptocurrency price, gold price, and the Dow Jones stock index level. Daily data from three distinct periods are utilized, with each period spanning four years. The first period, from October 2014 to September 2018, marked the initiation of official cryptocurrency price data. The second period, from October 2018 to May 2022, aimed to capture more recent trends before the effects of COVID-19 were fully embedded, and the third period, from January 2020 to December 2023, is the whole COVID-19 period with the initiation, embedded and terminal phases. Classical inductive statistical methods (descriptive, correlations, multiple linear regression) as well as time series analysis methods (autocorrelation, cross-correlation, Granger causality tests, ARIMA modeling) were used to analyze the data.

From the various analyses carried out, we found a causal effect from the DWJ and gold on Bitcoin. The intensity of the effect relationship is sensitive and varies depending on the type of analysis and the chosen statistical model. It is noted that the meaning given to causality is not causality in general (“x causes y”; this is a philosophical question) but a causality in the sense of Granger causality (“x forecasts y”). Differences are also observed both in the intensity of the effects and in the model of the effects between the three time periods of the examined data, especially between the COVID-19 period and the other two periods. In the first period of study, the effects acquire a more complex character with the participation and effects from the DWJ, demonstrating that Bitcoin acquires a character of a stock market product. In the second period, the predictive effects on Bitcoin mainly come from gold, demonstrating that in that period Bitcoin had a more monetary character. In the third period, the main characteristic of the prediction model is the short-term time prediction window; this means that the regression model mainly consists of short-term lags and differences. To sum-up, gold and the DWJ can forecast Bitcoin in a time horizon of some days, and the possible addition of more predictive variables (model enriching) may extend the goodness of fit of such predictions. Our finding regarding the effects of gold and the time-dependent asymmetry of these effects are in accordance with [30,31], in terms of the gold effects.

When discussing the limitations and practical implications of a predictive ARIMA model for Bitcoin using gold and the DWJ as predictors, it is important to consider both

the theoretical aspects of the model and the real-world applicability of the findings. Hence, in light of the findings of the present study, the following considerations should be noted. (a) Data sensitivity and volatility: Bitcoin and other cryptocurrencies are known for their high volatility, which can be influenced by factors not traditionally associated with financial markets, such as technological changes, regulatory news, and social media. The inclusion of gold and the DWJ as predictors might not capture the full scope of variables affecting Bitcoin. (b) Stationarity assumption: ARIMA models require the time series to be stationary. While differentiation and integration can help achieve stationarity, the dynamic and evolving nature of cryptocurrency markets might make it challenging to maintain this assumption over time. (c) External factors and black swan events: The model might not account for unexpected ‘black swan’ events or sudden changes in external factors (e.g., geopolitical events, sudden regulatory changes) that can significantly impact Bitcoin. Therefore, further research could focus on further enhancing the predictive model using financial, technological, etc., variables to meet these considerations. Furthermore, future research could also extend to comparing the findings of this model to alternative ones (i.e., like DCC-GARCH employed by [32]) for the same time periods).

Given the interconnectedness found in the model, the results may imply that investors wishing to diversify their holdings should consider Bitcoin in addition to more conventional assets, like stocks and gold. In this instance, the diversification strategy of the portfolio incorporates Bitcoin. Investors and portfolio managers can more effectively manage risk and protect themselves from market downturns by having a better understanding of the relationship between Bitcoin prices and traditional financial markets (through gold and the DWJ). Furthermore, the relationship between the price of Bitcoin and conventional assets may function as a gauge for overall market sentiment, offering insights into investor confidence and risk tolerance under various market circumstances. Traders may enhance trade execution and profitability by utilizing the model’s insights to create algorithmic trading strategies that take advantage of gold and the DWJ’s predictive power over Bitcoin prices. Finally, the findings might inform policymakers and regulators about the interconnectedness of digital and traditional financial markets, guiding the development of policies that ensure market stability and protect investors.

Author Contributions: Conceptualization, K.T. and P.B.; methodology, K.T., P.B. and A.R.; validation, K.T., P.B. and A.R.; formal analysis, D.P. and A.R.; data curation, D.P.; writing—original draft preparation, K.T., P.B., A.R. and D.P.; writing—review and editing, K.T., P.B., A.R. and D.P.; supervision, K.T. and P.B.; project administration, K.T. and P.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data publicly available.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System. 2008. Available online: <https://bitcoin.org/bitcoin.pdf> (accessed on 12 February 2024).
2. Bruyn, A. Blockchain an Introduction. 2017. Available online: https://beta.vu.nl/nl/Images/werkstukbruyn_tcm235-862258.pdf (accessed on 10 February 2024).
3. Popovski, V.; Soussou, N.M. A Brief History of Blockchain. Legaltech News. 2018. Available online: <https://www.law.com/legaltechnews/2018/05/14/a-brief-history-of-blockchain/?slreturn=20240311161456> (accessed on 20 January 2024).
4. Houben, R.; Snyers, A. Cryptocurrencies and Blockchain: Legal Context and Implications for Financial Crime, Money Laundering and Tax Evasion. 2018. Available online: <https://repository.uantwerpen.be/docman/irua/80a4a6/152140.pdf> (accessed on 22 January 2024).
5. Financial Action Task Force (FATF). Guidance for a Risk-Based Approach: Virtual Currencies. 2015. Available online: <https://www.fatf-gafi.org/en/publications/Fatfgeneral/Guidance-rba-virtual-currencies.html> (accessed on 2 February 2024).

6. International Monetary Fund (IMF). Gold in the IMF. 2018. Available online: <https://www.imf.org/en/About/Factsheets/Sheets/2016/08/01/14/51/Gold-in-the-IMF> (accessed on 15 January 2024).
7. Lardy, N.R. *Integrating China into the Global Economy*; Brookings Institution Press: Washington, DC, USA, 2003.
8. Investopedia. Gold Investment: Types, Advantages, and Risks. 2022. Available online: <https://www.investopedia.com/investing/types-gold-investment/> (accessed on 7 February 2024).
9. SchiffGold. How to Invest in Gold. 2022. Available online: <https://schiffgold.com/how-to-buy-gold/> (accessed on 17 February 2024).
10. Batten, J.A.; Lucey, B.M.; Peat, M. Gold and silver manipulation: What can be empirically verified? *Econ. Model.* **2016**, *56*, 168–176. [CrossRef]
11. Dyhrberg, A.H. Bitcoin, gold and the dollar—A GARCH volatility analysis. *Financ. Res. Lett.* **2016**, *16*, 85–92. [CrossRef]
12. Chan, S.; Chu, J.; Nadarajah, S.; Osterrieder, J. A Statistical Analysis of Cryptocurrencies. *J. Risk Financ. Manag.* **2017**, *10*, 12. [CrossRef]
13. Gkillas, K.; Katsiampa, P. An application of extreme value theory to cryptocurrencies. *Econ. Lett.* **2018**, *164*, 109–111. [CrossRef]
14. Biais, B.; Bisière, C.; Bouvard, M.; Casamatta, C. The Blockchain Folk Theorem. *Rev. Financ. Stud.* **2019**, *32*, 1662–1715. [CrossRef]
15. Härdle, W.K.; Harvey, C.R.; Reule, R.C. Understanding cryptocurrencies. *J. Financ. Econom.* **2020**, *18*, 181–208. [CrossRef]
16. Charfeddine, L.; Benlagha, N.; Maouchi, Y. Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Econ. Model.* **2020**, *85*, 198–217. [CrossRef]
17. Bommer, W.H.; Milevoj, E.; Rana, S. The intention to use cryptocurrency: A meta-analysis of what we know. *Emerg. Mark. Rev.* **2023**, *55*, 100962. [CrossRef]
18. Abbasi, G.A.; Tiew, L.Y.; Tang, J.; Goh, Y.N.; Thurasamy, R. The adoption of cryptocurrency as a disruptive force: Deep learning-based dual stage structural equation modelling and artificial neural network analysis. *PLoS ONE* **2021**, *16*, e0247582. [CrossRef]
19. Angerer, M.; Hoffmann, C.H.; Neitzert, F.; Kraus, S. Objective and subjective risks of investing. *Financ. Res. Lett.* **2021**, *40*, 101737. [CrossRef]
20. Gietzmann, M.; Grossetti, F. Blockchain and other distributed ledger technologies: Where is the accounting? *J. Account. Public Policy* **2021**, *40*, 106881. [CrossRef]
21. Schilling, L.; Uhlig, H. Some simple bitcoin economics. *J. Monet. Econ.* **2019**, *106*, 16–26. [CrossRef]
22. Benigno, P.; Schilling, L.M.; Uhlig, H. Cryptocurrencies, currency competition, and the impossible trinity. *J. Int. Econ.* **2022**, *136*, 103601. [CrossRef]
23. Goudenege, L.; Molent, A.; Zanette, A. Machine learning for pricing American options in high-dimensional Markovian and non-Markovian models. *Quant. Financ.* **2020**, *20*, 573–591. [CrossRef]
24. Alsubaie, S.M.; Mahmoud, K.H.; Bossman, A.; Asafo-Adjei, E. Vulnerability of sustainable Islamic stock returns to implied market volatilities: An asymmetric approach. *Discret. Dyn. Nat. Soc.* **2022**, *2022*, 3804871. [CrossRef]
25. Zhu, X.; Niu, Z.; Zhang, H.; Huang, J.; Zuo, X. Can gold and bitcoin hedge against the COVID-19 related news sentiment risk? New evidence from a NARDL approach. *Resour. Policy* **2022**, *79*, 103098. [CrossRef] [PubMed]
26. De Senna, V.; Souza, A.M. Impacts of short and long-term between cryptocurrencies and stock exchange indexes. *Qual. Quant.* **2023**, *57*, 97–119. [CrossRef]
27. Benhamed, A.; Messai, A.S.; El Montasser, G. On the Determinants of Bitcoin Returns and Volatility: What We Get from Gets? *Sustainability* **2023**, *15*, 1761. [CrossRef]
28. Karagiannopoulou, S.; Ragazou, K.; Passas, I.; Garefalakis, A.; Sariannidis, N. The Impact of the COVID-19 Pandemic on the Volatility of Cryptocurrencies. *Int. J. Financ. Stud.* **2023**, *11*, 50. [CrossRef]
29. Basdekis, C.; Christopoulos, A.; Katsampoxakis, I.; Nastas, V. The impact of the Ukrainian war on stock and energy markets: A wavelet coherence analysis. *Energies* **2022**, *15*, 8174. [CrossRef]
30. Jia, Z.; Tiwari, S.; Zhou, J.; Farooq, M.U.; Fareed, Z. Asymmetric nexus between Bitcoin, gold resources and stock market returns: Novel findings from quantile estimates. *Resour. Policy* **2023**, *81*, 103405. [CrossRef]
31. Rivai, A. The effect of gold, dollar and Composite Stock Price Index on cryptocurrency. *Int. J. Res. Bus. Soc. Sci.* **2023**, *12*, 231–236. [CrossRef]
32. Ibrahim, B.A.; Elamer, A.A.; Alasker, T.H.; Mohamed, M.A.; Abdou, H.A. Volatility contagion between cryptocurrencies, gold and stock markets pre-and-during COVID-19: Evidence using DCC-GARCH and cascade-correlation network. *Financ. Innov.* **2024**, *10*, 104. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.