Connectedness Between Cryptocurrency and Precious Metal Markets

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Abstract. This study examines the co-movement of cryptocurrency market returns across four indices (Bitcoin, Ethereum, Litecoin, and Ripple) and the gold market return, utilizing daily data from August 17, 2016, to June 15, 2022. We examine the connection between the returns of cryptocurrency and gold before and during the Covid-19 epidemic. We employ continuous wavelet analysis, a wavelet method deemed optimal for non-stationary time series, which is delineated into several frequency bands and segmented in the time domain. Our selection of variables is grounded on economic theory and aligns with the problem statement and aims aimed at addressing economic issues. Wavelet coherence analysis revealed a significant level of co-movement among cryptocurrency returns. Nonetheless, the co-movement between cryptocurrency returns and gold market returns exhibited a minimal connection throughout the sampled time period. This signifies a lack of opportunities for portfolio diversification across cryptocurrency markets during the COVID-19 pandemic. Our findings will be of significant interest to scholars, policymakers, and investment professionals concerned with the financial ramifications of COVID-19 and cryptocurrencies.

1 Introduction

In e-commerce, payment systems involve a reliable third party that facilitates the transaction processing. Thirteen years ago, there was no widely accessible alternative to cash in e-commerce, despite the evident necessity for certain types of electronic currency to fulfill this function, particularly in the realm of micropayments [11]. In 2009, Satoshi Nakamoto invented the inaugural cryptocurrency, "Bitcoin." This research presents a technique utilizing peer-to-peer networking that facilitates direct payments via the Internet, eliminating intermediaries [13].

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Despite being a recent innovation, Bitcoin has garnered significant attention as a financial asset. International investors are increasingly divesting from precious metals including gold, silver, and platinum in favor of Bitcoin [16]. The growing prominence of Bitcoin has led to the emergence of many modern virtual currencies (altcoins), including Ethereum, Litecoin, Dash, Mixin, Ripple, Peercoin, and Zcash. Most alternative cryptocurrencies rely on the same blockchain technology that facilitates online transactions without utilizing the central ledgers of financial institutions. [3]. Over the past decade, cryptocurrencies, primarily Bitcoin, have been designated as the New Gold by many media outlets, financial institutions, and databases.Cryptocurrencies are not directly associated with any monetary policy instruments or underlying fundamentals. Consequently,

Analyzing the primary variables among these cryptocurrencies and other financial asset classifications is arduous. The Commodity Futures Trading Commission (CFTC) has formally classified virtual currency as a commodity, comparable to gold, crude oil, or precious metals [12]. The finance literature highlights gold's roles as a surrogate currency, a safe-haven asset, an inflation hedge, and a means of enhancing risk diversification in investors' portfolios, which have garnered increased attention from policymakers, portfolio investors, and risk managers [10].

The developing trend in the literature examines the connections between Bitcoin and other cryptocurrencies, as well as various financial assets or commodities, including stocks.

The literature indicates that cryptocurrencies exhibit a high degree of correlation among themselves; however, their relationships with mainstream assets and commodity markets remain ambiguous (see, e.g., Kang et al. 2019, Adebola et al. 2019, Al-Yahyaee et al. 2018, Dyhrberg 2015, Selmi et al. 2017). [10, 2, 3, 17]

In the literature, limited research examine the impact of the COVID-19 epidemic on cryptocurrency and other asset markets. The explanation for this is the brief duration of the COVID-19 pandemic's emergence.

Specifically, we analyze daily data from before and during the pandemic periods concerning the returns of four cryptocurrencies: Bitcoin, Ethereum, Litecoin, and Ripple.

Gold. The outcomes of this endeavor will facilitate the establishment of a compelling investment climate for investors. This significantly impacts emerging economies

2 Methodology

Numerous signals surrounding us require analysis, including financial data, human speech, engine vibrations, music, medical images, seismic tremors, and various other types that must be effectively encoded, compressed, refined, reconstructed, illustrated, simplified, modeled, or contextualized. Numerous approaches exist for analyzing the aforementioned signals; nevertheless, wavelet analysis represents a contemporary and promising array of tools and techniques for this purpose.

The wavelet transform was initially presented by Alfred Haar in 1909 in his doctoral dissertation. Since that time, extensive study has been conducted on wavelets and the wavelet transform. The technique for decomposing a signal into wavelet coefficients and subsequently reconstructing the original signal was invented in 1981 by Jean Morlet and Alex Grossman. In 1986, Stéphane Mallat and Yves Meyer developed a multiresolution analysis employing wavelets. They expounded on the scaling function of wavelets for the first time, enabling mathematicians and researchers to create their own family of wavelets based on the established criteria. In 1998, Ingrid Daubechies employed the principles of multiresolution wavelet analysis to develop her own family of wavelets. Her collection of wavelet orthonormal basis functions has established the foundation for contemporary wavelet applications. Wavelet analysis can be conducted by several methods, including continuous wavelet transforms, discretized continuous wavelet transforms, and true discrete wavelets. convert.

The applications of wavelet analysis are increasingly diverse, encompassing sectors such as science, engineering, medicine, and finance. Wavelet analysis examines co-movement throughout time in conjunction with frequency, rather than assessing an average statistical relationship. Wavelet analysis offers an advantage due to its agility in processing various non-stationary signals [6]. The wavelet transform is a powerful technique that is particularly effective for analyzing multiscale, nonstationary phenomena happening within finite spatial and temporal domains. Wavelets propagate uniformly over time and are organized for certain intervals, which accounts for their confined characteristics in the temporal scale [15]. This analysis concurrently examines both temporal and spatial domains. This explains why waves can decompose statistics into diverse frequency components [7].

Numerous authors have employed the continuous wavelet transform (CWT) in finance and economics research e.g., Xingzhi Qiao, 2020; Zhuhua Jiang et al., 2020; Sun-Yong Choi, 2020; Lu Yang et al., 2016; Debdatta Pal et al., 2019; Faik Bilgili et al., 2020; Sang Hoon Kang et al., 2019; Lu Yang, Xiao Jing Cai, Shigeyuki Hamori, 2017; Rubaiyat Ahsan Bhuiyan et al., 2019; Rubaiyat Ahsan Bhuiyan et al., 2018. This study examines the continuous wavelet transform (CWT) to analyze the comovements across cryptocurrencies, including Bitcoin (BTC) and Ethereum (ETH).

3 Result

This section will thoroughly describe the empirical results from model estimation. As stated in our introduction, our three objectives:

1. To examine the interrelationships among four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Ripple.
2. To analyze the correlation between cryptocurrencies and the gold market.
3. To examine the influence of COVID-19 on the correlation between cryptocurrency and gold markets. We utilize descriptive statistics to analyze the variable series of cryptocurrency and gold markets.

In the preceding sections, we identified suitable models and estimation methods for the analysis. The wavelet method, regarded as the optimal technique for non-stationary time series, is delineated into distinct frequency bands, which are segmented in the time domain. Our selection of variables is grounded on economic theory and aligns with the problem statement and aims aimed at addressing economic issues. In light of extensive research, we analyze the returns of four cryptocurrencies—Bitcoin, Ethereum, Litecoin, and Ripple—alongside gold returns to assess co-movement across various time intervals, particularly during the COVID-19 pandemic, which differentiates our study from previous similar investigations.

We utilize the Continuous Wavelet Transform (CWT) on daily data spanning from 17th August 2015 to 15th June 2021. Data on cryptocurrencies and gold futures is obtained from the database of (http://www.investing.com). Analyzing data from a singular source is efficient and straightforward.

Table1. Summary descriptive statistics for log-returns

	Bitcoin	**Ethereum**	**Litecoin**	**Ripple**	**Gold**
Nobs	1469	1469	1469	1469	1469
Minimum	-46.472977	-55.071367	-44.901213	-54.856595	-5.113959
Maximum	22.511900	51.082562	53.979714	79.850770	5.775363
Quartile	-1.358781	-2.661870	-2.292579	-3.174870	-0.393560
Quartile	2.259432	3.527665	2.481517	2.700566	0.510639
Mean	0.344034	0.523155	0.258965	0.318233	0.034470
Median	0.294720	0.042236	0.000000	0.000000	0.038620
Sum	505.3858	768.5144	380.4202	467.4845	50.6361
SE Mean	0.123555	0.193142	0.173959	0.219990	0.024222
LCL Mean	0.101671	0.144291	-0.082269	-0.113295	-0.013043
UCL Mean	0.586397	0.902018	0.600200	0.749761	0.081983
Variance	22.425482	54.799277	44.454510	71.092963	0.861858
Stdev	4.735555	7.402653	6.667422	8.431664	0.928363
Skewness	-0.698611	0.355880	0.609665	1.678662	-0.010180
Kurtosis	9.537566	6.762649	11.253477	17.631343	5.169543

Table 1 illustrates that the averages of daily returns are consistently lower than the calculated standard deviations in every instance. All relevant returns have positive mean values. Moreover, the return distributions exhibit positive skewness for all assets except Bitcoin and Gold returns. Furthermore, the Gold returns exhibit the least volatility relative to all Cryptocurrency returns, as seen by their calculated standard deviations. All return series exhibit skewness and excess kurtosis. The results probability distributions of these return series are asymmetric and leptokurtic, hence defying normality.

We utilize the continuous wavelet coherence between the returns of cryptocurrency marketplaces and gold futures, as illustrated in Figures 1.

The cone of influence, shown by a solid curving line, denotes the area impacted by edge effects. The picture has color codes, each signifying distinct meanings: the power spectrum ranges from red (indicating high power) to blue (indicating low power). Figure 1 illustrates the wavelet coherence and phase difference between the returns of Bitcoin and gold futures to examine their co-movement and causality. The coherency spectrum extends from red (indicating high coherency) to blue (indicating low coherency) to assess the extent of co-movement. The R language was utilized to perform various computations. The figures 200, 1000, and 1400 represent the quantity of working days commencing from August 17, 2015.

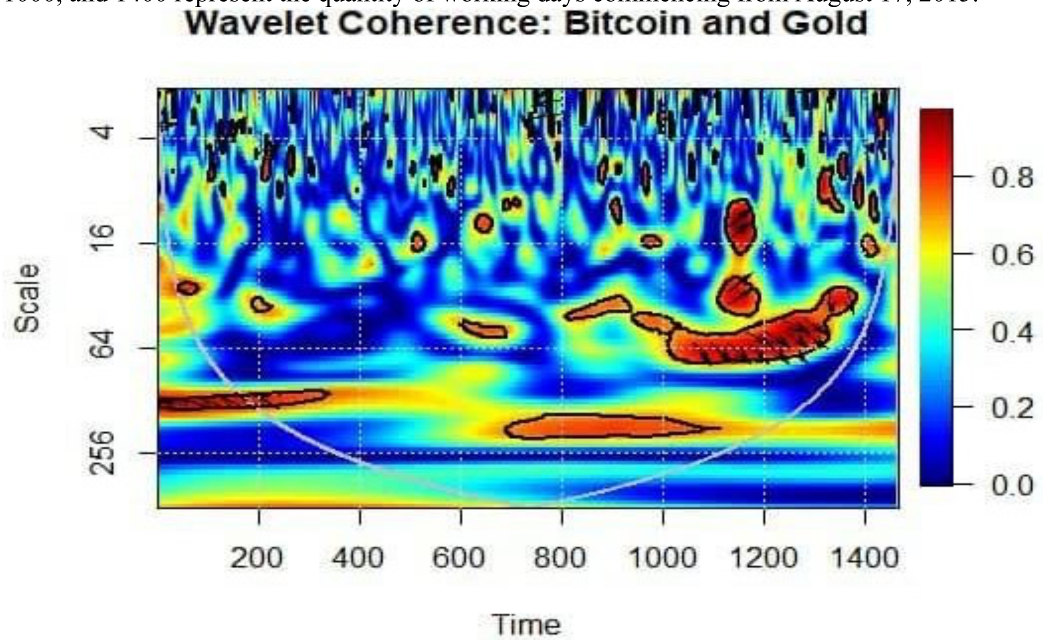

Fig. 1. Continuous wavelet transform: Bitcoin and Gold

We observe a significantly high degree of co-movement between Bitcoin and gold for the 1000-1400 time across the 16-64 days frequency band. Some evidence of relatively weaker, but significant coherence above the 64-256 days frequency cycle is also observed during 400 andmid -600. This supports the contagion effect during the global financial crisis, and the reduced short-run effectiveness of diversification benefits from combining Bitcoin and gold futures during crisis periods. In terms of the medium and long investment ranges, 64–256 days, the coherence diagram represents blue and light-blue regions, compared to red and yellow regions, which indicate a huge opportunity for investors.

We also identify causality and phase differences between Bitcoin and gold returns. Arrows indicate the phase differences between the Bitcoin and gold futures returns. For example, −→ and ←− indicate that both Bitcoin and gold returns are in phase and out of phase, respectively. ↗ and ↙ indicate Bitcoin returns are leading those of gold, while ↘ and ↖ indicate Bitcoin returns are lagging those of gold.

As shown in Fig. 1, we observe the most significant degree of co-movement between Bitcoin and gold futures returns for the 1000-1400 time across the 16-64 days frequency band. Co-movement appears to be relatively weak for the 256 days and above time-scale, while co-movement in the short-run (4–16 weeks band), although low on average, is highly variable. Thus, while a strategy of combining Bitcoin and gold futures in portfolios may generally offer diversification benefits across the short run, the effectiveness of such strategies will vary and may fail during periods of crisis.

4 Discussion

This section will thoroughly describe the empirical results from model estimation. As stated in our introduction, our three objectives: 1. To examine the interrelationships among four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Ripple. 2. To analyze the correlation between cryptocurrencies and the gold market. 3. To examine the influence of COVID-19 on the correlation between cryptocurrency and gold markets. We utilize descriptive statistics to analyze the variable series of cryptocurrency and gold markets.
This study investigates the co-movement between cryptocurrency returns and gold returns before and after the Covid-19 epidemic, using a dataset from August 2015 to June 2021. Four cryptocurrency variables, namely Bitcoin, Ethereum, Litecoin, and Ripple, together with a gold variable, are utilized. We employ Continuous Wavelet Transform (CWT) and descriptive statistical test indicators to achieve this.
This article's analysis has three primary purposes. The primary purpose was to examine the interaction among four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Ripple. This objective was investigated through Research Question 1: What are the co-movement links among Bitcoin, Litecoin, Ethereum, and Ripple? We discover evidence among cryptocurrency returns. The wavelet coherence findings demonstrate a significant level of co-movement among all cryptocurrency returns for the 2019–2021 period, particularly during the pandemic, primarily in short and mid-term investments. Notably, the strongest link is evident among the pairs of Bitcoin and Ethereum, Bitcoin and Litecoin, Ethereum and Litecoin, and Ripple and Litecoin at these intervals. This does not provide investors with chances for diversification.

The second purpose, which is to investigate the interaction between cryptocurrencies and the gold market, was addressed by Research Question 2: How to ascertain the correlation between cryptocurrency and gold markets? The contagion hypothesis is noted to intensify throughout the COVID-19 pandemic phase, as detailed in the section. The wavelet coherence analysis reveals a significant level of co-movement between Bitcoin and gold returns throughout the 1000-1400 time interval, inside the 32-64 days frequency range. Ultimately, while the co-movement in the 0–8 days band is often minimal, its fluctuation may diminish the short-term diversification advantages of Bitcoin-gold future portfolio combinations. The results for Ethereum and Gold indicate a significant degree of co-movement in returns throughout the 1000-1400 time period, spanning a frequency band of around 32 to 64 days, which does not present prospects for diversification. The Ethereum market is advisable for investors due to its minimal correlation with the Gold market in terms of daily returns, applicable to both short- and long-term investments. The wavelet coherence results for Litecoin and Gold, as well as Ripple and Gold, demonstrate consistent coherence across all market pairs analyzed.

We enhance the sparse recent empirical literature by examining the co-movements between the gold and cryptocurrency markets with wavelet coherence methods, therefore circumventing the nonstationary issues inherent in time series analysis.
Secondly, to the best of our knowledge, this paper selects four cryptocurrencies (Bitcoin, Ethereum, Litecoin, Ripple) and their relationship to gold, which collectively represent a significant portion of the cryptocurrency market capitalization, indicating their greater representativeness compared to those analyzed in prior research. Wavelet coherence analysis of the co-movement of cryptocurrencies is conducted, revealing that the interrelationship of one coin with others yields varying outcomes based on distinct investment horizons.

Finally, the influence of the Covid-19 pandemic on the gold and cryptocurrency markets, along with the evaluation of cryptocurrencies as a safe haven investment during this time.

5 Conculision

Cryptocurrencies have emerged as an alternative currency that may be used to buy goods within an increasing network of buyers and sellers who adopt it as a means of payment. Their appeal reflects their distinctive properties. Cryptocurrencies operate within a digital network system, largely detached from the influences of monetary policy and central bank regulation. Thereby, their liquidity (and number of Cryptocurrency), and consequently volatility, are related to the decentralized decision-making of those who participate in the market. Besides this, participants can take information on the number of transactions taking place daily, a feature not found in dealing with standard currencies. Furthermore, the influence of the pandemic on the Cryptocurrency markets is larger than that of the Gold market.

References

1. M. Abraham, Studying the patterns and long-run dynamics in cryptocurrency prices. Journal of Corporate Accounting and Finance 31(3), 98–113 (2019). https://doi.org/10.1002/jcaf.22427
2. S.S. Adebola, L.A. Gil-Alana, G. Madigu, Gold prices and the cryptocurrencies: Evidence of convergence and cointegration. Physica a Statistical Mechanics and Its Applications (2019). https://doi.org/10.1016/j.physa.2019.04.123
3. K.H. Yahyaee, W. Mensi, S. Yoon, Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. Finance Research Letters (2018). https://doi.org/10.1016/j.frl.2018.03.017
4. R.A. Bhuiyan, M.P. Rahman, B. Saiti, G.B.M. Ghani, Does the Malaysian Sovereign sukuk market offer portfolio diversification opportunities for global fixed-income investors? Evidence from wavelet coherence and multivariate-GARCH analyses. The North American Journal of Economics and Finance 47, 675–687 (2018). https://doi.org/10.1016/j.najef.2018.07
5. R.A. Bhuiyan, M.P. Rahman, B. Saiti, G.M. Ghani, Financial integration between sukuk and bond indices of emerging markets: Insights from wavelet coherence and multivariate-GARCH analysis. Borsa Istanbul Review 18(3), 218–230 (2017). https://doi.org/10.1016/j.bir.2017.11.006
6. F. Bilgili, E. Koçak, S. Kuşkaya, Ü. Bulut, Estimation of the co-movements between biofuel production and food prices: A wavelet-based analysis. Energy 213, 118777 (2020). https://doi.org/10.1016/j.energy.2020.118777
7. P.M. Crowley, An Intuitive Guide to Wavelets for Economists. SSRN Electronic Journal (2005). https://doi.org/10.2139/ssrn.787564
8. S. Choi, Industry volatility and economic uncertainty due to the COVID-19 pandemic: Evidence from wavelet coherence analysis. Finance Research Letters 37, 101783 (2020). https://doi.org/10.1016/j.frl.2020.101783
9. Z. Jiang, S-M. Yoon, Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. Energy Economics 90, 104835 (2020). https://doi.org/10.1016/j.eneco.2020.104835
10. S.H. Kang, R.P. McIver, J.A. Hernandez, Co-movements between Bitcoin and Gold: A wavelet coherence analysis. Physica a Statistical Mechanics and Its Applications 536, 120888 (2019). https://doi.org/10.1016/j.physa.2019.04.124
11. R.J. Kauffman, E.A. Walden, Economics and Electronic Commerce: Survey and Directions for research. International Journal of Electronic Commerce 5(4), 5–116 (2001). https://doi.org/10.1080/10864415.2001.11044222
12. T. Klein, H.P. Thu, T. Walther, Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. International Review of Financial Analysis 59, 105–116 (2018). https://doi.org/10.1016/j.irfa.2018.07.010

13. M. Polasik, A.I. Piotrowska, T.P. Wisniewski, R. Kotkowski, G. Lightfoot, Price fluctuations and the use of Bitcoin: An empirical inquiry. International Journal of Electronic Commerce 20(**1**), 9–49 (2015). https://doi.org/10.1080/10864415.201
14. X. Qiao, H. Zhu, L. Hau, Time-frequency co-movement of cryptocurrency return and volatility: Evidence from wavelet coherence analysis. International Review of Financial Analysis 71**,** 101541 (2020). https://doi.org/10.1016/j.irfa.2020.101541
15. J.B. Ramsey, Functional representation, approximation, bases and wavelets, in Dynamic modeling and econometrics in economics and finance, 1–20 (2014). https://doi.org/10.1007/978-3-319-07061-2-1
16. M.U. Rehman, N. Apergis, Determining the predictive power between cryptocurrencies and real time commodity futures: Evidence from quantile causality tests. Resources Policy 61**,** 603–616 (2018). https://doi.org/10.1016/j.resourpol.2018.08.015
17. R. Selmi, W. Mensi, S. Hammoudeh, J. Bouoiyour, Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Economics 74, 787–801 (2018). https://doi.org/10.1016/j.eneco.2018.07.007
18. L. Yang, X.J. Cai, H. Zhang, S. Hamori, Interdependence of foreign exchange markets: A wavelet coherence analysis. Economic Modelling 55**,** 6–14 (2016). https://doi.org/10.1016/j.econmod.2016.01.022
19. L. Yang, X.J. Cai, S. Hamori, Does the crude oil price influence the exchange rates of oil-importing and oil-exporting countries differently? A wavelet coherence analysis. International Review of Economics Finance 49, 536–547 (2017). https://doi.org/10.1016/j.iref.2017.03.015