Can cryptos hedge against inflation? Evidence from biwavelet analysis

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ABSTRACT

This paper aims to explore the role of cryptocurrencies as an effective hedging tool against inflation across different investment horizons. Specifically, we investigate the co-movement between the Consumer Price Index (CPI) in the US, Euro, and Japan, and the returns as well as volatilities of four key cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple). In doing so, we adopt the biwavelet coherence framework using monthly data spanning over the period from September 2015 to May 2023. Our results suggest that cryptocurrencies, except Ethereum, can serve as safe-haven and effective long-term hedging assets against inflation in the US and EU. On the other hand, Litecoin stands out as the only crypto that can effectively hedge assets in the medium term. In Japan, we observe significantly low to no co-movement between cryptocurrencies' returns and the CPI, suggesting the usefulness of the sampled cryptocurrencies as diversifiers against inflation. Our findings thus have implications for not only investors seeking to diversify their portfolios and mitigate inflation risk but also policymakers navigating the evolving landscape of digital assets and inflation management strategies.

1. Introduction

During the Global Financial Crisis of 2008 - 2009 or the recent highest peak in inflation over the last 40 years in the USA, the effect of inflation on investment portfolios has once again concerned investors globally. Numerous factors have contributed to rising inflation. First, the rising cost of raw materials and especially energy commodities such as crude oil can substantially drive up the selling prices of other products as it increases the cost of production. Second, government policies such as tax cuts or increased government spending to support economic growth and the recovery of businesses from the Covid-19 pandemic have also led to more money being circulated in the economy (Gholipour et al., 2023; Kaneva et al., 2022; Savitska et al., 2022), thereby boosting the aggregate money supply in the economy and pushing inflation up to a higher level. In addition, consumer demand, in general, has improved significantly during the post-Covid-19 period (Aday & Aday, 2020), facilitating the so-called 'demand-pull' inflation.

While higher levels of prices often generate higher profits for manufacturing companies, which can serve as good news for investors of their stocks and bonds, higher inflation can undermine the value of investments, particularly for fixed-income assets such as bonds

(Huberman & Schwert, 1985). In addition, economic theories also elaborate on other obvious damaging impacts of inflation, which is deteriorating the value of money (by reducing individuals' purchasing power and thus adversely affecting their standard of living) (Mishkin, 2017). This raises an intriguing question for investors: which investment objectives are best perceived as "safe" when inflation rises, and which investment portfolios can help to achieve a consistent level of returns? At the same time, investors are also interested in seeking a hedging asset and incorporating such an asset into their portfolios.

A "safe-haven asset" or "safe asset," theoretically, is considered an asset that is uncorrelated or negatively correlated with one or multiple other assets during periods of financial stress (Baur & McDermott, 2010). However, Baur and McDermott (2016) have pointed out the important difference between these two concepts: a "safe asset" is considered safe at all times, whilst a "safe-haven asset" is only safe (and only needs to be safe) during times of crisis or turmoil. So far, among the traditional asset classes, Treasury bonds and gold have received a wealth of support from scholars for their 'safe-haven' property. Even though, in theory, Treasury bonds can be regarded as risk-free or almost risk-free, empirical evidence is mixed. For instance, Spierdijk and Umar (2015) uncovered that T-bills (with maturities of one year and longer) are poor inflation hedgers regardless of maturity, issuer, risk rating, and investment horizon. Gold, on the other hand, is considered more price-volatile and riskier. However, gold protects investors from additional threats to which bonds are susceptible, including currency risk, default risk, and inflation (Baur & McDermott, 2016). Since gold is universally traded and cannot be over-printed like fiat money, previous research studies have largely agreed on its potential usage to hedge against inflation (Bampinas & Panagiotidis, 2015; Hoang et al., 2016).

Apart from Treasury bonds and gold, stocks have also been examined in terms of their capabilities to serve as a 'safe haven' against inflation; however, the empirical evidence is inconsistent. On the other hand, later studies have been conducted to investigate the long-run hedging capability of stocks using a longer span of data and cointegration analysis and their results confirm the inflation-hedging characteristic of stocks in the US market (Salisu et al., 2020).

In addition to the above traditional assets such as stocks, bonds, and gold, cryptocurrencies recently have attracted the attention of scholars due to their potential safe-haven characteristics. Several empirical studies have suggested that cryptocurrencies are effective hedgers and diversifiers. For instance, cryptocurrencies are shown to be weakly correlated with equities, especially during turbulent periods (Baur & McDermott, 2010). In addition, Ji et al. (2018) point out the relative isolation of Bitcoin from financial and economic assets including international equities, bonds, and currencies, as well as commodities. This result agrees with the finding of Corbet et al. (2018) in examining return and volatility spillovers between cryptocurrencies and major assets using the VAR model. However, the existing literature has been rather silent about the capabilities of cryptocurrencies as an investment asset to hedge against inflation. Supportive arguments posit that cryptocurrencies, with their generally limited supply stemming from their computational nature, mirror the economic rationale behind using gold as an inflation hedge, wherein gold's limited supply due to its physical nature contributes to its resilience against inflation (Baur & Dimpfl, 2018; Corbet et al., 2018; Dyhrberg, 2016). In contrast, counterarguments opposing the use of cryptocurrencies as an inflation hedge include the argument that the values of major cryptocurrencies exhibit excessive volatility (Sakurai & Kurosaki, 2023).

Given these opposing arguments, thus motivated, this paper aims to examine the association between the returns and volatilities of four cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP), and a change in inflation over the time and

across different ranges of frequencies. To this aim, we employ the biwavelet method to explore the co-movement between the Consumer Price Index and daily returns as well as volatilities of cryptocurrencies over the period from September 2015 to May 2023.

2. Literature review

Over the past three decades, inflation was not considered severe and persistent in developed markets (Neville et al., 2021). As a result, investors in these countries have to face the problem of having limited experience and solutions for the situation when inflation occurs. However, recently, inflation has been globally recognized after all of the movements of the FED about raising the interest rate to bring the inflation in the USA down. As a result, individuals intend to purchase bonds, silver, gold, and shares as a means of saving for their monetary value, which supports them against inflation (Chakravarty & Mitra, 2010). Overall, inflation has served as the main reason to shift the attention and money of investors and, indirectly affecting the price of investment properties.

First of all, a popular research topic among scholars is the influence of inflation on the volatility and return of the financial market. Among all the existing research, Sreenu et al. (2022) investigate the long-run and short-run relationship between Indian stock market returns and the inflation rate using GARCH and Error Correction Model (ECM). The authors uncover a long-run effect of the inflation rate on the volatility of stock market returns. On the other hand, Ginting et al. (2023) find that inflation does not affect stock prices in the banking sector which is moderated by profitability. One of the most studied assets as an effective hedging tool was gold. Although it is considered one of the effective hedging tools for inflation, controversy still exists. Worthington and Pahlavani (2007) provide empirical evidence on the relationship between US gold prices and the US Consumer Price Index (CPI) in the long run through the co-integration framework. Ghosh et al. (2004), Shahbaz et al. (2014), Bampinas and Panagiotidis (2015), all point out that gold is a good hedge against inflation. Similarly, Duong (2022) confirms the effective inflation-hedging feature of gold in the Vietnamese market from December 2001 to July 2020.

On another hand, a number of researchers have voiced their opinion that gold is an unreliable inflation-hedging tool. Blose (2010) uses the CPI to measure inflation and concludes that inflation does not affect gold prices during the sample period. Batten et al. (2014) provide estimates from co-integration tests for the period from 1985 to 2012 in the US market and discover no dynamic relationship between inflation and gold prices. Wang et al. (2011) study the cases of Japan and the US using short- and long-run threshold models and reject the hypothesis that gold is effective in hedging against inflation in the long run on the basis of the local monthly gold prices in six small and large gold markets from 1955 to 2015. Furthermore, Hoang et al. (2016) argue that gold can hedge against inflation only in the short run in the UK, USA, and India. In addition, Gambarelli et al. (2023), in exploring the role of gold as a safe-haven asset, declare that gold failed to act as a safe-haven asset during the Covid-19 market downturn.

With the controversy of traditional assets as an effective hedging tool for inflation, there has been a rising demand for an alternative store of value in case of inflation. Cryptocurrencies have been increasingly proposed ever since. Arguments in favor suggest that cryptocurrencies, characterized by their constrained supply resulting from their computational properties, parallel the economic justification for utilizing gold as a hedge against inflation, where the limited supply of gold owing to its physical attributes enhances its resistance to inflationary pressures (Baur & Dimpfl, 2018; Corbet et al., 2018; Dyhrberg, 2016). Conversely, counterarguments revolve around the contention that the values of prominent cryptocurrencies demonstrate excessive price

instability (Sakurai & Kurosaki, 2023). To reconcile these conflicting viewpoints, it is necessary to develop a macroeconomic framework elucidating the fundamental interplay between the values of cryptocurrency and inflation rates. However, endeavors to probe the underlying fundamentals of cryptocurrencies have thus far yielded limited success (Cheah & Fry, 2015; Liu & Tsyvinski, 2021). The influence of order flows from speculators may obscure the intrinsic value of cryptocurrencies within the market. Given the lack of a comprehensive macroeconomic theory, prior research predominantly relies on statistical or econometric methodologies to ascertain empirical evidence regarding cryptocurrency price dynamics. This is also the direction that this paper follows.

Empirically, cryptocurrencies have been examined whether they can serve as an effective hedging tool compared to traditional assets (Baur & Dimpfl, 2018; Phochanachan et al., 2022; Smales, 2022; Yermack, 2015). Such a large number of studies thus provide empirical evidence on the possibility of using these "digital assets" as the alternative hedging tool against inflation. For example, Félez-Viñas et al. (2021) point out that Ethereum operates not just the same but represents a more effective long-term value storage due to its significantly lower net issuance rate of tokens than Bitcoin, achieved by removing the fees associated with each transaction. The amount of Ethereum destroyed is higher than the creation of new tokens, resulting in Ethereum potentially becoming the world's first deflationary currency. Sakurai and Kurosaki (2023) explore the comovement between cryptocurrencies and the US inflation expected rates after the Covid-19 pandemic, and do not consider cryptocurrencies as an effective inflation hedging tool.

Similarly, Smales (2022) shows that cryptocurrency returns exhibit a negative relation during the monthly CPI announcements period, suggesting that cryptos fail to hedge during the most needed time. Pinchuk (2023) also examines the responses of major cryptocurrencies to macroeconomic news and concludes that Bitcoin responds negatively to inflation surprises. Volkov (2023) adopts two methods, including the Fisher coefficient and VAR model, to testify to the relationship between Bitcoin returns and inflation rates in the US, Euro area, and the Czech Republic over the period from November 2014 to October 2022. The Fisher correlation shows no relationship between the Bitcoin returns and inflation rates for all three regions, while the VAR method proves no positive correlation between the returns of Bitcoin and the inflation rate in the US.

3. Methodology and data

3.1. Biwavelet analysis

The wavelet coherence approach is used to identify both the time and frequency bands to detect and quantify the co-movement between two related time series variables. Torrence and Compo (1998) define the wavelet coherence of two-time series variables using smoothing in both time and frequency bands. Given the two time-series x(t) and y(t) with their cross-wavelet transforms $W_x(u,s)$ and $W_Y\ (u,s)$, the cross-wavelet transform is presented as:

$$W_{x,y}(u,s) = W_x(u,s)W_y^*(u,s) \quad (1)$$

Where 's' is the scale and 'u' is the position index; $W_x(u,s)$ and $W_y^*(u,s)$ are continuous wavelet transforms of two-time series variables x and y, respectively; and '*' sign displays the complex conjugate. The wavelet transform captures the local covariance between two-time series variables. The wavelet coherence approach by Torrence and Compo (1998) can compute the cross-wavelet power to show the areas with higher covariance between the time series variables at each scale. The wavelet coherence is used to display the time regions in which

co-movement in time series variables is present but may not have high wavelet power. We follow Torrence and Webster's (1999) approach, which is an extension of Torrence and Compo (1998), and define the squared wavelet coherence coefficient as:

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{x,y}(u,s))\right|^2}{S(s^{-1}|\,W_x(u,s)|^2)S\left(s^{-1}\left|\,W_y(u,s)\right|^2\right)} \quad (2)$$

Where 's' is a smoothing operator over time and space, R^2(u, s) is localized squared correlation in time and frequency, and the squared wavelet coefficient is in the range of $0 \leq R^2(u, s) \leq 1$. The higher values of the wavelet squared coherence R^2(u, s) mean a higher co-movement between the two-time series and vice versa. The wavelet squared coherence is restricted to positive values within the range of 0 to 1 and, therefore, a difference between negative and positive co-movements in two-time series cannot be made. To deal with the issue, Torrence and Compo (1998) suggest using the phase difference, which is used to detect the direction of co-movement (e.g., positive or negative co-movements between variables x and y).

The phase difference is defined as:

$$\emptyset_{x,y}(u,s) = \frac{lm\{S(s^{-1}W^{xy}(u,\ s))\}}{Re\{S(s^{-1}W^{xy}(u,\ s))\}} \quad (3)$$

Where lm and Re are the imaginary and the real parts of smoothed cross-wavelet transform, respectively. The result of a cross-wavelet coherence analysis is generally a figure, which has five major parts: the black arrows with eight directions (←, →, ↑, ↓, ↘, ↗, ↙, ↖), warm and cold colors, black contours, two axes, and the cone. The → (←) black arrows display an in-phase (out-of-phase) relationship or positive (negative) correlation, while ↗ (↙) directed arrows exhibit the leading effect of the first (second) series. For instance, the black arrows with direction '↘' in the wavelet coherence plots show an in-phase relationship or positive co-movement between two-time series with the maximum effect of the second time series. The black arrows with direction '↖' in the wavelet coherence plots show an out-of-phase relationship or negative co-movement between two-time series with the leading effect of the first time series. The phase difference of zero means both time series are moving together. The black curves in the plots show the regions with coherence significance at a 05% level, and the solid white bell-shaped line in wavelet coherence plots is the cone of influence.

3.2. Data

In this study, we utilize data from two different sources. The first data source is the US dollar-denominated closing prices of four key cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple) covering the period from September 2015 to May 2016. We retrieve the historical prices of cryptos from the website *coinmarketcap.com*. Using the crypto's Closing (C) price, we determine the daily realized return for each cryptocurrency by first differencing the logarithmic closing price.

Next, we calculate the monthly realized volatility of cryptos by employing the method proposed by Rogers and Satchell (1991), Rogers et al. (1994). The formula uses High (H), Low (L), Open (O), and Close (C) prices of cryptos on the first day of each month and is given by:

$$V_t = 100 * \sqrt{N * \left[ln\left(\frac{H_t}{O_t}\right) * ln\left(\frac{H_t}{C_t}\right) + ln\left(\frac{L_t}{O_t}\right) * ln\left(\frac{L_t}{C_t}\right)\right]} \quad (4)$$

Where V_t represents the realized volatility at month t and N is the number of trading months.

Second, we analyze the Consumer Price Index (CPI) of the US, EU, and Japan from September 2015 to May 2023. The reason behind the choice of these countries is due to the evidence of quantitatively important effects from these countries' inflation compensation not only on domestic but also on international inflation. As a result, it is vital to monitor the CPI changes in these countries (Aharon & Qadan, 2022; Bhattarai et al., 2020). On the other hand, the data for inflation (CPI) is recorded monthly, and the prices of four cryptocurrencies (BTC, ETH, XRP, and LTC) in this paper correspond to the price on the first day of the month.

Table 1 reports the descriptive statistics of the series under examination. The mean value of US CPI and EU CPI is positive, implying an increase in inflation in those two countries and areas over the sample period. Hence, the mean value of Japan's CPI is negative, demonstrating a decrease in inflation over time. The average returns of digital currencies do not change significantly, while all variables under consideration are stationary at a 1% significance level. It can also be seen from the skewness and kurtosis measures that all series are leptokurtic and significantly right-skewed.

Table 1

Summary Statistics

	Mean	Variance	Skewness	Excess Kurtosis	JB	ERS
US CPI	0.708***	0.986***	0.802***	1.300**	16.523***	-1.981***
	(0.000)		(0.002)	(0.029)	(0.000)	(0.051)
EU CPI	0.249***	0.362***	0.428***	2.983***	37.330***	-3.346***
	(0.000)		(0.082)	(0.001)	(0.000)	(0.001)
JAPAN CPI	-1.058	119.012***	-9.479***	87.900***	31332.303***	-0.932
	(0,352)		(0.000)	(0.000)	(0.000)	(0.354)
rBTC	0.007***	0.001***	0.001	1.927***	14.385***	-3.806***
	(0.024)		(0.996)	(0.006)	(0.001)	(0.000)
rETH	0.012**	0.002***	1.185***	2.654***	49.061***	-3.826***
	(0.019)		(0.000)	(0.001)	(0.000)	(0.000)
rLTC	0.013***	0.002***	1.019***	5.354***	127.169***	-3.437***
	(0.005)		(0.000)	(0.000)	(0.000)	(0.001)
rXRP	0.004	0.003***	1.239***	15.345***	936.251***	-3.556***
	(0.483)		(0.000)	(0.000)	(0.000)	(0.001)
vBTC	68.402***	3066.595***	1.241***	1.461**	32.129***	-4.146***
	(0.000)		(0.000)	(0.019)	(0.000)	(0.000)
vETH	101.885***	6749.497***	1.426***	2.452***	52.810***	-3.116***
	(0.000)		(0.000)	(0.002)	(0.000)	(0.003)
vLTC	104.641***	6507.719***	0.921***	0.171	13.271***	-3.607***
	(0.000)		(0.001)	(0.501)	(0.001)	(0.001)
vXRP	112.292***	81536.476***	8.201***	71.762***	20998.023***	-3.296***
	(0.000)		(0.000)	(0.000)	(0.000)	(0.001)

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

Source. Research findings

Table 2 reports the correlation matrix for the variables under examination. First, the returns and volatilities of cryptocurrencies are positively correlated with one another. Secondly, Bitcoin return is negatively correlated with the two categories: EU CPI and JAPAN CPI. Table 2 also shows a positive correlation between the US CPI and the return of four cryptos. However, Litecoin and Ripple's returns are negatively correlated with JAPAN CPI.

Table 2

Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) US CPI	1.000										
(2) EU CPI	0.316	1.000									
(3) JAPAN CPI	0.188	0.212	1.000								
(4) rBTC	0.018	-0.060	-0.042	1.000							
(5) rETH	0.181	0.132	0.001	0.336	1.000						
(6) rLTC	0.156	0.138	-0.042	0.531	0.459	1.000					
(7) rXRP	0.057	0.023	-0.004	0.372	0.408	0.433	1.000				
(8) vBTC	0.007	-0.006	-0.150	0.069	0.038	0.133	0.083	1.000			
(9) vETH	0.008	-0.033	-0.133	-0.038	0.055	0.006	0.067	0.394	1.000		
(10) vLTC	0.049	0.066	-0.097	0.038	0.006	0.188	0.050	0.475	0.365	1.000	
(11) vXRP	0.107	0.077	-0.055	0.135	0.048	0.069	0.152	0.355	0.315	0.369	1.000

Source. Research findings

4. Empirical results

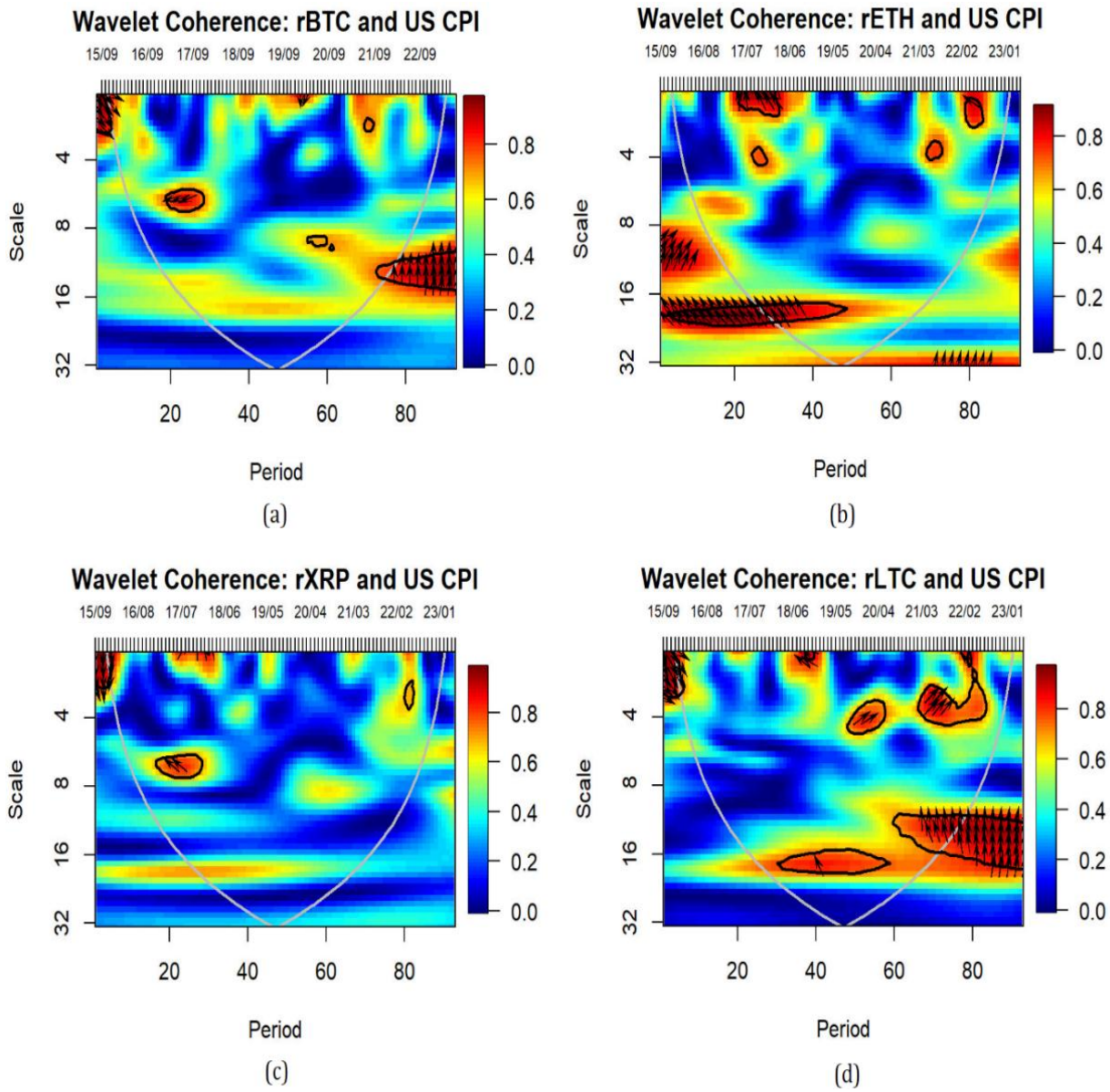
Figure (1) reports the results of the biwavelet analysis. The chart (1a) is dominated by shades of yellow and orange, showing the medium correlation between Bitcoin returns and the US CPI over the sample period. At around September 2015, Bitcoin returns and US CPI demonstrated a high degree of co-movement in the short term with a frequency of under four months. The direction of the arrows (↘) pointing to the right and downward indicates an in-phase relationship between the two variables with the leading effect of US CPI. However, over time, the correlation between BTC and US CPI is mainly demonstrated in the medium term in the frequency range between 08 and 16 months. Especially during the period from September 2021 to May 2023, despite the devaluation of Bitcoin on the market, the correlation is shown to be slightly positive with the leading role of Bitcoin returns. After the inflation hike in the USA, we can witness an expansion in the red and orange color, meaning an overall high co-movement of Bitcoin price and the US CPI.

Figure (1b) reports the wavelet coherence between the Ethereum returns and the US Consumer Price Index. We observe a significantly high correlation in the medium- and long-term from before September 2015 to May 2019. Specifically, we witness an overall leading role of Ethereum returns over the examined period. The direction of the arrows, however, goes reversely to each other between the frequency of 08 - 16 months and 16 - 24 months. The result shows that in the frequency band of 08 - 16 months, the positive co-movement is witnessed,

while an out-of-phase relationship is documented in the frequency band of 16 - 24 months. On the other hand, the wavelet coherence plot indicates a strong relationship in the long run, which becomes even more significant after the beginning of 2021 as the Consumer Price Index (CPI) in the US was increasing at a rapid rate. This finding lends support to the conclusion that Ethereum is not able to serve as a hedging tool for inflation in the long run for inflation in the US.

Figure 1

Crypto Returns and US Consumer Price Index (CPI)



Source. Data analysis result of the research

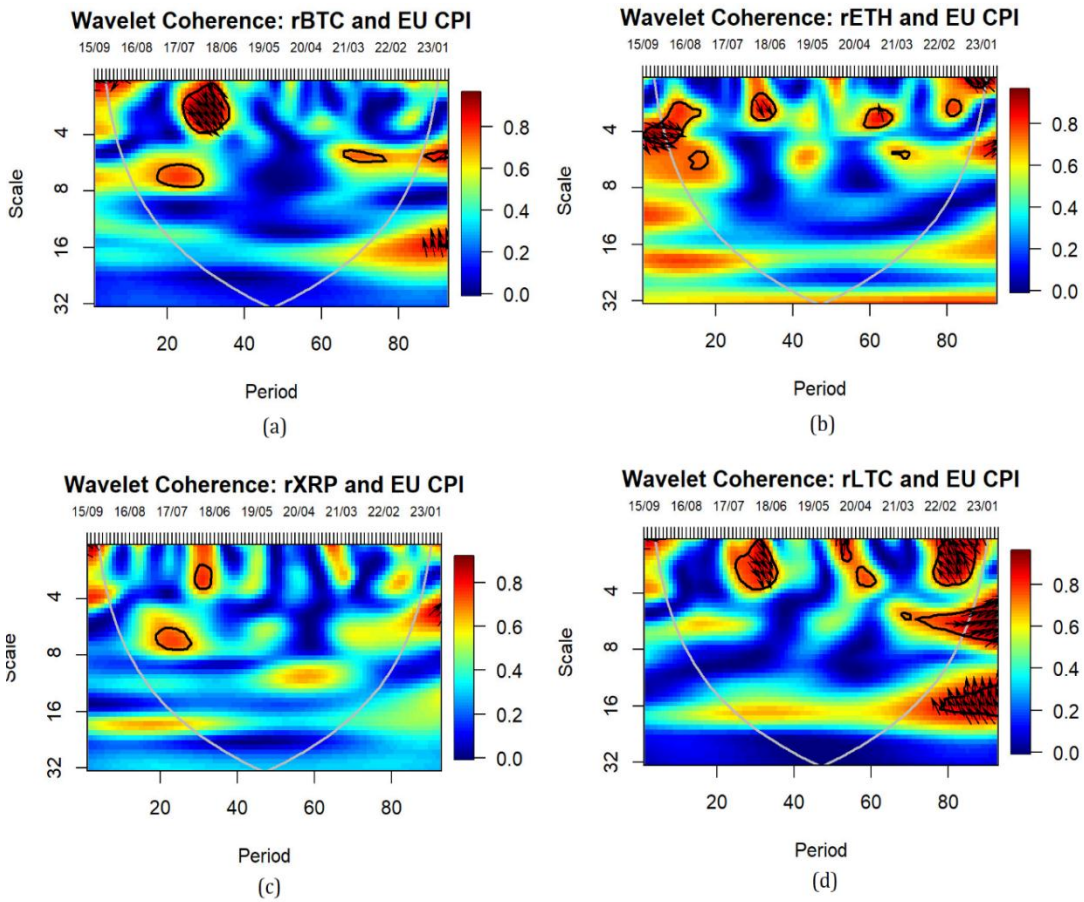
The wavelet coherence plot between the US CPI and Ripple returns in Figure (1c) shows weak to no co-movement between these two series. The blue shade is dominant over the period under examination, leaving only some significant correlation between the two variables at around October 2015 in the short term. An in-phase relationship is noticed with the downward direction of the arrows (↘), further indicating the leading effect of US CPI on the price returns of Ripple. The co-movement between the two variables even becomes weaker over time, even when the US CPI reaches its highest level in 40 years.

Regarding the wavelet coherence between the US CPI and Litecoin returns in Figure (1d), the two variables are highly co-moved. Before 2016, they were significantly correlated in the short term with the direction of the arrows (↘) going to the right and downwards indicating the in-phase relationship with the leading effect of US CPI on the price returns of Litecoin. However, since 2016, after the US inflation hit a four-decade peak, we observe an apparent opposite pattern in the direction of the arrows (↗) as they switched to upward-pointing, therefore implying the leading role of Litecoin returns on the US CPI. The arrows tend to move to the right over time in the short-term (04 months), showing an in-phase relationship which, however, becomes less obvious in the medium-term (08 - 16 months).

Next, we proceed with the results of the wavelet coherence between the EU CPI and crypto returns. Overall, the wavelet coherence plot between the Bitcoin returns and Europe CPI in Figure (2a) shows no or weak co-movement between the two series across ranges of higher frequency. Significant correlations are only observed from July 2017 to June 2018 at a lower frequency (up to 04 months). The direction of the arrows (↘) pointing downward and to the right demonstrates an in-phase relationship between two variables with the leading role of EU CPI on the price returns of Bitcoin. After February 2022, some occasional significant correlation is spotted during the medium term, mainly at around the 16-month frequency. In contrast to the previous time, an upward direction of the arrows shows the leading position of Bitcoin returns on the EU CPI.

Figure 2

Crypto Returns and EU Consumer Price Index (CPI)



Source. Data analysis result of the research

Regarding the wavelet coherence between the EU CPI and the returns of Ethereum, a significant correlation is especially evident in the short term over the band of 04 months and throughout the whole sample period. Nonetheless, it can also be seen from Figure (2b) that a significant co-movement between the two series is observed at the frequency band between 01 and 08 months. Before July 2017, a slightly downward-pointing-to-the-sideway direction of the arrows shows that the Europe CPI served as the leading cause of the price of Ethereum in the EU area. Some similar results are obtained throughout the studied period, mostly in the short run. Hence, the direction of the arrows tends to switch to upward-sloping after April 2016, confirming the leading effect of Ethereum returns on EU CPI. Similar to the results observed in the US, Ethereum is the only crypto in our sample that exhibits a high correlation in the long term (32 months), making it the only crypto incapable of being a hedging asset for inflation in the long run in the EU area.

The wavelet coherence results depicted in Figure (2c) between the EU CPI and Ripple returns demonstrate an overall weak co-movement between the two variables over the period under investigation. We witness occasional signals of high correlation from August 2016 to June 2018 in the short term. Right after mid-2016, an out-of-phase correlation is noticed at a frequency band of 04 - 08 months with the leading role of the EU CPI.

Figure (2d) reports the wavelet coherence results between the EU CPI and Litecoin returns. Overall, we witness a significantly high correlation between the two variables in the lower and medium-term at the frequency band between 04 and 24 months from March 2021 to the period right after the Ukraine war broke out. To be precise, over the frequency band of 01 - 04 months, the direction of the arrows (↖) going upward to the left indicates an out-of-phase relationship with the leading effect of the Litecoin returns on the EU CPI. In contrast, at longer frequency bands (over 16 months), the wavelet coherence plot shows a positive co-movement with the leading role of Litecoin returns.

Next, using the continuous wavelet coherence approach applied by Torrence and Webster (1999), we investigate the co-movement of the returns of four cryptocurrencies with the Japan CPI one by one. Regarding the wavelet coherence between the Japan CPI and Bitcoin returns, the overall green-to-blue color shades over Figure (3a) are indicative of the weak co-movement between the two variables. Only some notable co-movement between the inflation in Japan and the coin in the short run before October 2015 and after April 2016. A closer look at the upward and to the right direction of the arrows (↗) is observed showing the leading effect of Bitcoin returns.

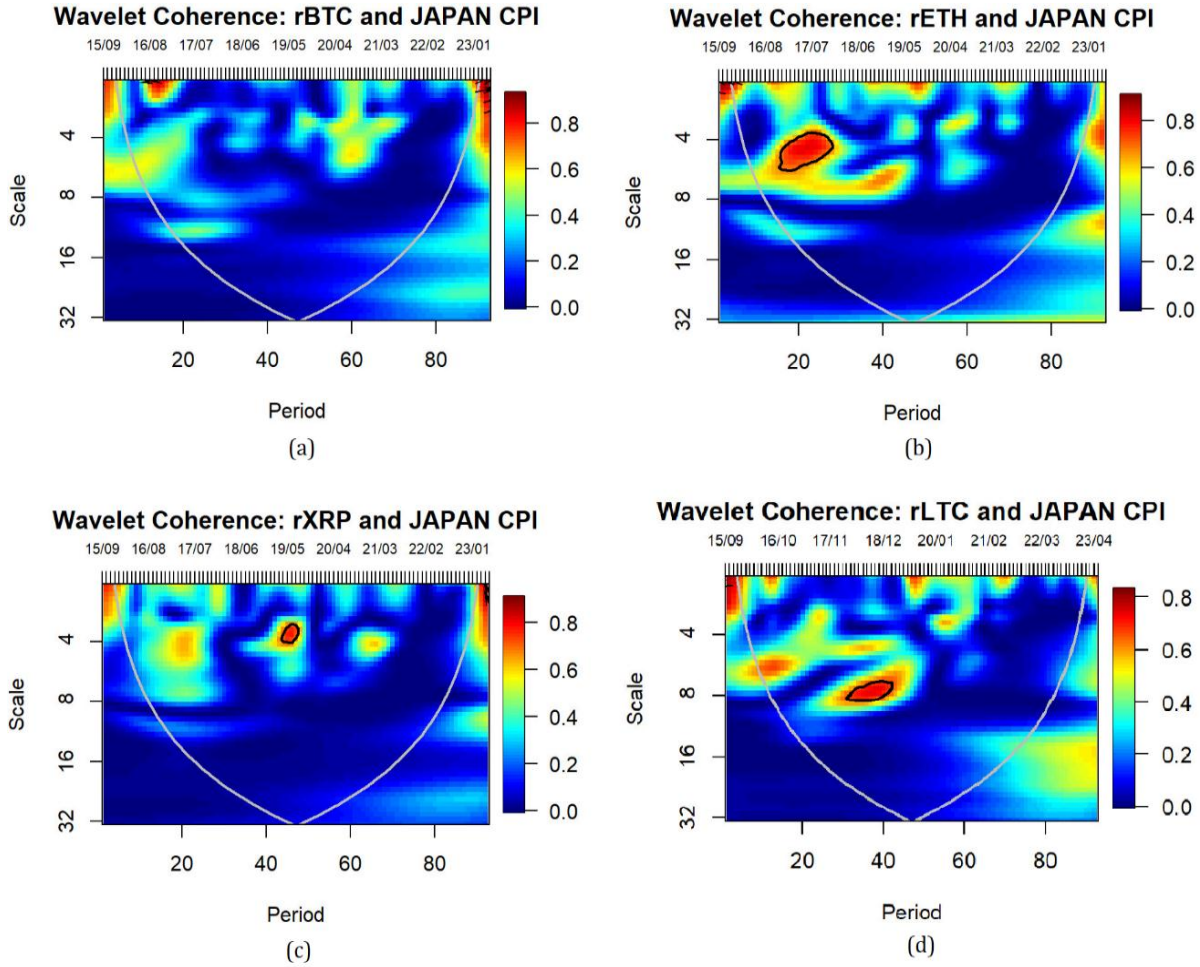
Figure (3b) reports the wavelet coherence between the Ethereum returns and Japan inflation. The highest correlation is observed during the period from 01 to 08 months and the correlation becomes weaker over ranges of higher frequencies. Occasional high correlations, demonstrated by the orange and red colors, are observed in the short run (at around 04 - 08 months) before 2018. After 2021, slight green shades at the frequency band of 32 months show that Ethereum is the only crypto to have a co-movement with Japanese inflation in the long run.

A similar result is also obtained regarding the correlation between Ripple returns and Japan CPI. Figure (3c) is mostly dominated by the shade of blue, suggesting almost no co-movement of the two variables during the medium and long term. Only some occasional correlation is observed during May 2019 and remarkable co-movement after January 2023, with the direction of the arrow going upward, indicating the leading effect of Japan CPI on Ripple returns. Similarly, weak to no co-movements between the Japan CPI with Litecoin are also

obvious in Figure (3d). A medium correlation between the Japan CPI and Litecoin returns is noticed in the medium and long run (08 - 32 months).

Figure 3

Crypto Returns and Japan Consumer Price Index (CPI)



Source. Data analysis result of the research

Next, we proceed with the results of the wavelet coherence between the US Consumer Price Index (CPI) and crypto volatilities, which are shown in Figure 4. Overall, we can see the dominance of orange and red shades in Figure (4a). The correlation is high, especially during the short term (01 - 08 months). However, a significant co-movement between the two series is observed in the long-term beginning from December 2018. To be precise, over the frequency band between 24 and 32 months, there exists an in-phase relationship, and the upward direction of the arrows (↗) indicates the leading effect of the Bitcoin volatility on the US CPI. On the other hand, in the short term after March 2022, the arrows exhibit the opposite direction, indicating an out-of-phase relationship with the leading role of US inflation.

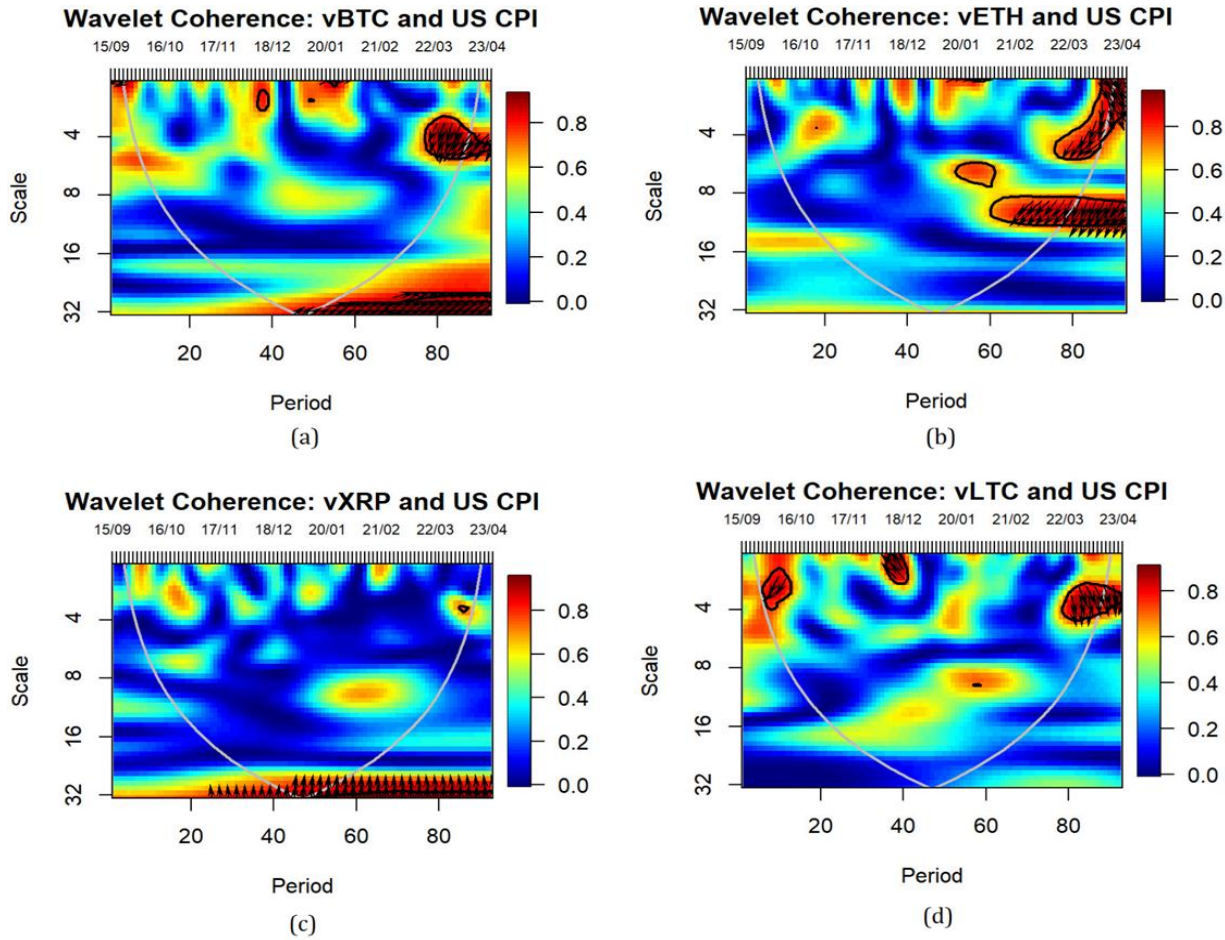
The empirical results demonstrate that in the short-term March 2022 marks the beginning of the period corresponding to high co-movement between the two variables. The arrows pointing downwards imply the leading effect of the US CPI on ETH volatility. During the early period, the direction of the arrows tended to point to the left, indicating a negative correlation. However, later until April 2023, the arrows went opposite to the right, suggesting an in-phase relationship between the two variables.

The wavelet coherence plot between the US Consumer Price Index with Ripple and Litecoin volatility shows the opposite results. While for Ripple volatility, we can only see high co-movement in the long-term between two variables with the leading effect of Ripple volatility on the US CPI, the coherence between Litecoin volatility and US CPI is interrupted and only remains high at certain times in the short-term (0 - 04 months).

We proceed with the results of the wavelet coherence between the EU CPI and cryptos volatility. In the long term, we will witness a similar result of the EU CPI with Bitcoin and Ripple volatilities. After December 2018, the coherence of EU CPI and the volatility of the two cryptos started becoming more significant. In both plots, the arrows face upwards, demonstrating that the crypto volatility leads the EU CPI. However, while the Bitcoin plots show a positive co-movement, the opposite is seen for Ripple. Meanwhile, for Ethereum and Litecoin, we gather evidence of little to no co-movement in the long term.

Figure 4

Crypto Volatilities and US Consumer Price Index (CPI)



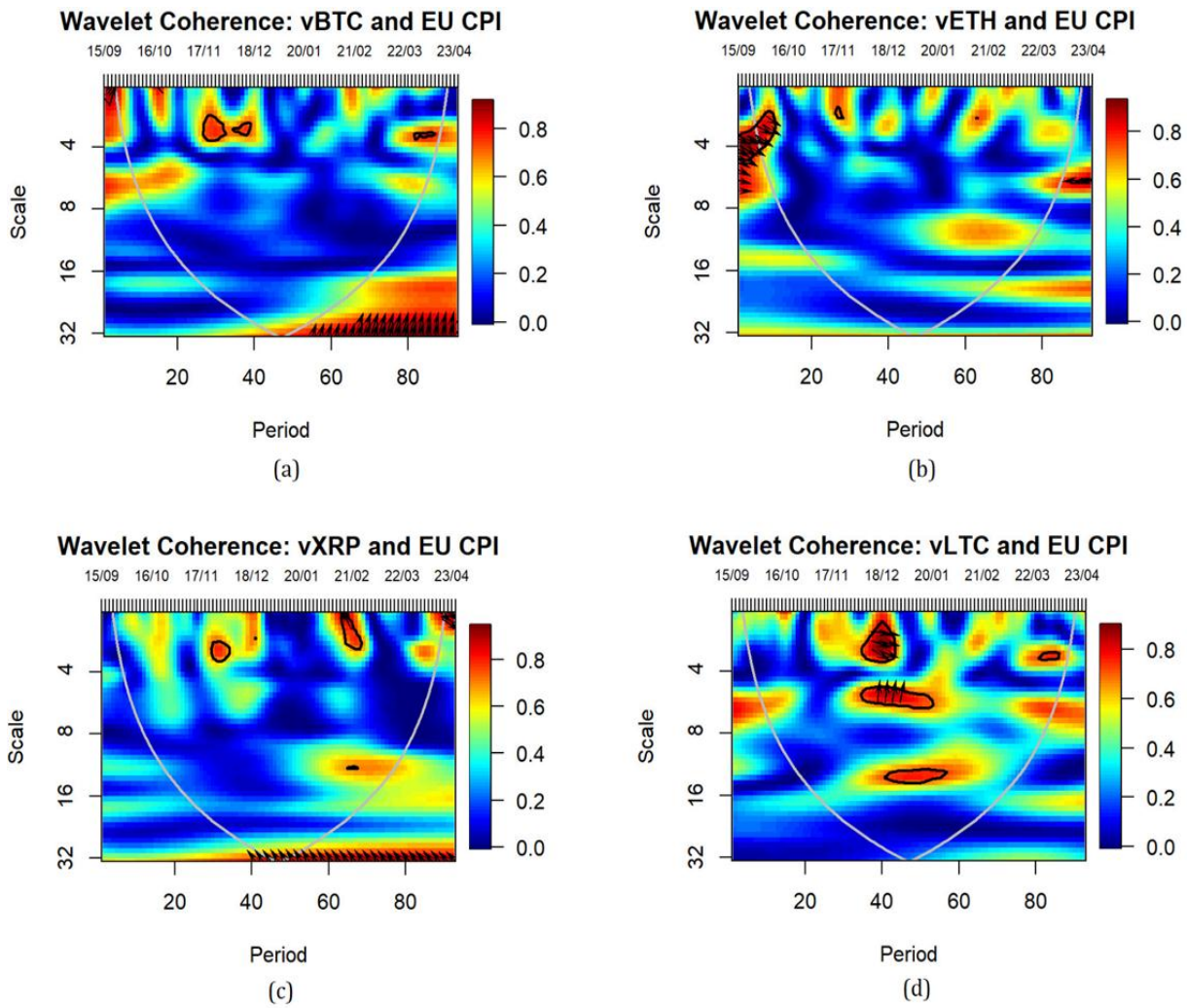
Source. Data analysis result of the research

In the short and medium term, the co-movement between the EU CPI and cryptos' volatilities remain high at certain times. While Litecoin only remained high during December 2018, and Ethereum showed a high co-movement before October 2016 in the short term. Even during the high inflation period after 2022, we observed very little to no co-movement. As a result, we can conclude that inflation does not significantly impact the volatility of cryptocurrencies.

Lastly, we investigated the coherence between Japan's Consumer Price Index and cryptocurrencies' volatility. Ripple and Bitcoin are the only cryptos that are covered in the long term. Especially after February 2021, the red color dominates the Bitcoin plot. The arrow's upward direction indicates a leading effect of Bitcoin volatility on the Japan Consumer Price Index. During the 16-month frequency, the arrows tend to go to the left, showing an out-of-phase relationship between the two variables, while over longer frequencies, the arrows change their direction to the right, showing an in-phase relationship.

Figure 5

Crypto Volatilities and EU Consumer Price Index (CPI)

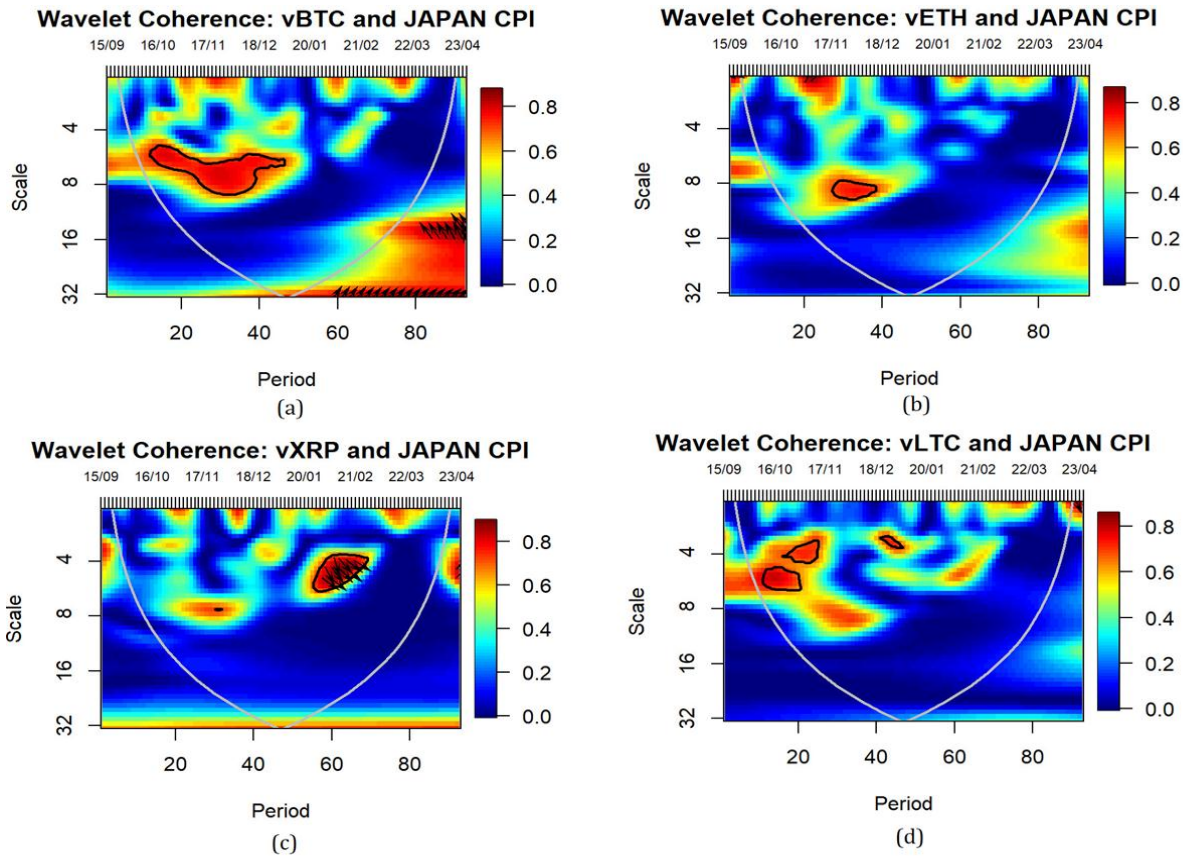


Source. Data analysis result of the research

The wavelet coherence results for Ethereum and Litecoin volatilities show little to no co-movement with the Japan CPI. Indeed, we witness only some co-movement in the short-term (04 - 08 months) before 2018. In the long-term, the dominance of the blue through the sample period indicates that inflation has no impact on the Litecoin and Ethereum volatility.

Figure 6

Crypto Volatilities and Japan Consumer Price Index (CPI)



Source. Data analysis result of the research

5. Discussion and conclusion

This study investigates the dynamic co-movement between the daily returns/volatilities of four major cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple) and the Consumer Price Index (CPI) of the US, Euro, and Japan over the period between September 2015 and May 2023. Following Torrence and Webster's (1999) approach, which extends Torrence and Compo's (1998) framework, we construct a wavelet coherence from each cryptocurrency's monthly returns and each economy's CPI.

The empirical results reveal differences in the co-movement between crypto returns and the Consumer Price Index (CPI) over different investment horizons. Our findings suggest that cryptocurrencies, except Ethereum, can serve as safe-haven and effective long-term hedging assets against inflation in the US and EU. On the other hand, Litecoin stands out as the only crypto that can effectively hedge assets in the medium term (08 - 16 months). In Japan, we observe significantly low to no co-movement between cryptocurrencies' returns and the CPI. The result indicates that the sample cryptocurrencies (including BTC, ETH, XRP, and LTC) can serve as safe-haven assets for inflation in Japan. In addition, our study also documents that after March 2021 the direction of the arrows is mainly upward-facing, hence indicating a leading effect of the sample cryptos' returns on the inflation in all three investigated areas.

These findings have important implications for traders, investors, and portfolio managers regarding asset allocation, and the management of risk exposure to avoid future unexpected losses, especially under the high levels of inflation in the US and worldwide. For investors in the US, except Ethereum, all three other cryptocurrencies can serve as hedging assets for inflation in

the long term. In the short term (under four months), all four investigated coins are considered good inflation-hedging tools. In the medium term, because of the current high inflation situation in the US, Ripple remains an influential hedging crypto due to its weak to no co-movement with the US CPI in the frequency of 08 - 16 months. Investors in the EU can use Bitcoin, Ripple, and Litecoin as practical long-term hedging tools for inflation. Geopolitical risk events such as the war in Ukraine make crypto returns highly correlated with the CPI, leaving only Bitcoin and Ripple to be able to hedge against inflation in the short term effectively. In the medium term, Ripple has the least co-movement with inflation in the 08 - 24 months frequency band. In Japan, we witness meager crypto returns and CPI co-movement. In the short term, Ethereum and Litecoin stand out as the most effective inflation-hedging assets. While in the long-term, Japan's CPI is slightly more correlated with crypto returns than in the US and EU areas, Ripple and Bitcoin are the most influential coins to hedge against inflation in the long term.

Our study, however, has certain limitations. Since our study only includes the four most popular cryptocurrencies, our results may not fully represent the entire cryptocurrency market. Future studies may include less popular cryptocurrencies to distinguish the responses of cryptocurrencies based on their varying levels of investors' attention. In addition, we have only investigated developed countries, therefore, our results would be less practical for monitoring inflation in developing and underdeveloped countries. Finally, investor sentiments within cryptocurrency markets are another understudied topic. Future research could further analyze the reactions of investors, especially long-term ones, during high episodes of inflation.

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