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Hedging effectiveness of bitcoin on latin American equity Indices: A multiscale analysis based on wavelets

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Abstract

Bitcoin volatility has created new dimensions for the investors Globally and attracted lot of other stakeholders to investigate various factors for its performance. This research examines the role of the Bitcoin as diversifier in the portfolio and performance as a hedger, safe-haven investment against Gold and Oil. We use a wavelet approach to capture time scale behaving of MSCI LATAM equity indices against Bitcoin and commodities under different market conditions. Our findings suggest that Bitcoin act as safe-haven device while Gold is a better hedger device against Oil which shows diversifier properties.

Keywords:Bitcoin, wavelets, hedging, cryptocurrencies, safe haven.

Introduction

Risks and returns are the integral components of the financial markets. There is evidence of accelerated growth of crypto currencies reflects the shift of the investors in both crises; recession of 2008 and COVID -19 health crisis. Returns and volatility spillovers have been widely explored in the finance literature while studies on crypto currencies has drawn a lot of attention from academicians, policy makers, government, service providers and investors. The evidence on return and shock spillovers between traditional financial market securities and crypto currencies, is evolving. According to Uzonwanne (2021), Bitcoin (BTC) is considered as inter centerpoint of attention as investment asset by the investors, international participants, regulators and media after its introduction by Nakamoto (2008). (Baur et al., 2018b; Bouri et al., 2017b). According to (Corbet et al., 2018a, 2018b), BTC is retained the position of leader during the global uncertainty the first decentralized digital currency of the crypto currency market.

During the 2008 global financial collapse the popularity of Bitcoin was strengthened Dyhrberg (2016). After the bail out of Cyprus in 2013 more attention was paid to the Bitcoin Luther and Salter (2017) . As per the research work of Bouri et al (2017a) Bitcoin had been considered to give a protection against uncertainty surrounding conventional economic and banking systems. During the much publicized and vexed demonetization policy enforced by Indian and Venezuelan governments along the restricted movement of capital Bitcoin was considered as an attractive option to hold cash. Previously, Gold was commonly considered to be safe-haven during financial and political uncertainties. Like wise, Bitcoin and Gold are considered to be identical assets that are used as investment assets and serve as flight to quality in times of market distress (Klein et al., 2018). Bitcoin also confines outside the politics and economics of the single country and contributes to the profitability during uncertainty and loss of faith and banking system stability. Baur et al. (2015) reported regarding the insignificant correlation between digital asset (Bitcoin) and traditional asset classes such as stocks, bonds and commodities in normal times and during periods of financial turmoil. Bitcoin role as instrument of hedge and safe haven was time varying towards in particular towards the investments of US stock market. Bouri et al. (2017a) evaluated the role of Bitcoin as a diversifier, a hedge, or a safe haven for movements in energy commodities and non-energy commodities. The results indicated that Bitcoin can act as an effective hedge and a safe-haven against movements in energy commodity indices, but not for non-energy commodities.

Gandal et al. (2018) analysed the Bitcoin rising and falling prices in recent years and concluded that price of Bitcoin gets a falling shock, following large investments in Bitcoin. Volatility Graph of Bitcoin is similar to that of the stock market. Studies of interdependence of foreign exchange markets and cryptocurrency markets have been attracting a vast research interest from the point of view of contagion, adversely impacting portfolio risk management, strategic asset allocation, and financial instruments pricing (Baumohl, 2019; Kristjanpoller and Bouri, 2019; Malik and Umar, 2019; Celeste et al., 2020).

The outbreak of COVID-19 pandemic in early 2020 crudely affected economies around the world and had destabilizing effects on global financial markets. Cryptocurrency market, March 13, 2020 saw the largest weekly drop in the price of Bitcoin (approximately 36%). The first wave of the pandemic witnessed an unprecedented scenario where the price of a barrel of WTI crude oil turned negative in April 2020 for the first time in history. With the rise of new variant Omicron there is a sharp decline in the price of bitcoin with $38000 as on 31 January 2022.

The energy industry has been one of the industries more severely affected by the pandemic because of restrictions in mobility and the blockade, producing a drastic reduction in the demand for oil and, hence, a sharp fall in oil prices because of oversupply. Ghazani and Khosravi (2020); Okorie and Lin (2020) highlighted that crude oil is one of the crucial commodity markets worldwide and serves as an underlying asset in the trading of different financial instruments in global financial markets, playing a key role in most economies. Moreover, over the last few years, it has become evident the growing significance of oil-dependent industries and the increased influence of oil price shocks on the global economy.

According to Yin et al. (2021), oil market shocks may appear as a crucial source of uncertainty for the cryptocurrency market, since oil price shocks might produce a risk level similar to macroeconomic news, mainly after the mid-2000s with the financialization of the oil market. In addition, some previous studies claim that changes in oil prices are significantly connected to, among others, inflation, real output, monetary policy, changes in international interest rates, etc., so changes in oil prices may be a key factor in the cryptocurrency uncertainty.

Therefore, the study of the oil price variations may be crucial for investors, companies, and resources policy makers, among others, mainly focusing the analysis on the impact of oil price fluctuations on other financial markets, such as the cryptocurrency market. In another research work Bouri et al. (2017a) accounted for five (economic, macroeconomic, monetary policy, financial and political) uncertainty indicators. This allowed them to capture the core effects of uncertainty on the relationship Bitcoin/oil and gold/oil. These indicators permitted them to better determine the hedging and safe haven properties of Bitcoin and gold change when considering the uncertainty effects.

Guesmi et al. (2019) examined dynamic movement of Bitcoin and other financial assets through Multivariate GARCH model and concluded that Bitcoin can offer diversification and hedging benefits for investors. Bitcoin does not share many common price determinants with those financial assets (Bouoiyour et al., 2016; Kristoufek, 2015). The dependency of price of Bitcoin is due to a unique set of characteristics, such as attractiveness (Kristoufek, 2015), energy prices (Li & Wang, 2017) and less on economic and financial variables. When compared to Gold, bitcoin has better terms of acceptance, history, tangibility, intrinsic value, low volatility, and consumption. Both Bitcoin and gold have non-political attributes and are regulated as commodities, especially in the US where Bitcoin is classified as a commodity by the CFTC. No central authority can control or adjust their mining and transactions (Baur et al., 2017), which makes them both independent of inflation. Bitcoin and gold do not generate cash-flows and are instead produced in a process called "mining". Specifically, the supply of Bitcoin is limited to no > 21 million coins, as dictated by its protocol. The inverted asymmetric reaction to positive and negative news is present in both gold (Baur, 2010) and Bitcoin (Bouri et al., 2017). Uzonwanne (2021) used a multivariate VARMA AGARCH model across five major stock markets for the transmission mechanism of return spillovers and volatility spillovers.

Finally, in emerging countries, where strict regulations on capital flows exists (e.g., China), Bitcoin is used to move money out of the country. This has been accentuated by the scrutiny of the Chinese government over the gold physical market, which has made Bitcoin an ideal alternative. According to Bekiros et al., (2017) during and post Gulf Financial crisis commodities, in general, and gold have lost their appeal as safe-haven assets and behaved more like risky assets.

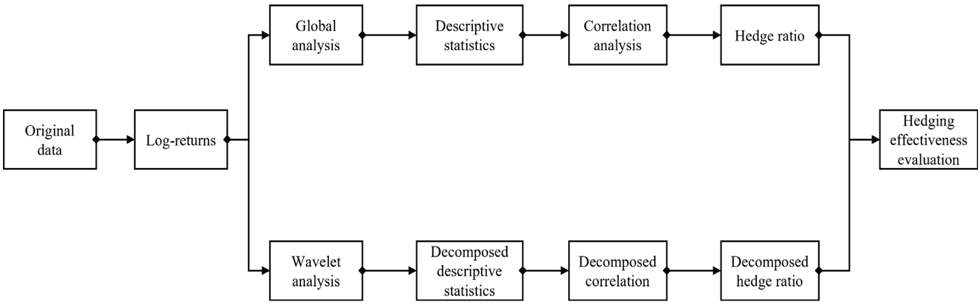
This study is useful for the stake holders like potential investors, financial advisors who want to have safe- haven asset. The rest of the paper proceeds as follows. Section 2 presents the methodological approach that is applied as we compare the weak and strong safe-haven abilities of Bitcoin, gold, and the Oil. Section 3 describes the dataset and section 4 discusses empirical results. Finally, section 5 includes the conclusions.

Methodology

The multiscaling approach based on wavelets performs a decomposition of the original time series into multiple scales which each scale is associated to a different window time. The decomposition is done using special mathematical functions which basis are tracked on the Fourier analysis.

However, the wavelet analysis allows to capture high frequencies in short time frames and low frequencies in long time frames.

Fig. 1. Methodology of hedging effectiveness evaluation based on wavelets.



As stated above, the wavelet-based approach considers a process of decomposition into multiple frequency-time scales of a time series, so the analysis called multiresolution decomposition, where each resolution level is referred to a timescale. This approach has its basis on the Fourier series analysis which the sine-cosine functions only capture the time series frequencies. Instead, the wavelet analysis allows to decompose the time series into its frequency components at different time scales by a filtering process which is possible to separate high frequencies from low frequencies. In the first case, high frequencies mostly occur in very short time intervals, whereas the second case indicates that low frequencies may occur in long time intervals. Expression (1) represents the decomposition of a time series *f(t)* into its components occurring in different resolution levels:

$$f(t) = \sum_k s_{j,k}\phi_{j,k}(t) + \sum_k d_{j,k}\phi_{j,k}(t) + \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \quad (1)$$

where $\emptyset(t)$ and $\psi(t)$ are the father and mother wavelet functions, respectively. The father wavelet function allows to approximate the smooth component of the time series, meanwhile the mother wavelet function approximates the detail components. On the other hand, $s_{j,k}$ are the smooth coefficients and $d_{j,k}$ … $d_{1,k}$ are the detail coefficients, where j and k are the scaling and translation parameters,obtained from the wavelet transform. Based on Daubechies (1988), expressions (2) and (3) define the discretized form of the father and mother wavelets:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi\left(2^{-j}t - k\right), \quad (2)$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(2^{-j}t - k\right). \quad (3)$$

Then, the general decomposed form of a time series *f(t)* may be represented in terms of its smooth (S_j) and detailed (D_j) series, as in expression (4):

The interaction analysis among time series is performed under the wavelet correlation and

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \quad (4)$$

coherence. The wavelet correlation is estimated by the Maximal Overlap Discrete Wavelet Transform (MODWT) which holds the main characteristic to analyze and discretize a time series *f(t)* on a scale-based additive decomposition as shown in expression (2), with the advantage that at each scale the wavelet coefficients $s_{j,k}$ and $d_{j,k}$ have the same length as the original time series. In that context, using as mother wavelet the Least Asymmetric Daubechies function, the wavelet correlation unbiased estimator is performed as shown in expression (5):

$$\tilde{\rho}_{X,Y}(\lambda_j) = \frac{\gamma_{X,Y}(\lambda_j)}{\nu_X(\lambda_j)\nu_Y(\lambda_j)}, \quad (5)$$

Where $\gamma_{X,Y}$ is the covariance between time series *X* and *Y* at scale λ_j, ν^2_X and ν^2_Y the variances of *X* and *Y*, respectively, at scale λ_j. Finally, $\lambda_j = 2^{j-1}$ stands for the timeframe at *j*-scale; for example, if original data comes from a daily frame, then at *1*-scale it will be obtained the decomposed correlation occurring at a $\lambda_1 = 1$ day window, $\lambda_2 = 2$-*day* window, and successively at *J*-level.

On the other hand, wavelet coherence is performed under the Continuous Wavelet Transform (CWT), which based on Graps (1995) is represented as in expression (6):

$$CWT_f(j,k) = \int_{-\infty}^{\infty} f(t) \overline{\frac{1}{\sqrt{j}} \psi\left(\frac{t-k}{j}\right)} dt, j > 0, b \in \mathbb{R}, \quad (6)$$

where $\overline{\psi(t)}$ stands for the complex conjugate of the mother wavelet, while *j* is the scaling factor and *k* the translation factor. In that context, Torrence and Compo (1998) defined the cross-wavelet transform (XWT) of two time series *X(t)* and *Y(t)* as in expression (7):

$$W_{X,Y} = W_X W_Y^*, \quad (7)$$

where *W* represents the CWT of the time series (see expression 6) and * denotes the complex conjugation. Given the XWT, Torrence and Webster (1999) define the wavelet coherence of two time series which closely matches the correlation coefficient on a local basis as follows:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right) \cdot S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)}, \quad (8)$$

where S is a smoothing operator. By such means, Grinsted et al. (2004) argue that the wavelet coherence is a powerful tool to analyze linkages between two time series. In addition, Aloui and Hkiri (2014) consider its importance for detecting stock market co-movements.

The multiscale hedging effectiveness (Khalfaoui, Boutahar & Boubaker; 2015) considers the ratio at different time scales (l_j) between the unconditional covariance of the equity index-cryptocurrency/commodity asset and the unconditional variance of the equity index, as shown in expression (9):

$$\beta_{C,E}(\lambda_j) = \frac{cov_{C,E}(\lambda_j)}{\nu_C(\lambda_j)}, \quad (9)$$

where $\beta_{C,E}(\lambda_j)$ represents the hedge ratio or sensitive of the equity index against the cryptocurrency or commodity at scale time (λ_j), $cov_{C,E}(\lambda_j)$ is the covariance between the equity index and the cryptocurrency or commodity, and $\nu_C(\lambda_j)$ represents the variance of the cryptocurrency/commodity asset. A low value would show a good hedging effectiveness.

All estimations were performed in R version 4.1.1.

Data

Dataset consists of weekly prices from March 18, 2016 to December 31, 2021 of the MSCI LATAM equity indices which belong to Peru (BVL), Brasil (BVSP), Colombia (COLCAP), Chile (IGPA), Argentina (MERVAL), and Mexico (MXX); the equity indices of Dow Jones Industrial (DJI) and the Standard & Poor's 500 (SP500); commodities such as the future prices of Gold (GOLD) and West Texas Intermediate (WTI); and, the three main cryptocurrencies like Bitcoin (BTC), Ethereum (ETH) and Xripple (XRP). The range of data was restricted to the listing prices of Ethereum since 2016.

Original data was transformed to log-returns as an approximation of percentage changes, shown in expression (10):

$$\Delta P\% = ln\frac{P_1}{P_0} \times 100 \quad (10)$$

where P_0 is the previous price and P_1 is the current price.

Equity index and commodity prices were downloaded from Refinitiv, and cryptocurrency prices were downloaded from Investing (www.investing.com).

Fig. 2 shows cryptocurrency prices behavior where the three of them registered a substantial price rise by the end of 2017. Later prices plummeted showing a negative trend where several factors explained their fall but the two most important were associated to the listing of future Bitcoins in the Chicago Mercantile Exchange and the government of China's bans to cryptos farming and trading. Almost by Q2 of 2019 a positive trend has shown the cryptocurrency market and later by the end of 2020 prices soared during the pandemic era when most countries entered to a recession period because of Covid-19. Besides crypto prices collapsed by mid of 2021, a second rally haven shown since then surpassing the maximum levels reached by the end of 2020 (See appendix A for whole time series prices).

Fig. 2. Main cryptocurrency prices.

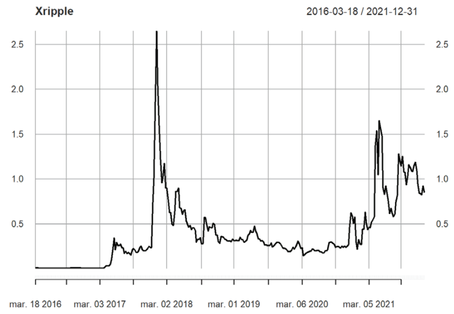


Table 1 shows descriptive statistics of log-return prices where cryptocurrencies have shown a better return performance. However as measured by the standard deviation, cryptocurrencies show higher volatility against equity indices and commodities. The most volatile cryptocurrency is recorded by Xripple but it has shown more frequent positive weekly returns than negative ones. Besides cryptocurrencies are showing in the period of study a higher volatility but COLCAP, DJI and SP500 are showing the most extreme values against cryptocurrencies as measured by kurtosis. Also, it is observed that Bitcoin and Ethereum are showing the lesser kurtosis values. In that sense, cryptocurrencies could not be considered as fat-tailed financial assets when compared to traditional assets. So, besides high volatility of cryptocurrencies but these alternative assets are not showing extreme movements as registered by traditional financial assets.

The level of interconnectedness among traditional financial assets and cryptocurrencies is shown in Fig. 4. It is observed that the global association as measured by the coefficient correlation registers the low degree of interaction of cryptocurrencies against equity index and commodity returns. Even the Bitcoin case shows a less level of co-movement when compared to the gold case. Also, it is observed that oil shows a low degree of association with LATAM equities but higher than cryptocurrencies. The interaction level of oil and the crypto assets also shows a low correlation.

Fig. 4. Global correlation.

Based on the descriptive statistical results, this article is motivated to analyze the possibility of cryptocurrencies to be considered as safe-haven assets or to serve as hedging devices. Cryptocurrencies' high volatility but a low kurtosis and low levels of association against equity indices and commodities may indicate new challenges in the FINTECH industry and regulatory purposes.

Results analysis

This section is divided into 2 subsections. The first one shows the wavelet coherence heat maps based on expression (8) and section two shows hedge ratios estimations on the global and multiresolution decomposition (MRD) approach.

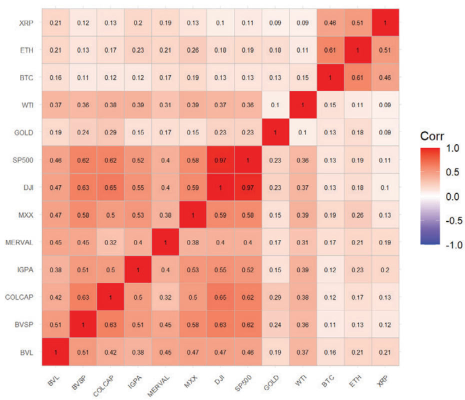
Fig. 5 shows the wavelet coherence of Bitcoin against MSCI LATAM and USA equity indices, and commodities (see Appendix B for whole coherence heatmaps). It is observed that Bitcoin has kept a low degree of association along time scales and across time. However, some episodes of high interconnectedness are registered but which time of occurrence is rapid and furious. Other cases show that in the long run where scales belong to window times

Table 1. Descriptive statistics of original log-return values.

Variable/ Statistic	Mean	Standard Deviation	Minimum	Maximum	Skew	Kurtosis
BVL	0.19%	2.70%	-13.68%	11.61%	-0.5812	6.0659
BVSP	0.24%	3.25%	-20.92%	11.08%	-1.4200	7.9226
COLCAP	0.02%	3.15%	-24.67%	22.14%	-1.9141	30.5677
IGPA	0.03%	2.81%	-19.19%	12.03%	-1.1175	9.6010
MERVAL	0.62%	5.56%	-37.76%	17.66%	-1.3438	7.8620
MXX	0.05%	2.17%	-10.56%	7.53%	-0.3427	3.0840
DJI	0.24%	2.60%	-19.00%	12.08%	-1.5582	14.6862
SP500	0.28%	2.40%	-16.23%	11.42%	-1.3956	11.7509
GOLD	0.11%	1.96%	-9.90%	10.10%	-0.2210	4.6377
WTI	0.21%	5.98%	-34.69%	27.58%	-0.7930	7.0115
BTC	1.58%	11.25%	-53.94%	36.20%	-0.3698	2.1797
ETH	1.95%	15.06%	-65.97%	49.89%	-0.1257	1.8723
XRP	1.55%	19.67%	-67.15%	114.54%	1.6472	7.2135

Note: 302 weekly observations.

Source: authors estimations.



Source. Authors estimations.

greater than 64 weeks, the the level of association remains high which is characterized as fundamental linkages. Even though that in most of the time the degree of interaction is low, but during the pandemic era because of Covid-19 it was registered a high level of association which lasted more than 16 weeks and has passed through from 2020 to 2021.

A specific example is the Bitcoin-MXX pairwise where the degree of association was higher during the Covid-19 era than in the end of 2017 when cryptocurrencies crashed. Besides it would be considered a greater interaction of Bitcoin and the USA equity indices, but the crypto crash in 2017 was fast and furious that didn't pass through to 2018.The most interaction level has been found when the Covid-19 era. It is observed that in the long run when time spans over 64 weeks, the association records high levels which is considered by fundamental linkages that could be explained by linkages of technology-based companies with the stock markets which are developing blockchain technology. Also, since the Covid-19 era crypto-investors have relied more their investment decisions on monetary policy stances.

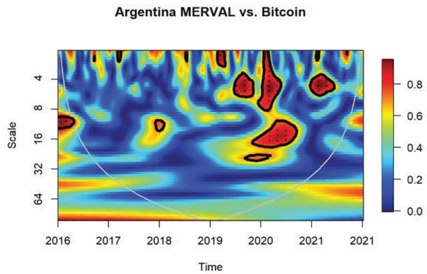
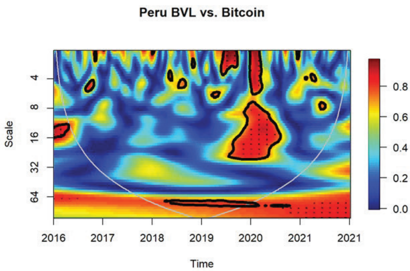
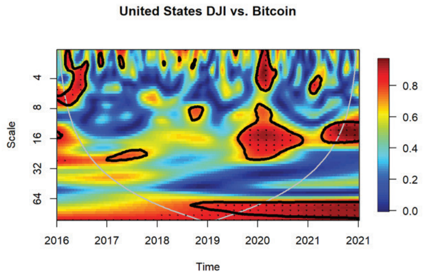
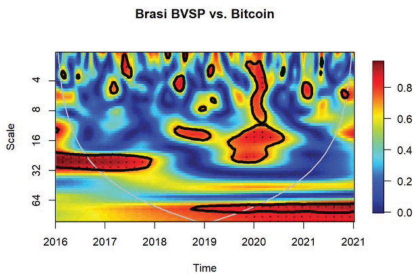
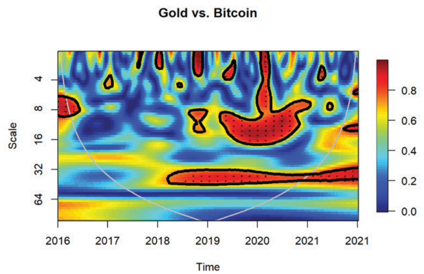


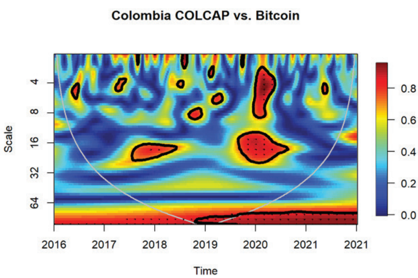
Fig. 5. Wavelet coherence of Bitcoin among the MSCI LATAM and USA equity indices, and commodities.

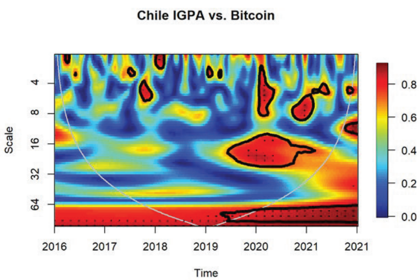


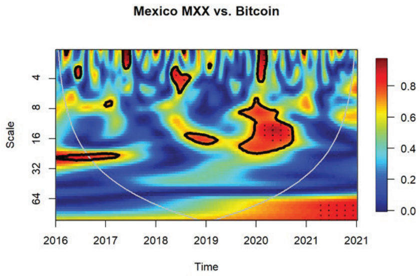


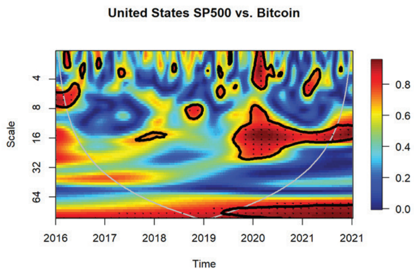


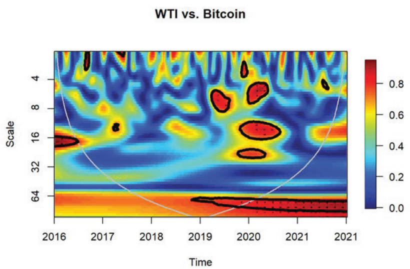












Source: Authors estimations.

Descriptive statistics estimated based on the MRD shows that volatility decreases as time scale increases where *D1* resembles original log-return prices when the window time runs between 1 and 2 weeks. However, in a medium term at scale *D2* when the time frame spans from 8 to 16 weeks it is observed a decrease in the volatility of all assets.

This happens since wavelets act as filtering functions in the MRD process where they denoise the original values as time scales increase. At high resolution levels, D7, when time spans from 64 to 128 weeks, it is recorded a dramatically change in kurtosis. So, even when equity indices that have shown extreme values now the probability to observe fat-tailed distributions in the long run reduces. In that sense as volatility and kurtosis diminish from the short to the long run, how do interconnectedness behave among assets?

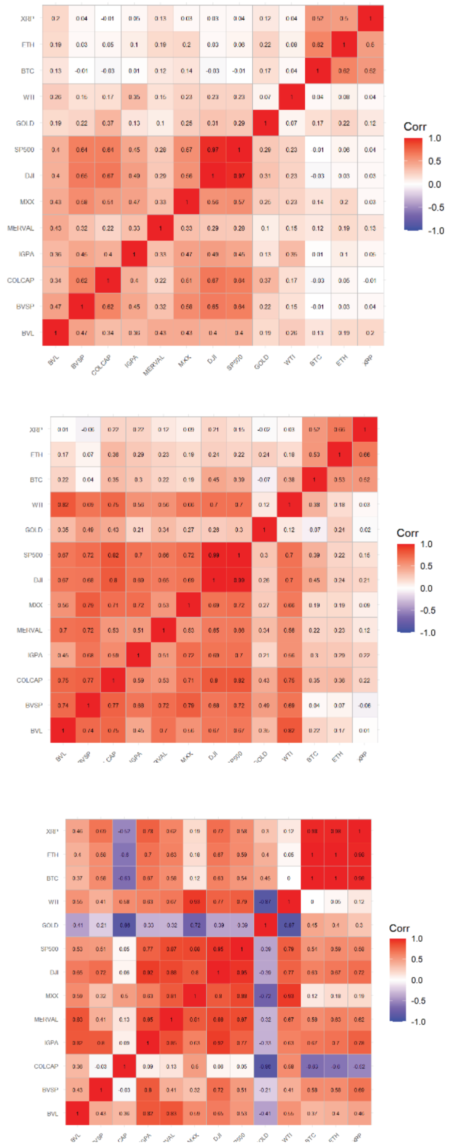
The decomposed correlation at D1, D4 and D7 scales are shown in fig. 7 where the degree of association increases from the short to the long run. This means that at low scales during time which spans from 1 to 2 weeks when high frequencies occur, the level of association of cryptocurrencies against equity indices and commodities still resembles a low degree of interaction. However, as time spans increases from 8 to 16 weeks, the degree of comovement increases in most of the cases and in a wide sense. Nevertheless, in other cases the association inverted from positive to negative. For example, Bitcoin and gold showed initially a positive relationship in the short run but in the medium run at D4 scale it happens a negative level of association.

When time spans from medium to long term at D7 scale, the degree of association even increases in most of the cases. The Bitcoin-gold case has turned now from a negative to positive relationship. However, now COLCAP against the three cryptocurrencies has shown a negative behavior. Also, it is important to observe that gold has shown a positive to negative behavior from low to high scales.

Table 2. Decomposed (MRD) descriptive statistics based on D1, D4, and D7 scales.

Variable/ Statistic	Scale	Mean	Standard Deviation	Minimum	Maximum	Skew	Kurtosis
BVL	D1	0.00%	1.6815%	-6.6669%	7.66%	0.0745	4.0267
	D4	-1.02E-19	0.6484%	-2.5691%	2.0100%	-0.3371	2.8443
	D7	3.0255E-20	0.0710%	-0.1389%	0.0805%	-0.7407	-0.8886
BVSP	D1	0.00%	2.1288%	-9.9286%	12.07%	0.1246	4.9324
	D4	1.47E-20	0.9185%	-3.5458%	2.8038%	-0.2563	2.3660
	D7	1.1241E-20	0.0609%	-0.1128%	0.0916%	-0.2987	-1.2109
COLCAP	D1	0.00%	2.0019%	-11.4109%	18.75%	1.7956	30.9461
	D4	2.15E-20	0.5839%	-2.3066%	1.6013%	-0.3084	2.4621
	D7	-5.358E-21	0.0971%	-0.2084%	0.1488%	-0.5659	-0.4755
IGPA	D1	0.00%	1.7531%	-7.6157%	7.27%	-0.0819	3.9495
	D4	-7.85E-20	0.5531%	-2.0378%	1.4989%	-0.3123	1.5395
	D7	-2.238E-21	0.1138%	-0.1961%	0.1795%	-0.1300	-1.1616
MERVAL	D1	0.00%	3.4795%	-15.9984%	14.29%	0.0453	2.5422
	D4	-2.20E-19	1.3982%	-4.7410%	3.8482%	-0.3043	1.6674
	D7	2.9249E-20	0.1044%	-0.1938%	0.1429%	-0.4988	-1.0129
MXX	D1	0.00%	1.4098%	-4.5037%	4.96%	0.0945	0.7728
	D4	-3.19E-21	0.5116%	-1.9696%	1.6173%	-0.1987	2.2738
	D7	7.9738E-21	0.0980%	-0.1575%	0.2015%	0.4552	-0.4855
DJI	D1	0.00%	1.8689%	-9.9070%	12.80%	0.3764	12.8542
	D4	-4.97E-20	0.4798%	-2.1553%	1.6485%	-0.4887	4.9909
	D7	-2.879E-20	0.0807%	-0.1277%	0.1308%	0.0010	-1.3538
SP500	D1	0.00%	1.7143%	-8.3314%	10.60%	0.2384	8.8946
	D4	-1.13E-20	0.4455%	-2.0537%	1.5247%	-0.5693	5.4861
	D7	-9.297E-21	0.0713%	-0.1053%	0.1363%	0.3120	-0.9905
GOLD	D1	0.00%	1.3957%	-5.8267%	8.05%	0.2266	6.0544
	D4	1.14E-20	0.3143%	-0.7071%	0.7868%	0.1514	-0.6990
	D7	-1.67E-20	0.1157%	-0.1608%	0.2139%	0.2352	-1.1647
WTI	D1	0.00%	3.2624%	-13.8861%	19.53%	0.3642	4.9901
	D4	-7.73E-20	1.7056%	-7.2108%	6.9405%	-0.0678	5.3314
	D7	4.6074E-20	0.3719%	-0.6348%	0.6247%	-0.0379	-1.1903
BTC	D1	0.00%	7.5534%	-33.1381%	27.72%	0.0003	2.6342
	D4	2.36E-19	2.1001%	-5.9436%	6.3926%	-0.0257	0.1944
	D7	1.2546E-19	0.9533%	-1.4936%	1.6310%	0.0505	-1.3172
ETH	D1	0.00%	9.4201%	-37.8546%	30.32%	-0.0671	1.0440
	D4	4.29E-19	2.7708%	-9.4910%	8.4514%	-0.0860	0.8660
	D7	-4.135E-19	1.7960%	-2.8619%	2.9781%	0.0054	-1.3406
XRP	D1	0.00%	11.4963%	-45.4927%	51.91%	0.3635	3.7317
	D4	5.47E-19	5.0488%	-14.0547%	16.5796%	0.2498	1.4437
	D7	-2.585E-19	1.7802%	-2.5326%	3.2466%	0.1988	-1.2156

Fig. 7. Decomposed correlation at D1, D4 and D7 scale levels.



Source: Authors estimations.

The decomposed correlation supports the wavelet coherence analysis where in most of the cases when the scale increases or when the window time spans from short to long run within a year and across years, the level of interaction shows a low degree of connectedness. The Bitcoin case shows a different pattern when competing with Ethereum and Xripple, while these altcoins show a low degree of association at high scales the Bitcoin records high levels of interaction in those scales.

Even when Bitcoin shows rapid and furious comovements at low scales which dissipate almost immediately, but at high scales spanning over 64 weeks the level of interaction increases.

In the standpoint of the theoretical comovements view this behavior is explained because of fundamental linkages. The exception is observed in the Bitcoin-gold pairwise where over 64 weeks and across time the interaction is negative. So, the change of degree of association is supported by the wavelet coherence. Finally, even though changes along scales and across time, all cryptocurrencies against equity indices and commodities showed a contagion phenomenon during the Covid-19 pandemic era[1].

Based on the wavelet coherence and decomposed correlation, what could be expected on cryptocurrencies to be considered as hedger, diversifier, or safe-haven devices? This question is answered by estimating the hedge ratio of equity indices against cryptocurrencies.

[1]When comovement shows a strong level of interaction but dissipates almost immediately it is known as contagion. On the other hand, when the level of interaction maintains in the long run it is known as a fundamental linkage (Gallegati, 2012).

independent. Since gold and oil have been considered as safe-haven assets when occurring high uncertainty periods or financial crises, then the analysis is based on a competition framework of cryptocurrencies against commodities.

Table. 3a and 3b shows the hedge ratio estimations of equity indices against Bitcoin and commodities. It is observed that in most of the cases Bitcoin and WTI indicate diversifying properties when time spans from short to long run, while gold is showing hedging capabilities as the ratio decreases and turns from positive to negative side when time spans from short to long run (from D1 to D7 scale). A specific case is that of the Mexican equity index (MXX) where ratio values against Bitcoin are relatively low and almost non statistically significant.

When compared to MXX against gold, ratio values decrease and change from positive to negative as time spans from short to long run which show high statistical significance.

The pairwise WTI-MXX show increasing ratio values as also the statistical significance. In that sense, Bitcoin may act as a safe-haven device, gold as hedging device, and oil as a diversifier device, when time spans from short to long run.

It is important to note that besides gold may hold safe-haven properties in the long run but in the short run it is acting better as a diversifier device. It is aligned with findings that are Baur and McDermott (2010) when examined the role of gold and identified it as a safe haven against

Cryptocurrency/ Commodity	Equity Index	Scale	Hedge Ratio	t-value
Bitcoin	BVL	Global	0.6834	2.8800
		D1	0.5630	2.1880
		D4	0.7100	3.8910
		D7	5.0020	6.9560
	BVSP	Global	0.3881	1.9530
		D1	-0.0453	-0.2210
		D4	0.1005	0.7620
		D7	9.0110	12.1800
	COLCAP	Global	0.4438	2.1700
		D1	-0.1100	-0.5050
		D4	1.2690	6.5280
		D7	-6.1450	-13.9000
	IGPA	Global	0.4924	2.1500
		D1	0.0328	0.1320
		D4	1.1220	5.3590
		D7	5.6480	15.8100
	MERVAL	Global	0.3363	2.9200
		D1	0.2623	2.1080
		D4	0.3375	3.9940
		D7	5.3250	12.4300
	MXX	Global	0.9681	3.2930
		D1	0.7372	2.4060
		D4	0.7736	3.3240
		D7	1.1880	2.1320
	DJI	Global	0.5787	2.3370
		D1	-0.1076	-0.4610
		D4	1.9810	8.7930
		D7	7.4550	14.1000
	SP500	Global	0.6152	2.2910
		D1	-0.0392	-0.1540
		D4	1.8330	7.3120
		D7	7.1670	10.9900

Cryptocurrency/ Commodity	Equity Index	Scale	Hedge Ratio	t-value
Gold	BVL	Global	0.1406	3.4300
		D1	0.1550	3.2940
		D4	0.1719	6.5670
		D7	-0.6706	-7.8250
	BVSP	Global	0.1473	4.3670
		D1	0.1433	3.8800
		D4	0.1661	9.6150
		D7	-0.3987	-3.7160
	COLCAP	Global	0.1807	5.2680
		D1	0.2595	6.9460
		D4	0.2308	8.2180
		D7	-1.0290	-29.6600
	IGPA	Global	0.1016	2.5590
		D1	0.1056	2.3190
		D4	0.1218	3.8000
		D7	-3.3200	-5.9830
	MERVAL	Global	0.0613	3.0640
		D1	0.0406	1.7640
		D4	0.0760	6.2230
		D7	-0.3517	-5.7940
	MXX	Global	0.1312	2.5470
		D1	0.2429	4.3830
		D4	0.1651	4.8320
		D7	-0.8523	-18.0700
	DJI	Global	0.1715	4.0500
		D1	0.2315	5.6480
		D4	0.1728	4.7370
		D7	-0.5603	-7.3570
	SP500	Global	0.1892	4.1290
		D1	0.2401	5.3450
		D4	0.2128	5.4800
		D7	-0.6351	-7.3630

stock in major emerging and developing countries Also, as the hedge ratio of the Mexican equity index against Oil strengthens and increases its statistical significance when time spans from short to long run, then Oil would act as a better safe-haven device in the very short run but a diversifier device in the long run. Nonetheless, since hedge ratios of MXX-gold are lesser than MXX-WTI and high statistical significance then gold could be considered as a better hedger device than oil at any window time.

If the ratio is significantly negative, then cryptocurrencies may have hedging capabilities. On the other side when the ratio is significantly positive then cryptocurrencies are acting well as diversifier devices. However, safe-haven properties are indicated when the ratio is significantly.

Table. 3.a. Hedge ratio estimations of equity indices against Bitcoin and gold.

Cryptocurrency/ Commodity	Equity Index	Scale	Hedge Ratio	t-value
WTI	BVL	Global	0.8149	6.8660
		D1	0.5101	4.7200
		D4	2.1640	25.0000
		D7	2.8560	11.2700
	BVSP	Global	0.6554	6.6010
		D1	0.2352	2.6900
		D4	1.2820	16.5200
		D7	2.5080	7.7950
	COLCAP	Global	0.7182	7.0830
		D1	0.2707	2.9180
		D4	2.2010	19.8600
		D7	2.2270	12.3800
	IGPA	Global	0.8318	7.3710
		D1	0.6516	6.4740
		D4	1.7130	11.5700
		D7	2.0590	14.0500
	MERVAL	Global	0.3288	5.5620
		D1	0.1446	2.7030
		D4	6.8400	11.7300
		D7	2.3870	15.6200
	MXX	Global	1.0860	7.4320
		D1	0.5394	4.1520
		D4	2.2040	15.2700
		D7	3.5380	44.6000
	DJI	Global	0.8429	6.8200
		D1	0.3987	4.0630
		D4	2.4860	16.9500
		D7	3.5440	20.8400
	SP500	Global	0.8919	6.6370
		D1	0.4432	4.1480
		D4	4.1280	22.3900
		D7	4.1280	22.3900

Conclusion

This article has performed a multiscale analysis approach of Bitcoin and two main altcoins against MSCI LATAM equity indices and commodities, in such a way to identify if Bitcoin may serve as a safe-haven, hedge or diversifier device. The analysis was performed under the wavelet approach which allows to decompose the original time series into multiple time scales where high frequencies are captured in low scales and low frequencies can be captured in high scales. In that sense, besides the possibility to identify the type of comovement among time series, the main issue in this research was to estimate the hedge ratio. If the hedge ratio is negative and statistically significant then the asset could be considered as a hedger device. On the other hand, if the ratio is high and statistically positive then the asset would be hold diversifier properties. A safe-haven asset would mean when comovements are independent.

Results show that in most of the cases Bitcoin against commodities is a better safe-haven device when time spans from short to long run. An exception is found in the pair wises Bitcoin-DJI and Bitcoin-SP500 where after acting as a safe-haven device in the short run it evolves as a diversifier device. When Bitcoin competes against Gold, this commodity holds better hedging properties when time spans from short to long run. Finally, since Oil showed high hedge ratios and statistically positive then this commodity has been acting better as diversifier.

Not only the research results are important for investment portfolios but for FINTECH based companies which are seeking to offer financial services to unbanked people where cryptocurrencies could be a next wealth store asset and a wide acceptable medium of exchange for commercial purposes. However, more research is needed to establish better game rules between the crypto-market and the banking sector.

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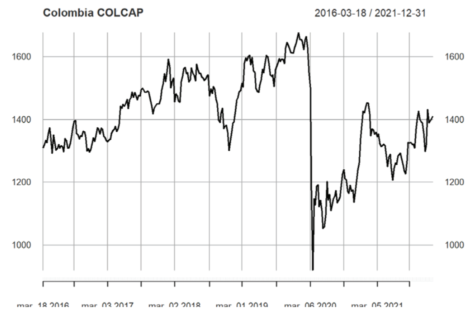
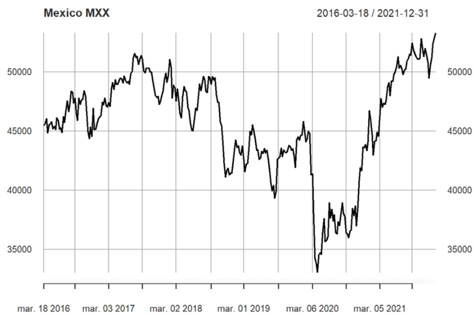
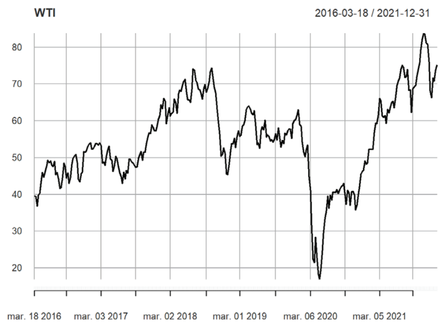
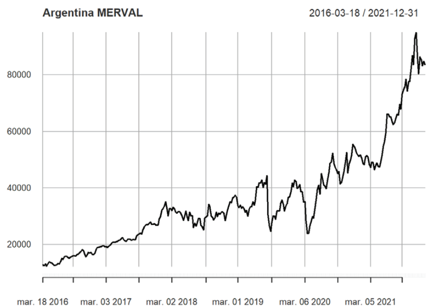
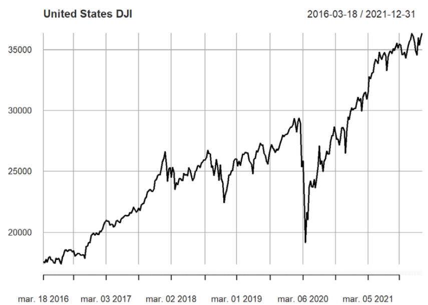
Appendix A. Equity and commodity prices.





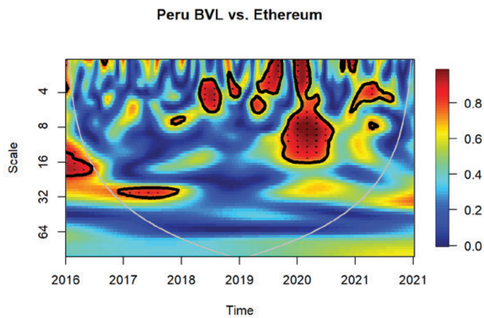


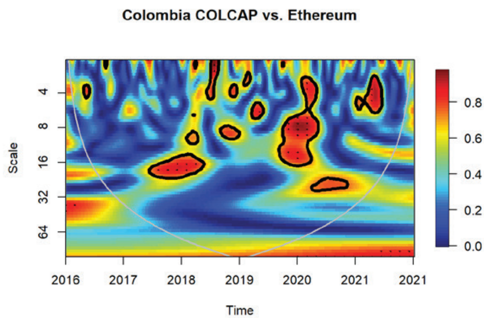


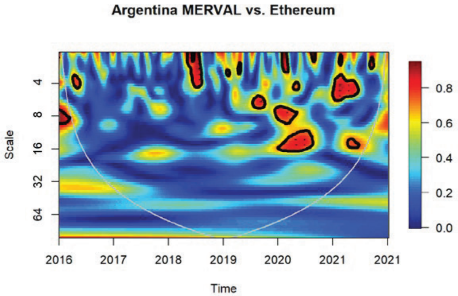


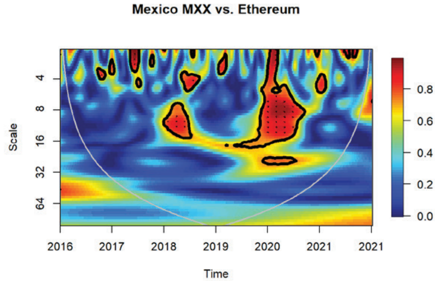
Appendix B. Wavelet Coherences..

B.1. Ethereum






Argentina MERVAL vs. Ethereum
Scale
Time


Mexico MXX vs. Ethereum
Scale
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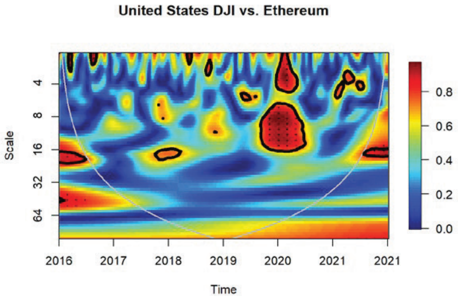
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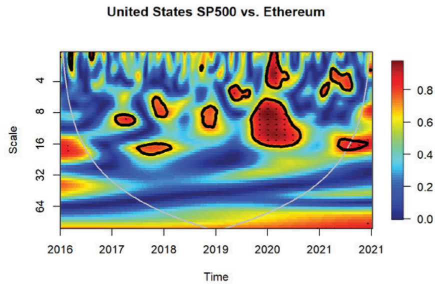
Scale
Time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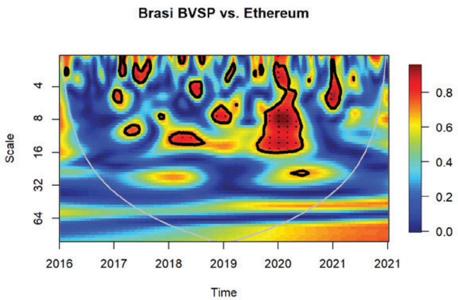
Scale
Time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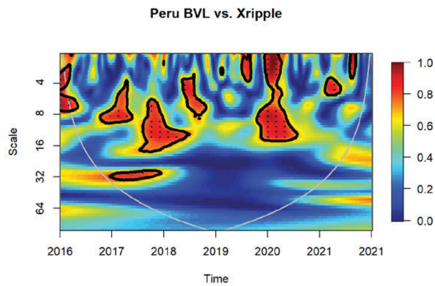
Peru BVL vs. Xripple
Scale
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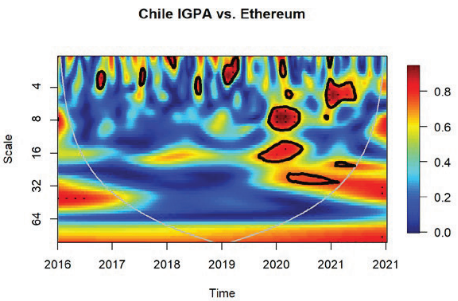
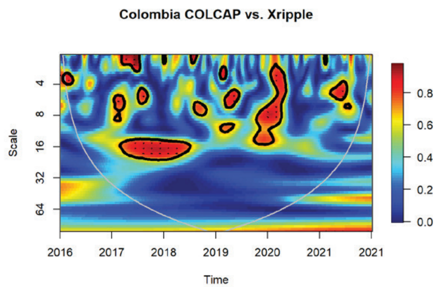
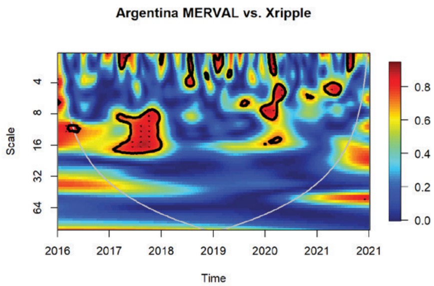

Chile IGPA vs. Ethereum
Scale
Time


Colombia COLCAP vs. Xripple
Scale
Time


Argentina MERVAL vs. Xripple
Scale
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Time
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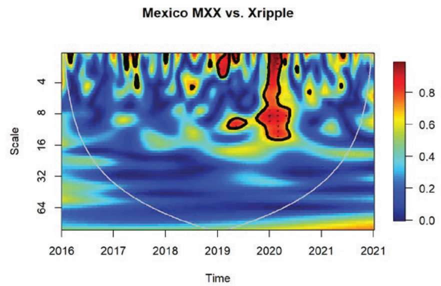
Mexico MXX vs. Xripple
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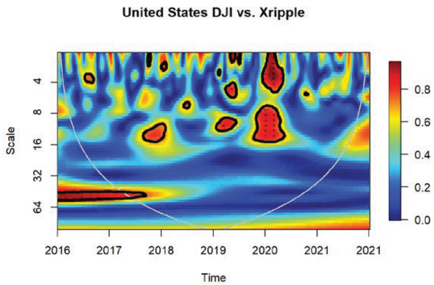
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Time
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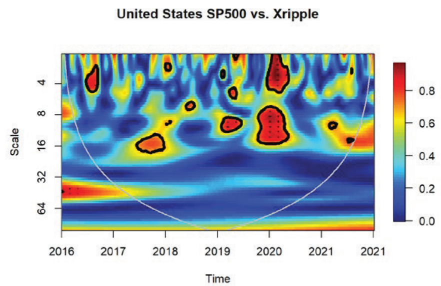
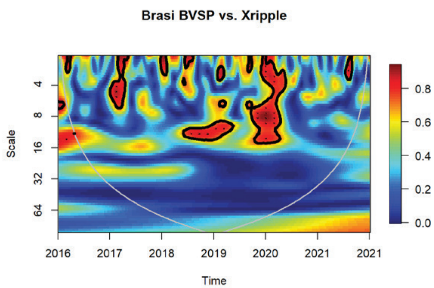
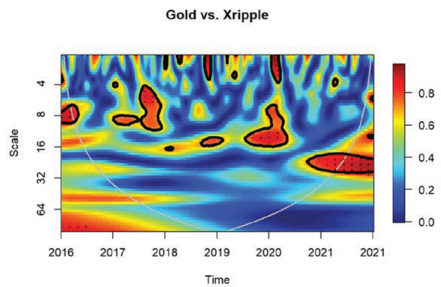
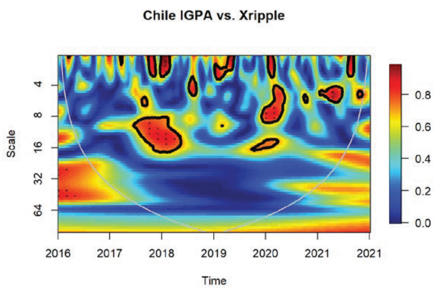
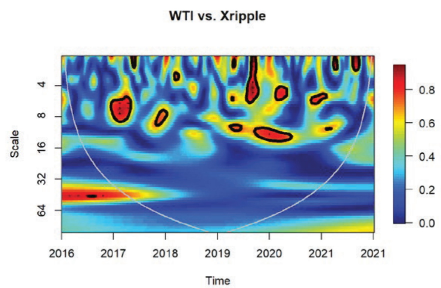

United States SP500 vs. Xripple
Scale
4 8 16 32 64
2016 2017 2018 2019 2020 2021 2021
Time
0.0 0.2 0.4 0.6 0.8


Brasi BVSP vs. Xripple
Scale
4 8 16 32 64
2016 2017 2018 2019 2020 2021 2021
Time
0.0 0.2 0.4 0.6 0.8


Gold vs. Xripple
Scale
4 8 16 32 64
2016 2017 2018 2019 2020 2021 2021
Time
0.0 0.2 0.4 0.6 0.8


Chile IGPA vs. Xripple
Scale
4 8 16 32 64
2016 2017 2018 2019 2020 2021 2021
Time
0.0 0.2 0.4 0.6 0.8


WTI vs. Xripple
Scale
4 8 16 32 64
2016 2017 2018 2019 2020 2021 2021
Time
0.0 0.2 0.4 0.6 0.8