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The Empirical Study of the Relationship between Stock Indices, Crypto Assets, and COVID-19 using Wavelet Coherence Analysis

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Abstract: *The study investigates the relationship between stock indices (namely US (S&P500), India (NIFTY 50), and Brazil (IBOVESPA)), crypto-assets (Bitcoin, Ethereum, and Ripple), and COVID-19 pandemic. The correlation and wavelet coherence analysis is employed to get an intuition of the strength of relationships between the stock indices, cryptocurrencies, and COVID cases/deaths. The paper finds that initially there was a negative relationship between cryptocurrencies and COVID-19 cases/deaths; however, eventually, with time it became positive. The traditional stock market indices of the US, India, and Brazil are found to have a positive relationship with COVID-19 cases/deaths. The stock markets are found to be more sensitive with a greater degree of coherence and react quickly. The study supports that hedging can be done using the assets like stock indices, and cryptocurrencies against the uncertain times raised by the pandemic.*

Keywords: *Cryptocurrencies, Stock Market Indices, Wavelet Coherence Analysis, COVID-19*

JEL Classification: *G10, G15, E50, C13*

1. Introduction

COVID-19 has impacted human race in all the possible ways. COVID-19 is a health and economic catastrophe at the same time. It has had an impact on humanity by altering their way of life and lifestyle. As governments wrestle with additional lockdown measures to combat the virus's spread, national economies and industries are examining the repercussions. Despite the availability of new vaccines, many people are still unsure how they will recover. Since the World Health Organization (WHO) professed a COVID epidemic, financial research has been ongoing.

According to Wenzhao Wang *et al.* (2020), the propagation of COVID-19 has had a significant short-term impact on stock movements in worldwide financial markets. According to Zaghum Umar *et al.* (2021), the coronavirus panic index and the volatility of major currencies including

EUR, GBP, RMB, and the eleven major cryptocurrencies have a high degree of coherence. They found that cross-currency hedges that work well in normal market conditions might fail in times of global crises. COVID-19 was discovered to have an influence on the efficiency of all five cryptocurrencies, according to Emna Mnif *et al.* (2020). Using a network analysis, David Vidal Tomas (2021) pinpoints the bitcoin market's shifts during the epidemic. COVID-19 had a major impact on cryptocurrencies during a brief moment of financial panic, according to this technique.

COVID-19 has caused fluctuations in the global financial assets (Gupta *et al.*, 2021; Bouri *et al.*, 2020; Salisu *et al.*, 2022; Muneer Shaik *et al.*, 2022). By assessing cumulative abnormal returns for WHO announcements linked to COVID-19, Singh, Gurmeet *et al.* (2021) adopt an event study-based technique to investigate the influence of COVID-19 in the stock market. COVID-19 has a considerable influence on global financial markets, according to the study, although the effect varies for established and emerging nations. Demir *et al.* (2020) used wavelet coherence analysis to examine the relationship between cryptocurrencies and COVID-19 cases/deaths, finding that there is a negative relationship between Bitcoin price and the number of reported cases and deaths at first, but that the relationship becomes positive later. The findings for Ethereum and Ripple are similar, although the linkages are weaker. This supports the hedging function of cryptocurrencies in the face of COVID-19's uncertainties.

In this study, we analyze the relationship between financial assets like stock indices, cryptocurrencies, and COVID death/cases. The daily prices of cryptocurrencies are considered namely Bitcoin (BTC), Ripples (XRP), and Ethereum (ETH). We took daily prices of stock market indices namely S&P500 (US), NIFTY50 (India), and IBOVESPA (Brazil) for the period of 11/03/2019 to 11/03/2021. The correlation analysis, and further wavelet coherence analysis is employed to get an intuition of strength of relationships between the stock indices, cryptocurrencies and COVID cases/deaths. The analysis is carried out for three different periods, pre-WHO announcement of COVID-19 pandemic (11-03-2019 to 11-03-2020), post-WHO announcement of COVID-19 pandemic (11-03-2020 to 11-03-2021), and the overall time period (11-03-2019 to 11-03-2021).

This study will help analyze the COVID waves and its short-term and long-term impact in the future.

2. Literature Review

Just after the announcement of COVID 19 pandemic by WHO, almost all of the countries in the world made decision of nation-wide lockdown. Nobody knew what was about to happen and how the financial markets will react. The conditional correlation grew between cryptocurrencies, stock indices, and oil, according to Ghorbel *et al.* (2021), confirming the influence of coronavirus infection between them. According to Thomas C. *et al.* (2020), even a little Bitcoin exposure significantly raises portfolio downside risk. The findings raise doubt on Bitcoin's potential to protect investors from market volatility.

Rubbaniy, G *et al.* (2021) discovered that, despite the lack of evidence of correlated trading when cryptocurrency-specific anxiety dominates the market, crypto investors appear to replicate the trading decisions of others outside of the COVID-19 pandemic lockdown times. Using the multifractal analysis, a study by Emna Mnif et.al. (2020) examined the positive impact on the cryptocurrency market efficiency. According to a study by Nader Alber *et al.* (2020) on the influence of COVID-19 spread on stock market returns in GCC nations, there are considerable disparities in stock market returns and they appear to be sensitive to new coronavirus mortality. Furthermore, this has been validated for the month of March, with no indication of these impacts for the months of April and May 2020.

Lahmiri, S *et al.* (2020) compared the behaviour of cryptocurrencies to that of international stock markets and discovered that cryptoassets are highly impacted by the COVID than foreign stock markets, whereas in terms of stability, investing in digital assets during major crises such as the COVID-19 pandemic could be considered riskier than investing in equities. According to Klaus Grobys (2020), Bitcoin cannot hedge the enormous risk in the US stock market, and so it cannot be used to hedge in a pandemic. According to Kristoufek (2015), Bitcoin is a one-of-a-kind asset that combines the characteristics of a traditional financial asset with those of a speculative asset. COVID-19 might be viewed as an opportunity to put bitcoin's safe haven capabilities to the test.

3. Data

In this study, the relationship between cryptocurrency prices and COVID 19 cases/deaths, stock market indices and COVID cases & deaths are examined. The worldwide COVID cases (WCC) and worldwide deaths due to COVID (WCD) data is used and downloaded from Johns Hopkins Coronavirus Resource Center Database[1]. The three cryptocurrencies (BTC, ETH, XRP) are used because the combined market share of these three are more than 78% of the cryptocurrency market. The stock market indices of developed (US) and emerging nations (India, and Brazil) are considered in this study. The Data period is from 11/03/2019 to 11/03/2021 with 731 observations. The daily prices of stock indices and cryptocurrency variables (namely, BTC, ETH, XRP, S&P500, NIFTY50, IBOVESPA) are downloaded from investing.com website.

4. Methodology

In this section, we discuss the methods of correlation analysis and wavelet coherence analysis that are employed in this study.

4.1. Correlation Analysis

The correlation analysis is used to evaluate the strength of relationship between two variables. A high correlation implies a strong relationship between variables whereas weak correlation means the variables are hardly related. Traditionally, three different ways are used in correlation analysis by Pearson (1895), Spearman (1904), and Kendall (1970).

Spearman's Rank Correlation Coefficient: It is used to see if there is any significant relationship between the two datasets we are considering. The underlying assumption here is that the data used is ordinal.

$$r_s = 1 - \frac{6\Sigma D^2}{n(n^2-1)} \tag{1}$$

This coefficient needs a data table that displays the raw data, its rankings, and their differences. A scatter graph will display the squared difference between the two ranks, indicating whether the two variables have a positive, negative, or no association at all.

Pearson Product-movement coefficient: This is the most common correlation analysis, because it assesses the strength of the 'linear' correlations between the raw data from both variables rather than their rankings. Because it is a dimensionless coefficient, there are no data-related limits to consider. This research has included Pearson correlation to find out the relationship and its strength.

$$r = \frac{\Sigma(X-\overline{X})(Y-\overline{Y})}{\sqrt{\Sigma(X-\overline{X})}\sqrt{\Sigma(Y-\overline{Y})^2}} \tag{2}$$

Where $\overline{X}, \overline{Y}$ is the mean of X, Y variables respectively.

4.2. Wavelet Coherence Analysis

A wavelet is a mathematical function that divides a continuous-time signal or function into scale components. Each scale component will usually be assigned a frequency range. After that, each scale component can be studied at a resolution that corresponds to its scale. This analysis is being used in most of the domains. Wavelets come as a solution of the lack of Fourier Transform which is the dot product between real signal and various frequency of sine wave. The basic formula of Wavelets is

$$X_{a,b} = \int_{-\infty}^{\infty} x(t)\varphi_{a,b}(t)dt \tag{3}$$

X is the real signal, φ is the mother wavelet, a is the scale and b is the translation. The frequency of the mother wavelet is inversely proportional to the scale. The equation thus becomes

$$\varphi(t) = e^{-\frac{\left(\frac{t-b}{a}\right)^2}{2}} \cos\left(5\left(\frac{t-b}{a}\right)\right) \tag{4}$$

The Fourier Transform only allows for one type of transformation, while the Wavelet Transform allows for a variety of transformations. This method can be used to analyze time scale series in various level stationary conditions (Olayeni, 2016).

Torrence and Compo (1998) defined cross wavelet transforms of two time series x(t) and y(t) as:

$$W_{xy}(u,s) = W_x(u,s)W_y^*(u,s), \tag{5}$$

where $W_x(u, s)$ and $W^*_y(u, s)$ are continuous wavelet transforms of $x(t)$ and $y(t)$, respectively, u is a position index, and s denotes the scale, while the symbol * denotes a complex conjugate.

The wavelet coherence can detect regions in the time-frequency space where the time series under investigation co-move but do not necessarily have a high common power. The squared wavelet coherence coefficient is defined as:

$$R^2(u,s) = \frac{|S(s^{-1} W_{xy}(u,s))|^2}{S(S^{-1} |W_x(u,s)|^2 S(s^{-1} |W_y(u,s)|^2}, \tag{6}$$

where S is a smoothing operator. The squared wavelet coherence coefficient is in the range $0 \leq R^2(u, s) \leq 1$. Closer values to zero indicate a weak correlation, while closer values to one indicate a strong correlation. As a result, the squared wavelet coherence, which is equivalent to the squared correlation coefficient in linear regression, calculates the local linear correlation between two stationary time series at each scale.

5. Empirical Findings

The empirical analysis is carried out for three different time periods as mentioned below.

- Pre-WHO announcement as a Pandemic (11-03-2019 to 11-03-2020)
- Post-WHO announcement as a Pandemic (11-03-2020 to 11-03-2021)
- Overall Total time period (11-03-2019 to 11-03-2021)

5.1. Correlation Analysis

Figure 1 shows the results of correlation analysis for Pre-WHO announcement as a Pandemic (11-03-2019 to 11-03-2020) time period. We observe that the correlation is moderate to strong between the BTC and ETH (0.64), ETH and XRP (0.72), S&P500 and NIFTY50 (0.63), S&P500 and IBOVESPA (0.93), and NIFTY50 and IBOVESPA (0.56). The correlation between stock indices, and cryptocurrencies with respect to COVID-19 cases/deaths (WCC, WCD) are very low.

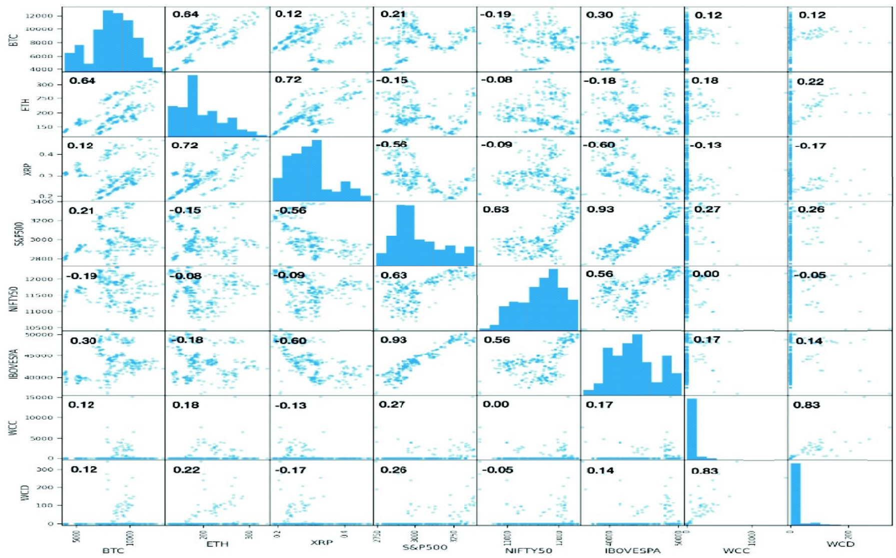
Figure 2 shows the results of correlation analysis for Post-WHO announcement as a Pandemic (11-03-2020 to 11-03-2021) time period. We observe that the correlation is moderate to strong between the BTC and ETH (0.98), ETH and XRP (0.66), S&P500 and NIFTY50 (0.95), S&P500 and IBOVESPA (0.96), and NIFTY50 and IBOVESPA (0.94). All the other combination of variables is hardly correlated before COVID-19 declaration. Interestingly, the correlation between stock indices, cryptocurrencies with respect to COVID-19 cases/deaths (WCC, WCD) are strong and positive. Especially, the traditional stock market indices are very strongly correlated relative to the cryptocurrencies with WCC, WCD after the COVID-19 pandemic announcement by WHO.

Figure 3 shows the results of correlation analysis for overall time period (11-03-2020 to 11-03-2021). We observe the correlation between S&P 500 and WCC (0.78), and S&P 500 and WCD (0.71) is strong and positive compared to other stock market indices like NIFTY 50, and IBOVESPA. In case of cryptocurrencies, the correlation is strong and positive between BTC, and ETH with respect to WCC, WCD; whereas the correlation is low between XRP and WCC/WCD.

5.2. Wavelet Coherence Analysis

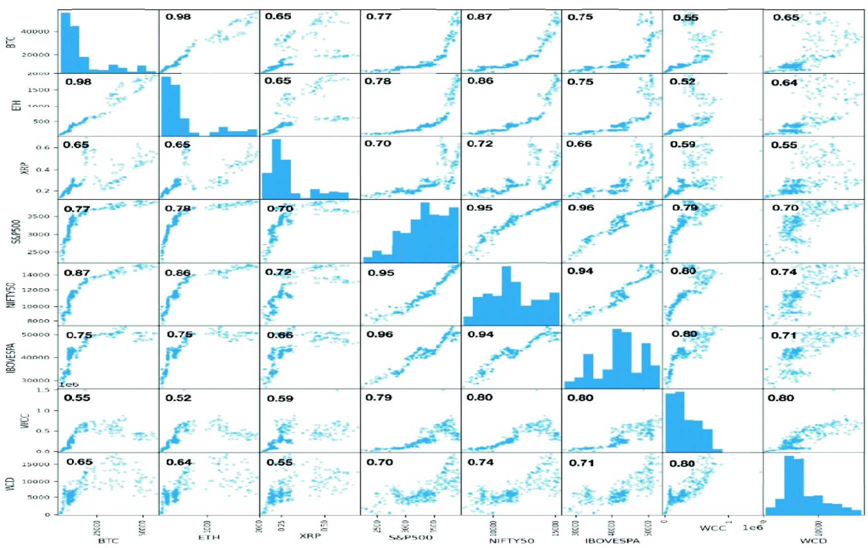
Colors in the wavelet coherence analysis graphical description represent the degree and direction of correlation, with red indicating high coherence and blue indicating low coherence. The scale, which ranges from 0 to 1, is shown on the right-hand side of the plots.

Figure 1: Pre-WHO announcement as a Pandemic (11-03-2019 to 11-03-2020)



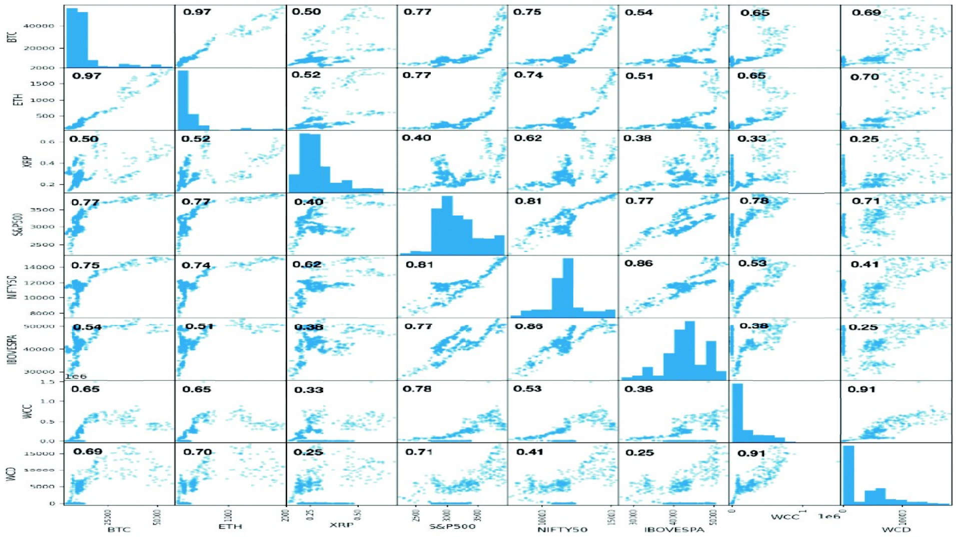
Note: The Pre-WHO announcement correlation analysis results for stock indices (S&P 500, NIFTY 50, IBOVESPA), cryptocurrencies (BTC, ETH, XRP), and COVID-19 cases/deaths (WCC, WCD) are shown.

Figure 2: Post-WHO announcement as a Pandemic (11-03-2020 to 11-03-2021)



Note: The Post-WHO announcement correlation analysis results for stock indices (S&P 500, NIFTY 50, IBOVESPA), cryptocurrencies (BTC, ETH, XRP), and COVID-19 cases/deaths (WCC, WCD) are shown.

Figure 3: Overall Time Period (11-03-2019 to 11-03-2021)



Note: The Overall time period correlation analysis results for stock indices (S&P 500, NIFTY 50, IBOVESPA), cryptocurrencies (BTC, ETH, XRP), and COVID-19 cases/deaths (WCC, WCD) are shown.

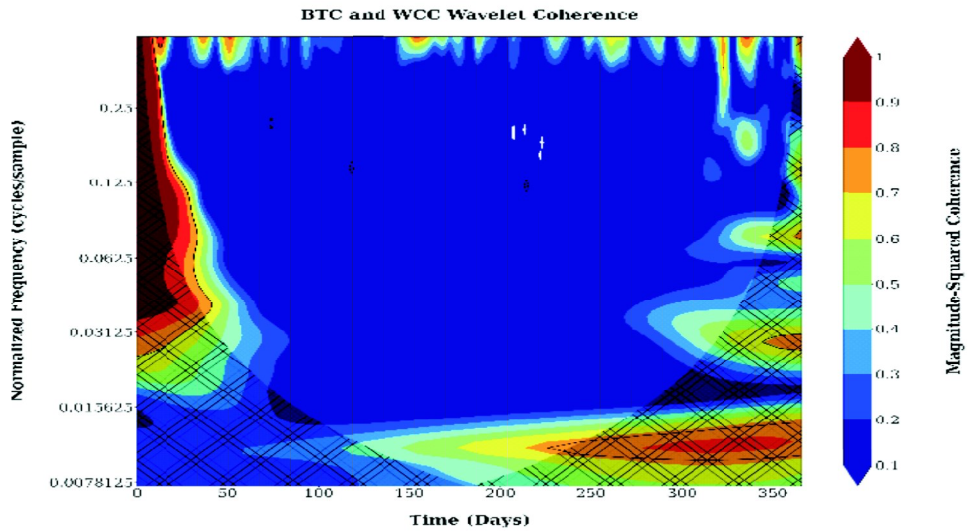
The results from **Figures 4a to 4f** show that before the announcement of pandemic by WHO, all the 6 variables considered have no coherence with WCD and WCC as such but we see there is slight movement by the end of the observation period. The relationship is observed to be negative initially, but later it became positive. Tradition market on the other hand shows a greater degree of relationship and seems to be more sensitive as compared to cryptocurrency market.

Figures 5a to 5f display the results of wavelet coherence analysis after the WHO announcement of the pandemic period. The results show that for a certain period of time (100 days approximately) after the announcement of the pandemic, almost all of the cryptocurrency variables taken into consideration have shown positive coherence with WCC/WCD and then coherence decreased as the time passed. Further, we observe that the stock indices seem to be more sensitive and we see a high coherence magnitude after the announce of the pandemic compared to the cryptocurrencies.

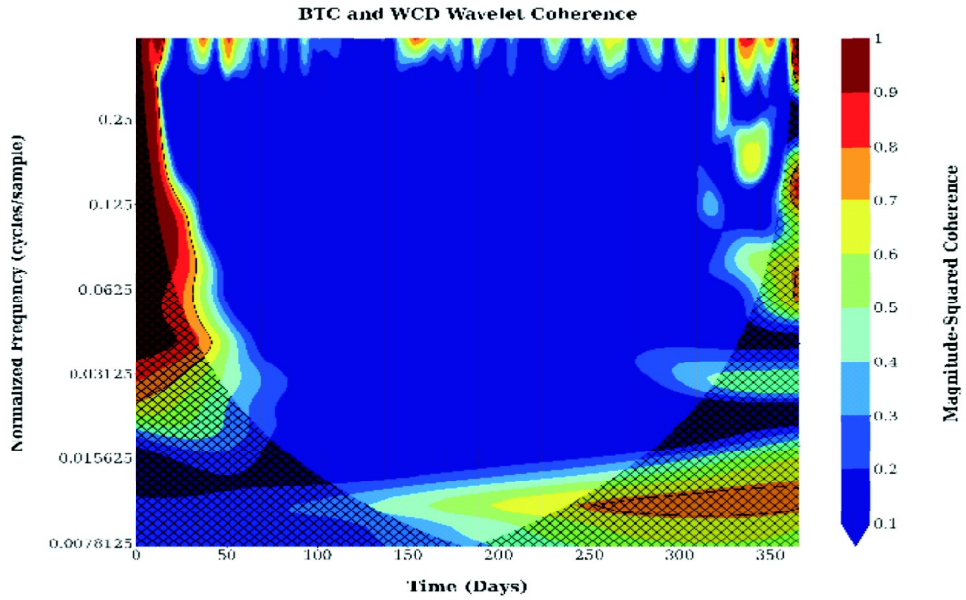
Figures 6a to 6f display the results of wavelet coherence analysis for the overall sample period.

Considering the total time period, we see the co-movements of ETH and WCC has less interaction but the directional change is similar to BTC. Traditional markets seem more sensitive and we see a coherence magnitude of 0.8-0.9 in all the variables considered (figure 6 d, e, f). We see after announcement of vaccine of COVID-19, we again see a change in magnitude and thus the impact of WCC/WCD decreased eventually and markets are coming back on track.

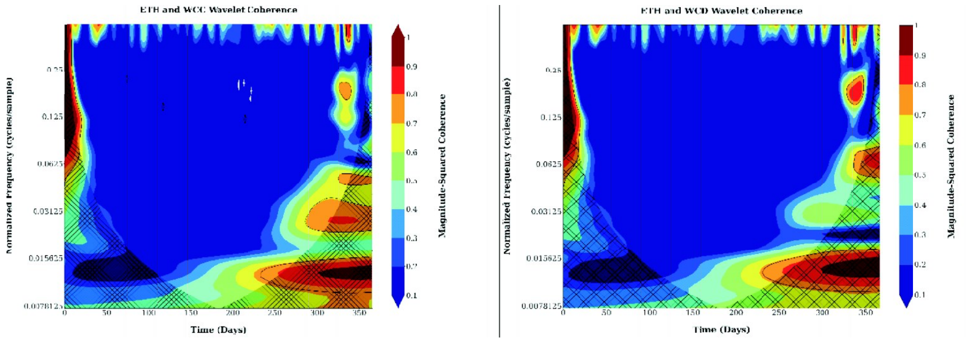
Figure 4: Wavelet Analysis: Pre-WHO announcement (11-03-2019 to 11-03-2020)



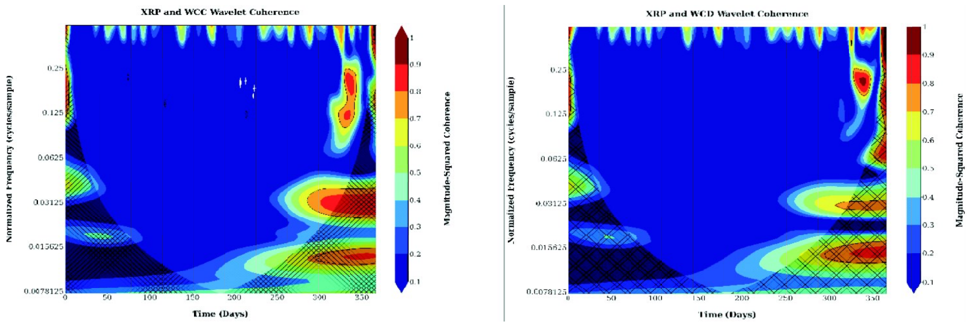
4a. BTC and WCC/WCD



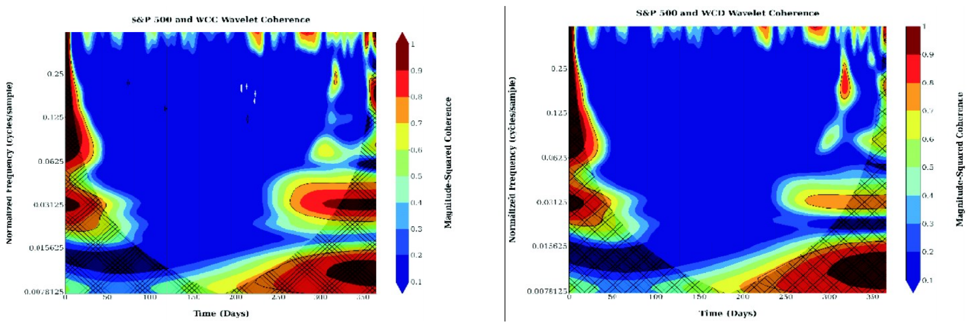
4b. ETH and WCC/WCD



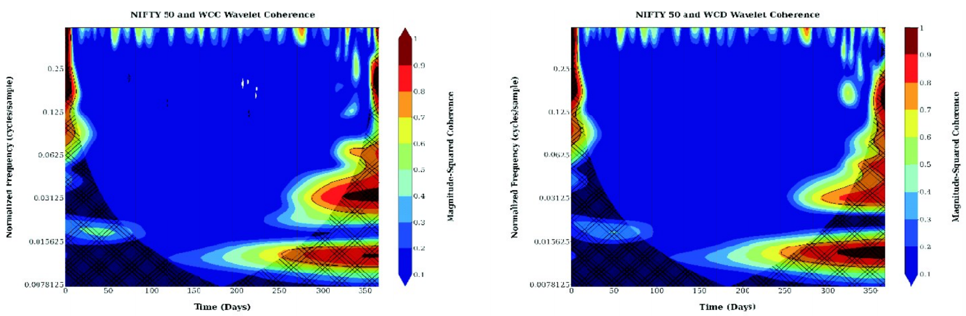
4c. XRP and WCC/WCD



4d. S&P 500 and WCC/WCD



4e. NIFTY 50 and WCC/WCD



4f. IBOVESPA and WCC/WCD

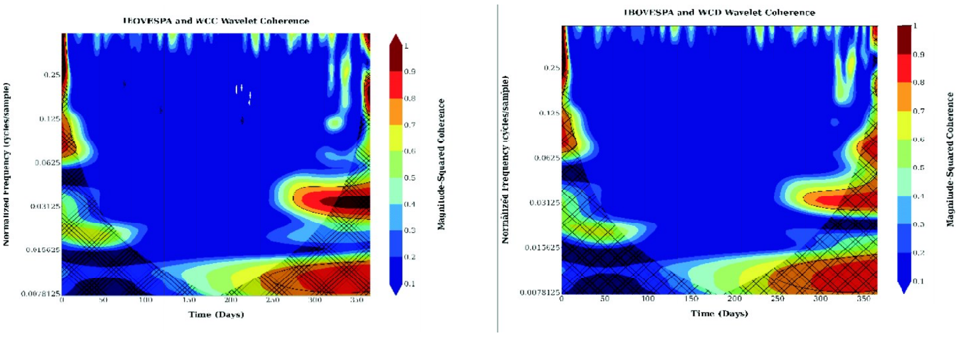
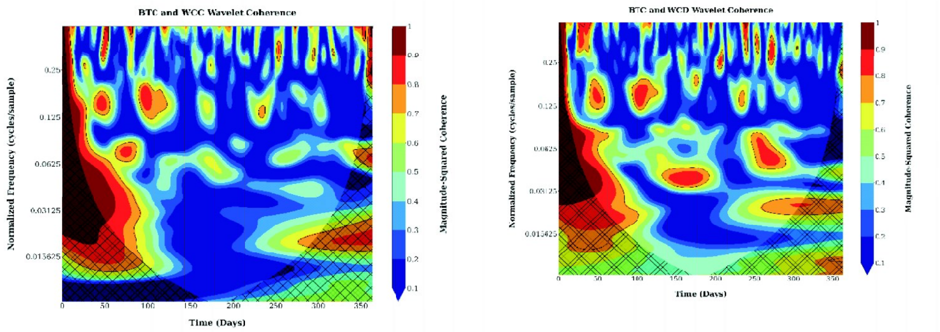
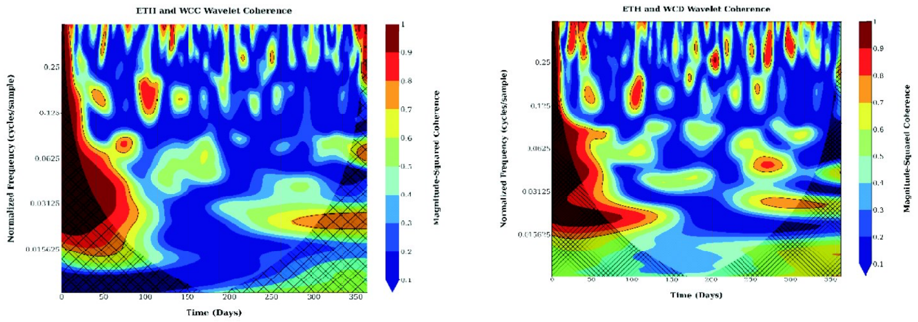


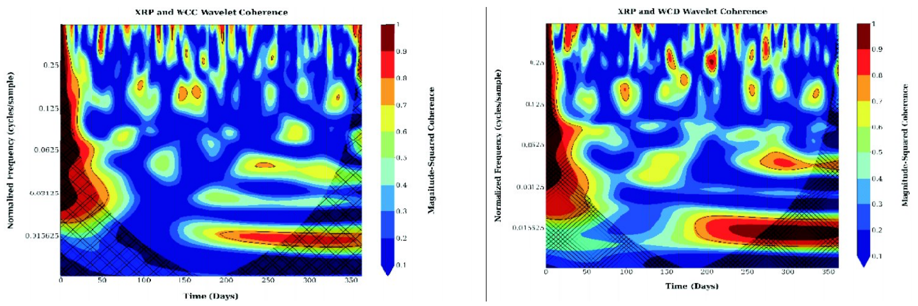
Figure 5: Wavelet Analysis: Pre-WHO announcement (11-03-2020 to 11-03-2021)



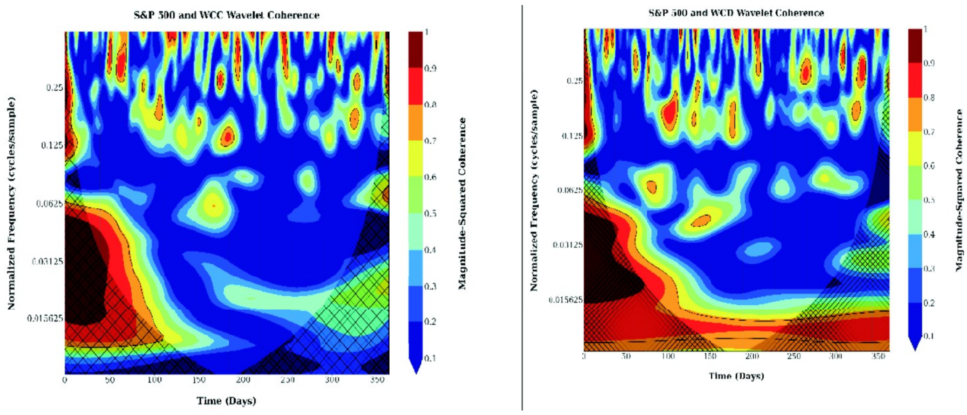
5a. BTC and WCC/WCD



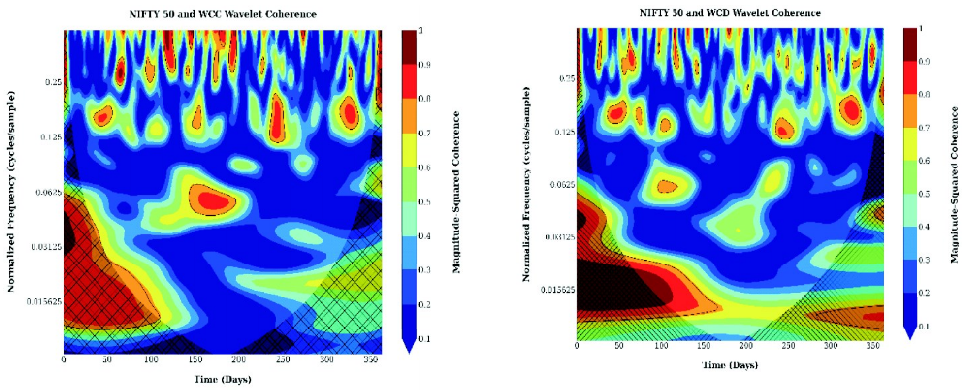
5b. ETH and WCC/WCD



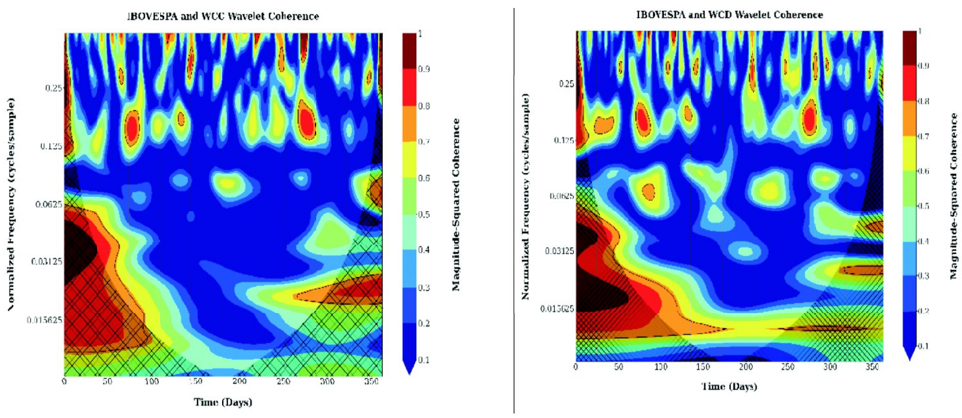
5c. XRP and WCC/WCD



5d. S&P 500 and WCC/WCD

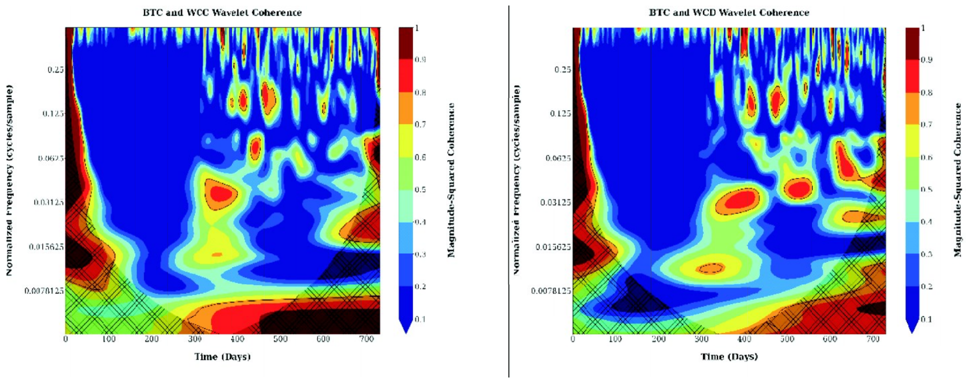


5e. NIFTY 50 and WCC/WCD

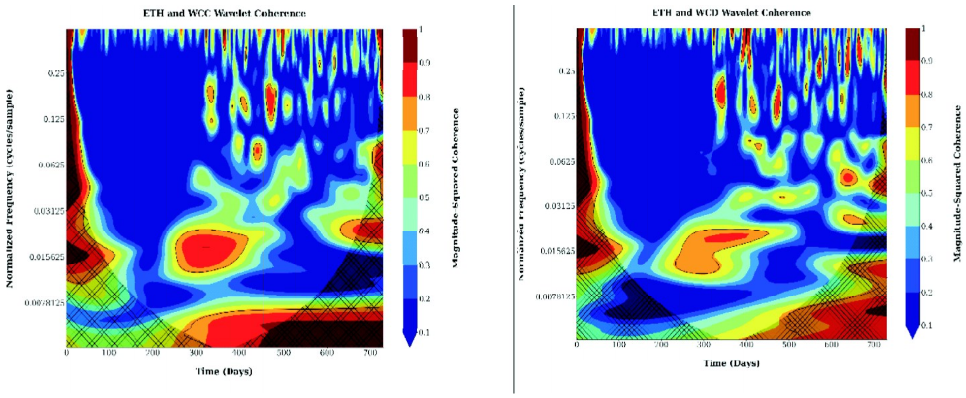


5f. IBOVESPA and WCC/WCD

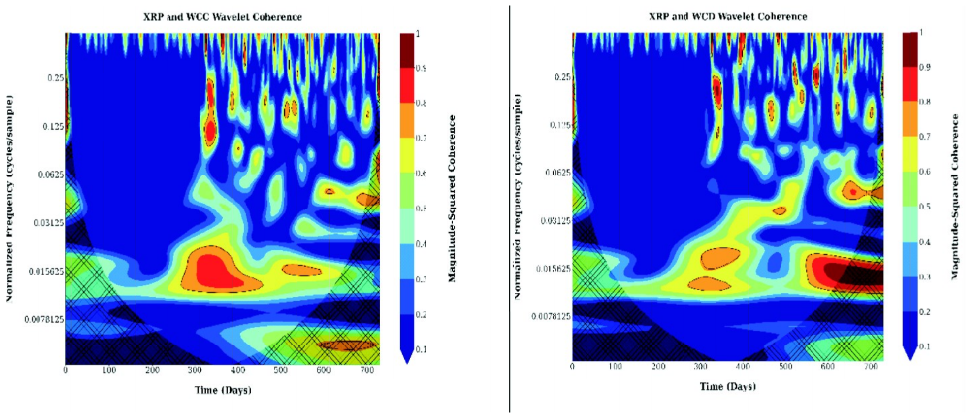
Figure 6: Overall Time Period (11-03-2019 to 11-03-2020)



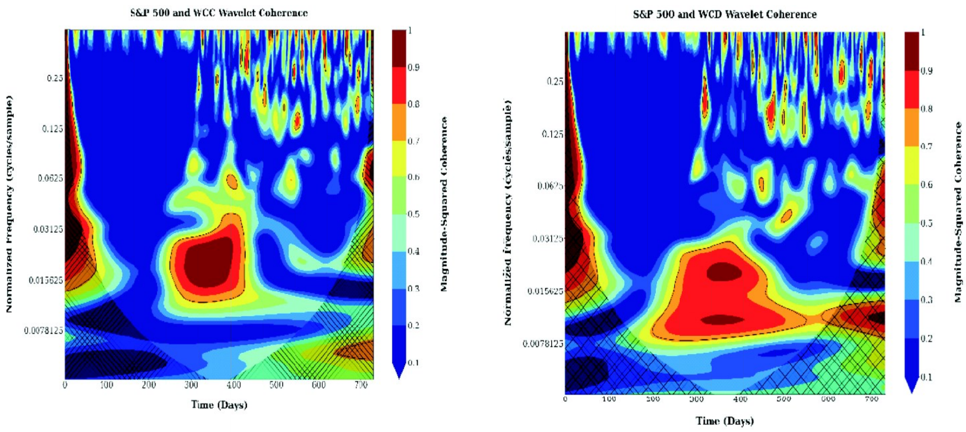
6a. BTC and WCC/WCD



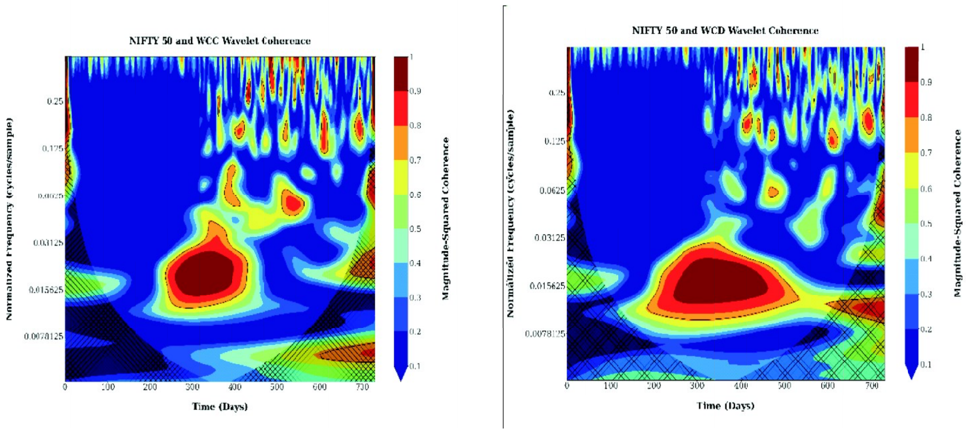
6b. ETH and WCC/WCD



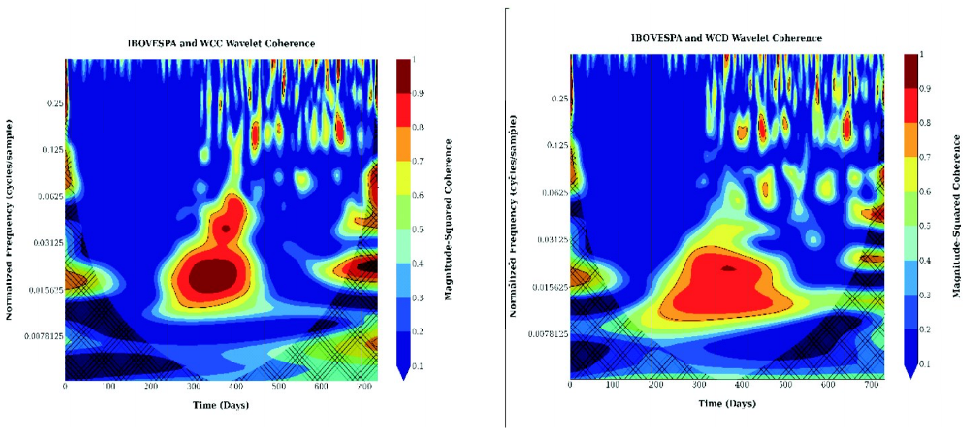
6c. XRP and WCC/WCD



6d. S&P 500 and WCC/WCD



6e. NIFTY 50 and WCC/WCD



6f. IBOVESPA and WCC/WCD

6. Conclusion

This paper investigates the relationship between stock indices, cryptocurrencies, and COVID-19 cases/death. The wavelet coherence analysis shows that there is a positive relationship between the prices of cryptocurrencies and COVID-19 cases reported and deaths. Traditional markets like stock indices are found to be more sensitive with greater degree of coherence and reacted quickly. The study supports the hedging role of stock indices, and cryptocurrencies against the uncertainty triggered due to COVID-19 pandemic.

Further studies can examine impact of COVID-19 on the prices on other financial assets. The world was not prepared at the time of announcement of pandemic but it is now. We can see if the relationship is sustained or not and what will be the impact later on with the new variants of the virus.

Note

1. *https://coronavirus.jhu.edu*

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