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Cryptocurrencies as a Safe Haven Investment During the COVID-19 Outbreak: A Comprehensive Analysis

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Abstract:

Purpose: *Using the onset of the COVID-19 pandemic, this paper examines cryptocurrencies as haven investments for stocks, analyzing our time-varying realizations in response to the economic shock caused by the growing pandemic.*
Design/Methodology/Approach: *Utilizing daily data on COVID-19 measures and daily prices for four cryptocurrencies and four stock assets throughout the year 2020, we apply both the VAR-DCC-GARCH and Wavelet Coherency models.*
Findings: *Our paper provides new evidence that Bitcoin and Ethereum are highly correlated with the selected stocks over both short and long horizons. However, Litecoin and XRP are negatively correlated with the stocks throughout the entire COVID-19 period. We find that Bitcoin serves as a strong safe haven asset for all the selected stocks during the COVID-19 era, while Litecoin is a weak safe haven investment, and XRP has the lowest potential as a safe haven investment for all the stocks studied.*
Practical Implications: *This study provides diversification and hedging strategies for investors and policymakers, suggesting that cryptocurrencies acted as haven investments, similar to precious metals during historic crises, and functioned like fiat money during any economic shocks that may occur.*
Originality Value: *This article addresses a gap in the literature regarding cryptocurrencies as an alternative investment during economic disturbances, particularly in the context of the COVID-19 pandemic.*

Keywords: *Cryptocurrencies, stocks, safe haven, co-movement, VAR-DCC-GARCH, wavelet transform, wavelet coherency.*

JEL codes: *G11, G15, E44, F37, D53, M12, M54.*

Paper Type: *Research article.*

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1. Introduction

The risk management within the investment and the attitude towards the risk by the investors recalibrate the economic system in general, (Akerlof, 1978). It is in this perspective, the innovation in the finance industry shapes the century by introducing successive financial products with different characteristics and typologies to make sure that serve the investment sector in terms of stability and rentability and available for all type of risk attitude such as risk taken and risk aversion.

However, the systemic risk of these products didn't confirm the properties of safe havens investment. Within reframe of the technologies in all the sectors and the realm for the economic sector with different sectors. The introduction of the new technologies within the economic system builds a good infrastructure for the borne of the cryptocurrencies surrounding by the main goals for the macroeconomic system such as the stability.

Within that occurrence, of this innovation, the cryptocurrencies was overcoming until recently one biggest extra-economic shock, the health crisis, which is classified as a multidimensional crisis as it does influence all the sectors including the capital market. Stock markets all over the world have responded in terms of growing risks and changing intermarket linkages within the frame of the world-wide health crisis COVID-19, (Zhang *et al.*, 2020). The pandemic was previously studied in many health crises like for example the SARS 2012, and the outbreak of the flu H1N1 as it is coincided with a severe global financial downturn (Peckham, 2013).

The emergence of the health pandemic 2020 was followed by a strict measure in the health sectors as well as the others such as "stay at home", partial time for work, distance; these measures were considered as main tools to be able to have a control over the spread and to maintain the economic system. Within these measures, a disequilibrium in the supply and demand was setting up leading it by the disruption of the production system size.

It is basic on the economic system frame and the nature of the financial market that each economy overcome this crisis as equity prices have plummeted as well as internationally traded commodity, followed by a collapse in the oil prices and high volatility of the equity markets leading to a higher uncertainty. Within that frame, the cryptocurrencies was influenced as much as the other assets such as oil, metals like silver and gold and the stock markets in terms of volatility, and returns.

The cryptocurrencies are one of the assets that was highly influenced by the pandemic in terms of investment. For that reason we will study the safe haven properties of the cryptocurrencies including a wide range of global cryptocurrencies for the sampled dataset. The related literature studying that topics are quite limited within the conclusion of that the impact of pre-COVID-19 and post-COVID-19 is highly different and in some studies they are proved the opposition of that studies in terms of safe haven properties investment (Antonakakis *et al.,* 2017). As it is assumed that the post crisis is followed by high volatility and uncertainties for all markets (Gencer and Musoglu, 2014), including the stock market.

Our main purpose within this paper is to study the case of cryptocurrencies as hedging asset in portfolio diversification and haven in non-stabilized market environment and higher economic uncertainties following by crisis. According to (Hussain Shahzad *et al.,* 2020) a safe haven asset is taken the properties of uncorrelated or negatively uncorrelated with other assets or portfolio during times of market turmoil, the safe haven properties of an assets allow the hedger to have a portfolio down-risk.

With reference to this definition, our empirical model is taken the properties of safe haven investment and use the GARCH model to study the cryptocurrencies models within COVID-19 period.

The rest of the study is classified as follow, section 2 is dedicated for the related literature on safe haven properties investment for all the concerned assets, section 3 analyzes the development of the cryptocurrencies within the selected period with comparison to the other assets such as stocks assets. Section 4 provides a discussion on the methodology conducted in this study, followed by the empirical results, and the last section is rendered for policy recommendation and concluding remark.

2. Literature Review

The purpose of this article is to shed the light about the impact of the cryptocurrencies on the economic system within the health crisis outbreak, we take the case of the cryptocurrency and their penetration on the financial system and what is their main properties as a safe haven investment. Kumah and Odei-Mensah (2021) provide evidence of interconnectedness between the cryptocurrencies and other markets.

The literature which studying the impact of the cryptocurrencies as a safe haven investment it is quite important as it is a source of hedging which reaching the similar properties of downside risk as much as the gold, the currencies, long dated treasury bonds, the oil and the government bonds. The COVID-19 health crisis is known as the most important shock occurred from the lessor of the cryptocurrencies. Within this part we will focus on the main literature review which examines further the safe haven properties of cryptocurrencies comparing to the other stock markets before and during the COVID-19 pandemic.

2.1 Cryptocurrencies in the Pre-COVID-19 Period

The literature review studying and testing the safe haven investment for cryptocurrencies is diverse and the main driver conducting this assumption is the independence in monetary policy. Bouri *et al.* (2017) studying the impact of bitcoin as hedge for global uncertainty using the first principal component of the VIX indices as measure for a sample of 14 developed and developing equity markets, the authors argue that bitcoin does act as a hedge against uncertainty positively at both higher quantiles and shorter frequency movements of bitcoin returns. Within this overview there are several researches which have studied the development of the cryptocurrencies, such as the Bitcoin, in the rapidly growing cryptocurrency market price and information flows such as Akyildirim *et al.* (2020), Corbet *et al.* (2018), Brandvold *et al.* (2015).

The studies which are studying the bitcoin as a safe haven investment for the investors are mainly focucing on a general conclusion that the cryptocurrencies do not confirm the properties of the safe-haven investments. In that purpose, Corbet *et al.* (2018) shed the light on the evidence speculative behaviour manifesting in terms of bubbles that prevent their property of safe haven investment to be occurred. At the same perspective Klein *et al.* (2018) contrast the hedging and safe haven properties of gold and Bitcoin and finding a positive correlation with downward moves in developed markets. The evidence that cryptocurrencies should rule it out as safe haven properties for cryptocurrencies is conducted previously arguing that it is more volatile, less liquid and costlier to transact than any other asset.

2.2 Cryptocurrencies in the Post-COVID-19 Period

Conversely the literature studying the cryptocurrencies during the COVID-19 crisis is variant in terms of the methodologies used for that. Guesmi *et al.* (2019) argue that the downside portfolio risk is quite important within the inclusion of Bitcoin in a portfolio comprising of gold, oil and emerging market stocks.

Jiang *et al.* (2021) examine the interconnectedness between the EPU and cryptocurrencies and those between COVID-19 pandemic and cryptocurrencies proofing that cryptocurrencies act as good hedging tools against high EPU but not during period of moderate or low EPU and that their hedging properties do not remain all the time.

In the same perspective by shedding the light on their characteristics, Shahzad *et al.* (2019) use cross quantilogram approach and find out that Bitcoin, gold and commodity index are weak safe havens but that this behaviour is time-varying, using a different approach based at the hourly frequency. Urquhart and Zhang (2020) find that Bitcoin is acting as hedge diversifier and safe haven for a range of international currencies.

In contrast to these studies prior COVID-19 pandemic Wang *et al.* (2019) using a wide range of cryptocurrencies argue that digital currencies act as safe haven for most international studies indicators. Kumah and Odei-Mensah, (2021) find evidence that the stock market is highly exposed to cryptocurrency market disruption from the medium term and international investors seeking to hedge their price risk in stock market using cryptocurrencies may have to look at the short term. Kliber *et al.* (2019) examine the time varying hedging and safe haven properties of Bitcoin using a multivariate stochastic volatility model with dynamic conditional correlation.

The authors find out that Bitcoin is acted as a weak hedge in all markets when investment in US dollars is considered a safe haven as in Venezuela by examining the co-movements between Bitcoin and the Dow-Jones world stock market index, regional Islamic stock markets and Sukuk market. Mensi *et al.* (2019) use Wavelet transformation techniques to find out the evidence of diversification with Bitcoin, but this result is consistent to be smaller for longer-term investors compared to short term investors.

Disli *et al.* (2021) assesses the role of gold, crude oil and cryptocurrencies as a safe haven for equity market investors, the authors find out that within the onset of the COVID-19 pandemic oil, gold and Bitcoin do not exhibit safe haven characteristics. However with the outbreak of the pandemic gold, oil and Bitcoin exhibited low coherency with stock market indexes across almost all considered investment horizons. Corbet *et al.* (2020) study the relationship between the largest cryptocurrencies and the development of the COVID-19 outbreak considering it as the scale of economic shock centralized within the rapidly escalating pandemic.

The authors prove a significant rise in both return and volume suggesting that the digital assets are a safe haven similar to precious metals during the crisis as in COVID-19 pandemic. Colon *et al.* 2020 study the impact of the COVID-19 pandemic as the largest widespread condition market since the lessor of the cryptocurrency test the haven properties of the largest cryptocurrencies from the international perspective.

The sampled cryptocurrencies confirm a difference in terms of safe havens properties based of the difference market impaired downside risk hedging. Dwita *et al.* (2021) reveals that safe haven features that Ethereum is possibly a better safe haven than Bitcoin for stocks during the pandemic.

Mokni *et al.* (2022) examines cryptocurrencies and gold as safe haven investment against the EPU before and during the ongoing COVID-19 crisis, finding out that cryptocurrencies and gold are as strong hedge investment or safe haven investment against EPU before and during the COVID-19 pandemic.

At the same perspective Maitra *et al.* (2022) provide a comparative approach before and during the COVID-19 pandemic to examine the cryptocurrencies and stocks as safe haven investment finding out that the cryptocurrencies cannot provide incremental gains by hedging stock market during the COVID-19 pandemic. Corbet *et al.* (2020) studying the safe havens properties of the cryptocurrencies using the return as the main indicator within a GARCH model, found out that a developed significant and pronounced time varying price volatility effects as investors identified both the severity and the nature of the pandemic trajectory and potential economic repercussion.

Segnon and Bekiros (2020) studied the dynamic governing the mean and variance processes of the Bitcoin and find out that the Markov switching multifractal and FIGARCH models are performing well.

The literature studying efficiency as one of the properties of safe haven investments during the COVID-19 crisis is diverse, ranging from inefficiency, as observed by Urquhart (2016), to findings of efficiency in other studies. Naeem *et al.* (2021) examine the asymmetric efficiency for hourly wide range of cryptocurrencies using asymmetric multifractal detrended fluctuation analysis, the authors find out that the COVID-19 outbreak have adverse effects on the efficiency of leading cryptocurrencies confirming that the market efficiency is time varying.

Zargar and Kumar (2019) and Chu *et al.* (2019) examine the efficiency of the Bitcoin and a wide range of cryptocurrencies respectively using a daily data and using different methodologies find out that the given complexity of the cryptocurrency markets as reflected by the evidence of non-linearity and asymmetric multifractality. In the same perspective, concerning the study the safe haven properties of the cryptocurrencies, several studies were focused on the stability, specially the effects have been identified of the gold and cryptocurrency-based contagion effects (Corbet *et al.*, 2020).

2.3 Cryptocurrencies within the COVID-19 Crisis

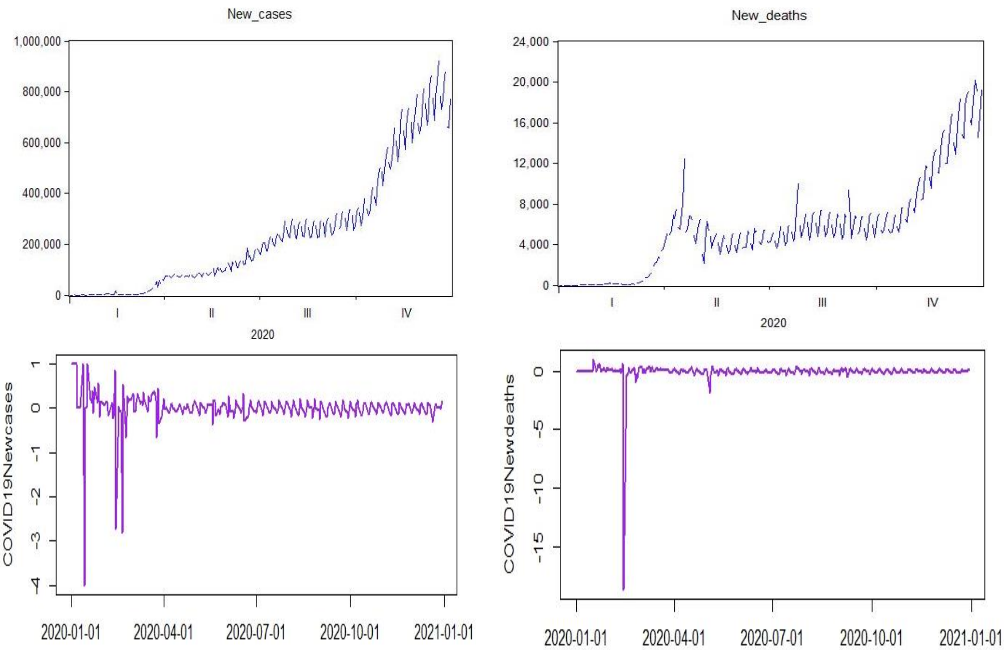
In the first half of this decade, the international economic system has matured in response to economic and extra-economic shocks, followed by significant institutional reforms within organizations. The COVID-19 pandemic was the major crisis during this period, demonstrating the importance of the sharing economy and hedge funds as key components of the economic system and financial tools to mitigate idiosyncratic risks and unexpected volatility in stock markets, as well as instability in prices and macroeconomic aggregates. The COVID-19 pandemic, as the most significant health crisis of the century, has proven its far-reaching economic, health, and political impacts worldwide.

The total cumulative number of confirmed cases and death has reach 63.012.924 and 1.353.716 respectively (30-12-2020, worldwide). Figure 1 shows the daily new cases as well as cumulative cases and death for COVID-19 virus until December 2020. The global increase of the case of COVID-19 attracted global media. The first wave was in November 2019, following by the real serious rise from the beginning of 2020. The unexpected crisis and the unprepared institutions for this frame was the main reason for the spread of the virus within communities.

The measure given by the WHO (World Health Organization) brings a rise for limiting the spread between nations such as vaccine, lockdown, distancing, etc. However its severity and scale still varied by regions. According to Figure 1 it is assumed that the peak phase of the crisis is passed and currently are going back gradually to the normalcy, as there is open, and the lockdown start partial measure. The severity of this crisis is not the same as the other crisis which occurred within the system whether political social or financial crisis. Like any other crisis, the last phase of the crisis, after the peak or post crisis era, there is a big uncertainties and volatilities within the financial market and the whole sectors of the economy, (Antonakakis *et al.*, 2017).

According to Fan *et al.* (2018) the expected annual loss from pandemic risk to be approximately 500 billion dollars, or 0.6% of global income. The SARS crisis known as respiratory syndrome in 2003 was costing the world wide between 30 and 100 billion (Smith, 2006). Ang *et al.* (2021) evaluate the socioeconomic factors in containing the spread and mortality of COVID-19 find out that the higher number of infection or death are associated to the level of GDP and the socio economic factors such as education.

Figure 1. *COVID 19 Pandemic Indicators*



Source: *Own study.*

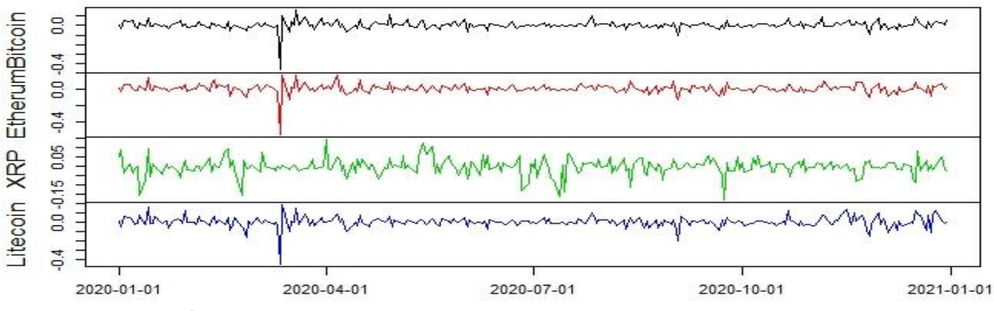
The COVID-19 crisis cost is beyond this sum. COVID-19 is a global crisis which lead to a long-term shifting in costs of equity, the expectation of the rise in the perceived equity risk is reasonable within that environment. The COVID-19 has been considered a “once-in-a-century” pandemic (Gates, 2020). Fernandes (2020) estimate the cost of the COVID-19 to be 2.8% slowdown median economy, and at the extreme case could fall by more than 15%.

Figure 2 shows the different trend of capitalization within the studied period. Bitcoin is the largest cryptocurrencies among all the currencies in all over the world, despite the inauguration of the COVID-19 pandemic, the Bitcoin keep their rank in terms of capitalization with a rise and more pronounced trend during the onset of the COVID -19. Ethereum is the second largest crypto and it maintain an increase trajectory in terms of their capitalization during the COVID-19 comparing to the other periods.

When comparing Bitcoin and Ethereum to other cryptocurrencies such as XRP and Dash, smaller cryptocurrencies tend to exhibit higher levels of volatility. Bitcoin played its hedge fund role from the early stages of the COVID-19 spread, showing a steady rise in value compared to other assets and cryptocurrencies. Dyhrberg (2016) considers Bitcoin a hedge against bearish market conditions.

The relationship between Bitcoin and other cryptocurrencies is not symmetric, as evidenced by differences in correlations driven by intra-market characteristics (Aste, 2019; Czapliński and Nazmutdinova, 2019), which may reasonably explain the asymmetric and non-linear association during the COVID-19 period. This is further confirmed by the correlation matrix, discussed later, which compares all cryptocurrencies during and before the pandemic.

Figure 2. *Market Cap for Wide range of cryptocurrencies*



Source: *Own study.*

Figure 3 present the time series of each cryptocurrency, which show that the trends of some cryptocurrencies are similar. Figure 3 plots the daily closing price for a wide range of cryptocurrencies selected for this study during the three phases of the health crisis which is the prior crisis, the peak and the post crisis, from September 2018 to December 2020.

All cryptos have experienced a high volatility with the beginning of the crisis, proving that the COVID-19 was a pulse for the dynamic variation of the trend within that period. The capitalization of cryptocurrencies maintains a trend differently prior the COVID-19, however, within receiving the same shock they maintain the same trend reaction to the recurring measures of the pandemic such as the lockdown. There is a highest rise of capitalization for all the type of crypto for different markets.

Bitcoin prices fell by 19% between January and March 23, with a severe drop of 36% on March 13. This decline was followed by other hedge funds and assets, such as stocks: the S&P, S&P 500, FTSE 100, and Nikkei 225 fell by 33%, 9.51%, 10.87%, and 4.41%, respectively, between February and March. Crude oil also plummeted to -$37.63 per barrel in April, while gold declined by 3.35%. However, Bitcoin was one of the few hedge assets that was less affected by the crisis in terms of the percentage drop compared to other hedge funds.

Our data analysis is focused on the case of the crypto currencies without taking into account the original country launching, it is a cross section data analysis based on daily data for different wide range of cryptocurrencies (4 cryptocurrencies), Bitcoin, Litecoin, Ethereum and XRP, and different wide range of stock assets (4 stocks), SP, FTSE, DGJI, and MSCI, the sample period is for the whole year of the pandemic 2020.

We collect high frequency market data for the purpose of this analysis for cryptocurrencies from Coinmarket.com, and for stock assets from the Datastream dataset, and COVID-19 health crisis indicators such as the number of death and the number of cases is from WHO dataset and authors calculations. The selection of data for cryptocurrencies is based on different measures first the price, and second the level of capitalization. We are studying the dataset within three large categories of crypto, the first category is for the closing price under 10, the second is between 10 and 50, and the third is for more than 50 for all the categories.

Based on this classification, we selected four cryptocurrencies. Table 1 reports the descriptive statistics for all the data used in this study. The price returns for both cryptocurrencies and stocks are calculated as the difference between the closing and opening prices. Regarding the COVID-19 indicators, they are calculated based on the growth rate of each indicator during the Pre-COVID-19 and Post-COVID-19 periods.

The average and mean returns for the sampled cryptocurrencies are both negative during the Pre-COVID-19 period; however, they are positive for Bitcoin, Ethereum, and Litecoin in the Post-COVID-19 period, confirming that these cryptocurrencies were positively impacted during the pandemic.

In contrast, the mean and the average of the XRP during the pandemic is negative. In contrast for the stocks, are positive in both periods with amelioration during the pandemic time; this confirms that the return of stocks is ameliorated during the pandemic due to the high demand and the reorientation of the investment to the capital market instead of real sphere. The volatility of the stock market and the cryptocurrencies is accentuated during the pandemic comparing to the Pre-COVID-19 period. This confirms that the price return is affected randomly by the pandemic within the daily volatility of the demand and supply.

In both periods, most cryptocurrencies and stocks are skewed to the left, except for Litecoin and XRP. For both the Pre-COVID-19 and Post-COVID-19 sub-periods, there is evidence of autocorrelation and an ARCH effect in the price returns of all cryptocurrencies and stocks. The ADF test confirms that the return datasets for cryptocurrencies and stocks are stationary in both periods.

The kurtosis is significantly higher than 3 in the Post-COVID-19 period for both cryptocurrencies and stocks, whereas in the Pre-COVID-19 period, the kurtosis for all assets was not less than 3. The Jarque-Bera test statistics reject the hypothesis of normality in both periods.

Table 2 demonstrates the correlation matrix for both periods for cryptocurrencies and stocks as well as the COVID-19 indicators. There is a general impact for the pandemic within the studied dataset, proving a significant amelioration and positive correlation between cryptocurrencies and stocks from the Pre-COVID-19 period to the Post-COVID-19 period.

In contrast, there is a negative and significant correlation between the COVID-19 indicators and all cryptocurrencies and stocks. This correlation matrix identify the interconnectedness of the financial market within that frame and the financialization of the economy and the more openness for the financial market within that time rather that the real economy.

3. Research Methodology

3.1 Research Models

Within this paper we aim to study the safe haven properties of the cryptocurrencies within the COVID-19 crisis starting from 01/01/2020 through 31/12/2020, and studying the volatility of the daily return as well as the return performance at day t. We analyze the relationship between a broad range of cryptocurrencies, for around 20 cryptos, using the GARCH model.

VAR-DCC- GARCH Estimator:
The GARCH estimator is commonly used in the literature to study volatility (Bollerslev, 1986), following the introduction of the ARCH model by Engle (1982).

The empirical application of the ARCH model often avoids issues with negative variance parameter estimates by imposing a fixed lag structure (Engle, 1982). To address this, an extension of the ARCH model class was developed, providing longer memory and a more flexible lag structure.

Econometric Estimation Methodology:

There are many varieties of GARCH models for studying volatility that varies over time and across different assets, including the volatility of death rates and COVID-19 cases. We employ the VAR-DCC-GARCH framework to model the volatility of returns for a wide range of cryptocurrencies. The VAR framework allows us to determine how stock prices and cryptocurrencies evolve together during the two periods of Pre-COVID-19 and Post-COVID-19. The DCC-GARCH model then reveals how the dynamic volatility of these prices is interrelated. Before detailing the DCC-GARCH model, we present the VAR model for cryptocurrencies and stocks, considering the indicators of the COVID-19 pandemic.

VAR MODEL:

The measurement of return spillovers is based on vector autoregression (VAR) models, focusing on the impact of price intensity and duration between cryptocurrencies and the stock market before and during the COVID-19 outbreak, including the volatility of death rates and COVID-19 cases. The VAR model used in this study is described as follows:

$$Y_t = A_0 + \sum_{i=1}^{P} A_t Y_{t-i} + \varepsilon_t$$

$$Y_t = [\ln(C_t/C_{t-1}), \ln(S_t/S_{t-1}), \ln\,(COVID19_t/DCOVID19_{t-1})]'$$

$$\begin{aligned} Y_{Ct} = A_1 + \mu_{1,1}^{C} Y_{C(t-1)} + \mu_{1,2}^{C} Y_{c(t-2)} + \cdots \ldots.\ldots. + \mu_{1,p}^{C} Y_{S(t-T)} + \mu_{1,1}^{S} Y_{S(t-1)} + \mu_{1,2}^{S} Y_{S(t-2)} \\ + \cdots \ldots \ldots. + \mu_{1,k}^{S} Y_{S(t-T)} + \mu_{1,1}^{COVID19} Y_{COVID19(t-1)} + \mu_{1,2}^{COVID19} Y_{COVID19(t-2)} \\ + \cdots \ldots.\ldots. + \mu_{1,q}^{COVID19} Y_{COVID19(t-T)} + \varepsilon_C \end{aligned}$$

$$\begin{aligned} Y_{St} = A_2 + \mu_{2,1}^{S} Y_{S(t-1)} + \mu_{2,2}^{S} Y_{S(t-2)} + \cdots \ldots.\ldots. + \mu_{2,k}^{S} Y_{S(t-T)} + \mu_{2,1}^{C} Y_{C(t-1)} + \mu_{2,2}^{C} Y_{c(t-2)} \\ + \cdots \ldots \ldots. + \mu_{2,p}^{C} Y_{S(t-T)} + \mu_{2,1}^{COVID19} Y_{COVID19(t-1)} + \mu_{2,2}^{COVID19} Y_{COVID19(t-2)} \\ + \cdots \ldots \ldots + \mu_{2,q}^{COVID19} Y_{COVID19(t-T)} + \varepsilon_S \end{aligned}$$

$$\begin{aligned} Y_{COVID19\,t} = A_3 + \mu_{3,1}^{COVID19} Y_{COVID19(t-1)} + \mu_{3,2}^{COVID19} Y_{COVID19(t-2)} + \\ \cdots.\ldots. + \mu_{3,q}^{COVID19} Y_{COVID19(t-T)} + \mu_{3,1}^{S} Y_{S(t-1)} + \mu_{3,2}^{S} Y_{S(t-2)} + \cdots \ldots \ldots. + \mu_{3,k}^{S} Y_{S(t-T)} + \\ \mu_{3,1}^{C} Y_{C(t-1)} + \mu_{3,2}^{C} Y_{c(t-2)} + \cdots.\ldots.\ldots. + \mu_{3,p}^{C} Y_{S(t-T)} + \varepsilon_{COVID19} \end{aligned}$$

P is the number of cryptocurrencies, k is the number of stocks, q is the number of variables describing the health crisis COVID 19, T is the time-period of the study. C_t is the price of the cryptocurrencies in the period t, S_t is the price of the stocks in the period t, $COVID19_t$ is the COVID 19 indicator such as the number of cases during the pandemic period. A_t is 3×3 parameter matrix of lagged variables, $\varepsilon_t = [\varepsilon_{1,t}, \ \varepsilon_{2,t}, \varepsilon_{3,t} \ ]'$,

$$E(\varepsilon_t) = 0 \ , \ E(\varepsilon_t \, \varepsilon_t') = \sigma^2 \quad , E(\varepsilon_t \, \varepsilon_t') = 0 \ , \ t \neq s$$

As an efficient causal analysis method, impulse response function can be used to analyse the relationship between variables. Residual in VAR model reflects the impact from external system on system variables, the coefficient matrix in the moving average form, is also impulse response coefficient matrix as follow:

$$F_t = C_0 + B_0 \varepsilon_t' + B_1 \varepsilon_{t-1}' + \cdots + B_n \varepsilon_{t-n}' + \cdots$$

Where $F_t = [f_{1,t}, \ f_{2,t}, f_{3,t} \ ]'$ and $B_n = [b_{ij,n}]$ are 3×3 coefficient matrixes, $b_{ij,n}$ reflects the impact of $f_{i,t-n}$ on $f_{i,t}$ during the period of *t-n*. Therefore, the accumulative response of $f_{i,t}$ to $f_{j,t}$ is written as follow $\sum_{t=0}^{m} b_{ij,t}$

VAR-DCC-Model:

The DCC GARCH is introduced to solve this problem. The number *f* parameters to be estimated in the model increases linearly and not exponentially, which make this model deal the dimension and duration. The model decomposes the matrix H_t where H_t is triangular matrix representing the conditional variance –covariance matrix.

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix}$$

The model composes the matrix H_t as follows: $H_t = D_t R_t D_t$, $e_t | \Psi_{t-1} \sim N(0, H_t)$, e_t is the residual vector composed by the residues of all the markets, Ψ_{t-1} is the market information available at time t-1, H_t is the dynamic condition covariance matrix, D_t represent the diagonal matrix of time varying standard deviation of multivariate GARCH model with all three categories of volatiles variables returns, with $(\sigma_{i,t}^2)^{1/2}$ on *ith* diagonal.

$$D_t = \begin{bmatrix} \sqrt{\sigma_{C,t}^2} & 0 & 0 \\ 0 & \sqrt{\sigma_{S,t}^2} & 0 \\ 0 & 0 & \sqrt{\sigma_{COVID19,t}^2} \end{bmatrix}$$

$$R_t = \begin{bmatrix} \varepsilon_{CC,t} & \varepsilon_{CS,t} & \varepsilon_{C\ COVID19,t} \\ \varepsilon_{SC,t} & \varepsilon_{SS,t} & \varepsilon_{S\ COVID\ 19} \\ \varepsilon_{COVID\ 19\ C,t} & \varepsilon_{COVID\ 19\ S,t} & \varepsilon_{COVID19\ COVID19,t} \end{bmatrix} = \begin{bmatrix} 1 & \varepsilon_{CS,t} & \varepsilon_{C\ COVID19,t} \\ \varepsilon_{SC,t} & 1 & \varepsilon_{S\ COVID\ 19} \\ \varepsilon_{COVID\ 19\ C,t} & \varepsilon_{COVID\ 19\ S,t} & 1 \end{bmatrix}$$

R has to definite positive and all the parameters should be equal to or less than one. In order to fulfil this condition, R_t has been modelled as follow:

$$R_t = diag(Q_{C\ S\ COVID\ 19,t})^* Q_{C\ S\ COVID\ 19,t} diag(Q_{C\ S\ COVID\ 19,t})^*$$

$Q_{C\ S\ COVID\ 19,t} = (q_{pkqt})$ is a symmetric positive define matrix. $Q_{C\ S\ COVID\ 19,t}$ is assumed to vary according to a GARCH process:

$$Q_{C\ S\ COVID\ 19,t} = (1 - \theta_1 - \theta_2)Q^* + \theta_1(\varepsilon_{c,t-1}\varepsilon_{S,t-1}\varepsilon_{COVID19,t-1}) + \theta_2(Q_{C\ S\ COVID\ 19,t-1}) + \theta_3(Q_{C\ S\ COVID\ 19,t-1})$$

θ_1, θ_2 and θ_3 are scalar parameters to capture the effects of the previous shocks and previous dynamic conditional correlation on current dynamic conditional correlation, are nonnegative and satisfy $\theta_1 + \theta_2 < 1$. $Q_{C\ S\ COVID\ 19,t}$ is the unconditional variance between series k, p and q and follows a GARCH process, Q^* is the unconditional covariance between the series estimated in step 1. The parameters θ_1 and θ_2 are estimated by maximizing the log-likelihood function. The log likelihood function is expressed as follow:

$$\boldsymbol{L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi)) + 2\log(|D_t|) + \log(|R_t|) + \varepsilon_t^{\prime} R_t^{-1}\varepsilon_t}$$

The modified model of (Cappiello et al., 2006) for incorporating the asymmetrical effect Allow the studied model VAR-DCC-GARCH to be written as follow :

$$Y_t = A_0 + \sum_{i=1}^{P} A_t Y_{t-i} + \varepsilon_t$$

$$H_t = D_t R_t D_t$$

$$R_t = diag(Q_{C\ S\ COVID\ 19,t})^* Q_{C\ S\ COVID\ 19,t} diag(Q_{C\ S\ COVID\ 19,t})^*$$

$$Q_{C\ S\ COVID\ 19,t} = (1 - \theta_1 - \theta_2)Q^* + \theta_1(\varepsilon_{c,t-1}\varepsilon_{S,t-1}\varepsilon_{COVID19,t-1}) + \theta_2(Q_{C\ S\ COVID\ 19,t-1}) + \theta_3(Q_{C\ S\ COVID\ 19,t-1})$$

3.2 Relationship between Variables: Wavelet Analysis

Within the second frame of this study, we use the Wavelet approach to capture the co-movement of the two time series of cryptocurrencies and COVID-19 indicators in time and frequencies which allow for variety of scaled localizations (Rua and Nunes, 2009).

We employ the Wavelet Coherence and the Wavelet Power Spectrum to measure the co-movement of the COVID-19 indicators and the pulse reaction of the cryptocurrencies. The Wavelet coherence shed the light on co-movement between cryptocurrencies and stocks as well as COVID-19 indicators, in comparison to the conventional casualty and correlation analysis.

The main frame for Wavelet coherence using the cross Wavelet transform and cross Wavelet is developed by Torrence and Compo (1998). The approach of Torrence and Campo (1998) is described as follow. The cross Wavelet transform of two time-series $x(t)$ and $y(t)$ using their own cross wavelet transform with continuous wavelet transform $(CWT) W_n^x(u,s)$ and $W_n^y(u,s)$ as follow:

$$W_n^{xy}(u,s) = (CWT) W_n^x(u,s) W_n^{y*}(u,s)$$

u is marking the location and s is the scale. The $*$ denotes the complex conjugate. The cross wavelet transform capture the local covariance between the two time series $x(t)$ and $y(t)$ at each scale. The wavelet coherence detect co-movement between time-series in the time-frequency domain, Torrence and Webster (1999) can be defined as follow:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W^{xy}(u,s)\right)\right|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)}$$

S is a smoothing operator over time as well as scale and $0 \leq R^2(u,s) \leq 1$ (Rua and Nunes, 2009). The Wavelet squared coherence, $R^2(u,s)$, is between 0 and 1. The high value show a high co-movement between the two-time series. Within the standard correlation of two time series, the wavelet squared coherence is restricted to positive values. Within that explaining, the wavelet squared coherence cannot identify between positive or negative co-movement, as well as between positive and negative correlation. The phase difference wavelet approach (Terrence and Compo, 1998) captures the two possible co-movement. Thus, this approach give causal relationships between the tow time series. The wavelet coherence phase difference of time series is defined as:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{S\left(s^{-1}W^{xy}(u,s)\right)\}}{\Re\{S\left(s^{-1}W^{xy}(u,s)\right)\}}\right)$$

$\Im$ and $\Re$ are the imaginary part and the real part of the smoothed cross wavelet transform. Phase is indicated by black arrows on the wavelet coherence plots. A zero phase – difference means that the time series move together. The arrows point to the left (right) when time series are in phase (out of phase) or are positively (negatively) correlated. An upward pointing arrow means the first time series is leading the second by $\pi/2$, where as an arrow pointing down indicates that the second time series leads the first by $\pi/2$. A combination of position is general common.

4. Results

4.1 VAR-DCC-GARCH Analysis

The estimated results of the VAR-DCC–GARCH model is displayed in Table 3 based on the specification of the model in the previous description. According to our sample studied, Bitcoin is the safe haven investment for the MSCI, FTSE, SP and DJGI investors. Within that, we will analyze each crypto comparing to the stock market and the COVID-19 indicators. Studying the correlation between the Bitcoin and the world assets MSCI, FTSE, SP and DJGI, Bitcoin is a safe haven investment for SP World Hedged comparing to the other stocks.

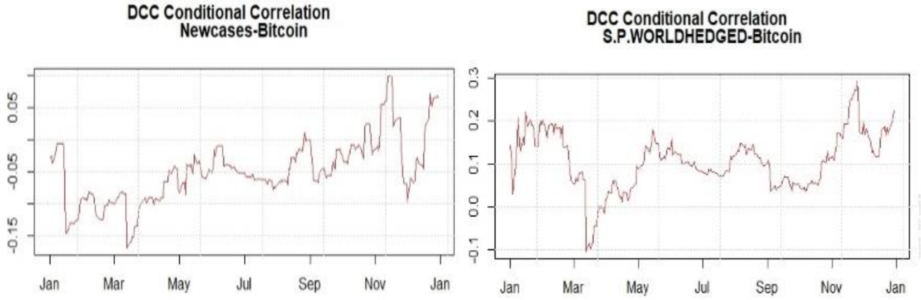
Figure 5 plots the dynamic conditional correlations obtained from the VAR-DCC-GARCH model. We observe a time varying correlation over the sample period for SP, in the Appendix 3 shows the rest of the DCC plots for the whole investment stocks. We evaluate a peak down in March within the excessive contagion spread start of COVID-19 following by a fluctuation for the rise between April and December.

The increase level of the DCC during the time January to March is due to the fiscal policies conducted by the international organizations and government supporting the stimulus packages as well as the interest free debt and many other regulatory measures helping to beneficiate from the diversification of the portfolio for investors, however the correlation is negative, and this can be explained as a low return during that time for the Bitcoin and the rest of the stocks.

An increase of the DCC for the rest of the period from April to December with a positive value in the majority of the fluctuations approve that the economic was updated to the new measures and stimulus packages given as targeted policies reorientation of the economic system within a new frame for the future perspective for investment. The Main trend for the DCC between Bitcoin and SP, and Bitcoin and COVID-19 new cases is opposite in the start of the pandemic and continuing similarly from April to the end of the period.

The decrease level of the Bitcoin and the COVID-19 cases and even a negative correlation between the New COVID-19 cases and Bitcoin, approve and that start of the pandemic is totally disconnected from economic sphere for their evolution, and spread and the rise of the cases was for the non-preparedness in advance for that extra-economic shock. From April to December we view a significant positive correlation between the COVID and the Bitcoin with a rise trend. This reflect that this period was with high risk aversion, and the Bitcoin was considered as a safe haven investment within a health crisis framework.

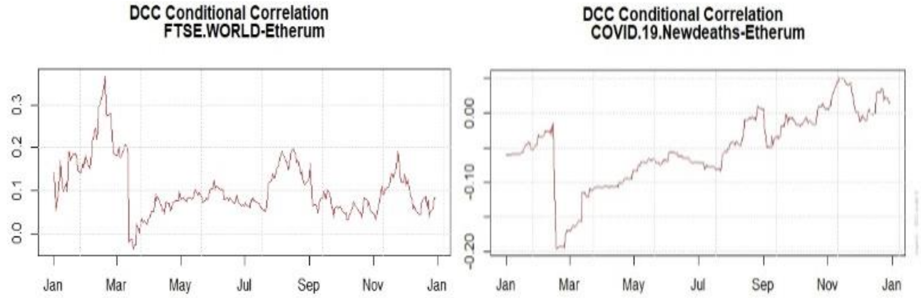
Figure 5. *Dynamic Conditional Correlation between Bitcoin and SP World* Hedged, and Bitcoin and COVID19 New Cases



Source: *Own study.*

Studying the case of the Ethereum comparing to the other stock assets, Figure 6, we find that Ethereum is safe investment for the FTSE comparing to the other investors. Ethereum is the second largest cryptocurrencies after the Bitcoin, comparing the trajectory of the DCC for the Ethereum and Bitcoin in terms of investment and COVID 19, we saw a similar trend in most investment cases, as well as related to COVID 19 indicators. The similar trend is explaining by the capitalization of the Ethereum which is quite similar as bitcoin and the size of demand for that crypto as it is the second largest cryptocurrencies after Bitcoin.

Figure 6. *Dynamic Conditional Correlation between Ethereum and FTSE World, and Bitcoin and COVID19 New Deaths*

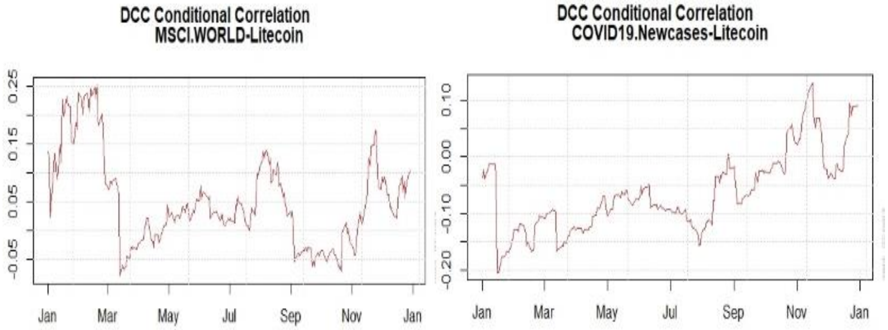


Source: *Own study.*

The Litecoin is a middle size cryptocurrencies comparing to the Ethereum, the trend of the DCC differt basic on their size and their capitalization. According to Figure 7, the trajectory of the DCC Litecoin is the opposite comparing to the Bitcoin and the Etherum. The Litecoin is a safe haven investment for MSCI investors comparing to the other investors. There is a signifcant negative correlation between the Litecoin and the majority of stocks investment. The first period of the pandemic is followed by an increase for the the DCC until March and after it is followed by an important decrease which is the phase of the accentuation of the health crisis followed by lockdown and many other restriction measures within investment such the depreciation of the currencies.

The correlation between the Litecoin and MSCI is in the rise after March followed by high volatility until december 2020. This volatility is explained by the openness of the investors to the new tools of paymenet as safe haven within an environment with high risk compatible for the risk takers and the risk averse investors. The correlation between the COVID19 new cases and the Litecoin is positive and with an increase trend. From January the trend is characterised by a decrease followed by a fluctuations for a rise of the correlation between the number of cases and the Litecoin.

Figure 7. *Dynamic Conditional Correlation between Litecoin and MSCI World, and Bitcoin and COVID19 New Cases*



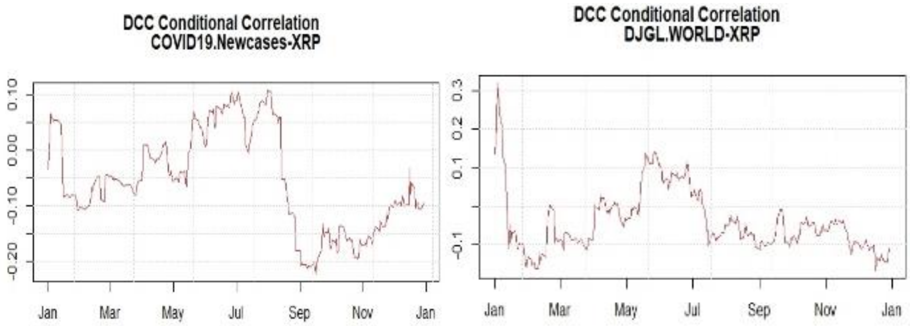
Source: *Own study.*

The XRP cryptocurrencies is a small size crypto comparing to the other studied cryptocurrencies. The XRP is lowest safe haven investment for DJGI investors. However, within the trend of the DCC it is quite clear that the COVID-19 pandemic affects negatively the correlation between the XRP and the DJGI investment.

In Figure 8, given that trajectory is explained that the diversification of the portfolio is followed by the risk management and the attitude of the investor towards the risk within the frame of the pandemic.

The investors are highly risk averse towards using the XRP the decrease of return which is followed by big volatility for decrease.

Figure 8. *Dynamic Conditional Correlation between XRP and FTSE World, and Bitcoin and COVID19 New Cases*



Source: *Own study.*

Basic on the VAR DCC GARCH results, the studied commodities such as Bitcoin, Ethereum, Litecoin and XRP are safe haven investment for the stock market within the analyzed period and in the framework of COVID-19 health crisis. Within the pandemic, the economic system was targeted to be more financialized rather than relying on the real investment, by promoting the use of the digital money in the stock market and enhancing the capitalization of the economy within a new frame base on the digitalization of the payment system within an economy facing a peak of uncertainty and overcoming the health crisis within many economic measures such as the stimulus packages, the fiscal policies reconstruction, the labour structure, and the production system.

4.2 Wavelet Transformation

The wavelet power spectrum is the absolute value of the square of the wavelet transformation. Which measure the correlation at each scale or frequency and at each time. The horizontal axis refer to index and the vertical axis refer to frequency component from scale 1(1 day) to scale 256. It is similar to the estimation from Monte Carlo simulations using phase randomized surrogate series, the white contour indicate 5% significance. The cone of influence, shown by a solid curved line indicate the one affected by edge effects.

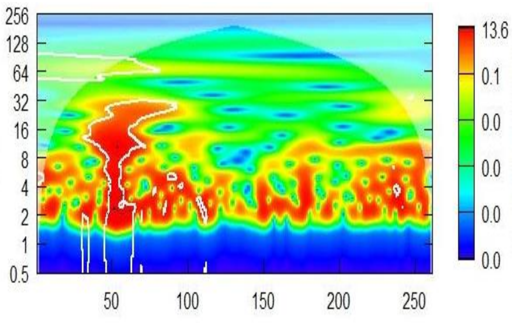
The range of power is from red (high power) to blue (low power). As shown in Appendix 2-2, all stocks such as SP, DGJL, MSCI and FTSE are showing a high power during all the period of COVID-19 in the short and medium run during the first half of 2020. The selected stocks assets are among the top highest yield in the stocks market, which allow us to give a general assessment about the capital market during the COVID-19. Basic on the Wavelet transformation, it imply that there is a high variation during the period of COVID-19. For the next half of 2020, the time and frequency of variation for stocks are very low.

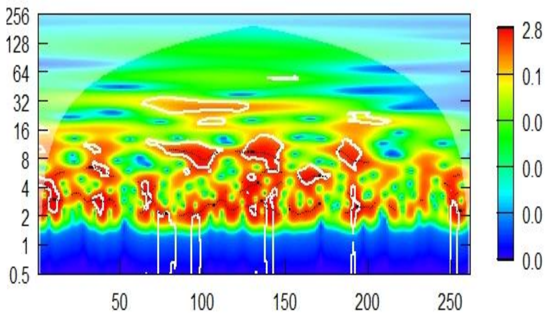
In general, the selected stocks show similar reaction to the COVID-19 shock. Figure 9 show the Wavelet transformation for all the sampled cryptocurrencies such as Bitcoin, Ethereum, Litecoin, and XRP. Bitcoin and Ethereum show the most important power during whole period with a pronounced effect during the third month of the year. Litecoin show less pronounced effect in the third month of the period with low scale. However, the XRP is the lowest power with similar low scale during the whole period. Basic on the WT, we can conclude that the size-capitalization of the cryptocurrencies is a catalyst for the variability towards the pandemic crisis.

The interpretation of the Figure 10 for wavelet transformation for COVID-19 indicators show a different trend of variability in terms of frequency and scale comparing to the stocks and the cryptocurrencies. The COVID-19 New cases show a variability with a scale very high in the first three months followed by a stable low scale of frequency for the rest of the period. The new cases show less variability at the beginning of the pandemic comparing to the variability of the new deaths as it is explained by a virus which is not yet discovered the treatment a diverse prescription is proposed by the international organizations.

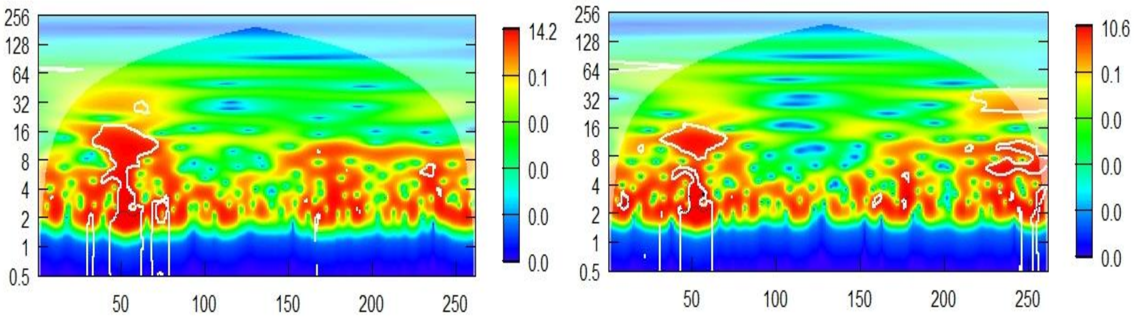
The stable trend for both indicators for the next nine months is explained by the measures giving by the international organizations and local authorities in the pandemic such as lockdown, face mask, etc., as well as the fiscal policies proposed by the international financial organizations. Within the Wavelet Transformation approch we can understand that all commodities are safe haven investment for the stock market within the analyzed value and return in the studied period of the COVID19 frame crisis.

Figure 9. *Wavelet Transformation for the selected cryptocurrencies*
Wavelet Transformation for Bitcoin (Left), Wavelet Transformation for XRP (Left)



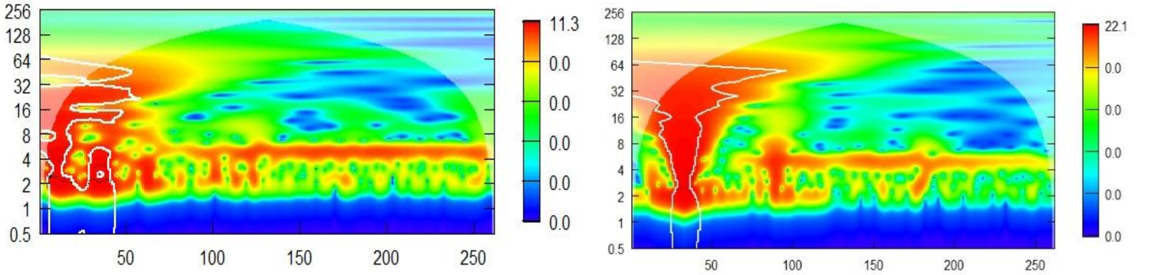


Wavelet Transformation Ethereum (Left), Wavelet Transformation Litecoin (Right)



Source: *Own study.*

Figure 10. *The Wavelet transformation for COVID-19 proxies during the pandemic: COVID-19 New cases and COVID-19 New Death*



Source: *Own study.*

4.3 Wavelet Coherency

The following part presents the WC graphs for the studied cryptocurrencies stock markets as well as the COVID-19 indicators. The maps are classified per crypto and dependencies with the other stocks and COVID-19 indicators. The Bivariate wavelet coherence analysis give insights on how the cryptocurrencies and the stocks have evolved over time and across frequencies during the COVID-19 period. The Wavelet coherence detect short and long run time series co-movements and assess their changing behaviour over time.

On each part of cryptocurrencies there is two maps one for stocks and the other for COVID indicator followed by the rest of the maps at the Appendix. The figures represent the time scales for 1 to 256 days. For the analysis of the Wavelet coherence we rely on the colors as well as the arrows on the significance of 5% range. The colour pallet represents the strength of wavelet coherence, the hotter the colour the higher the coherence and thus the dependence between series.

The coherency ranges from red (high coherency) to blue (low coherency) to measure the degree of co-movement in scale frequency. The red colored area at the bottom and the top of the wavelet coherence plot exhibits powerful coherent co-movement at low and high frequencies. The colored blue at the bottom and the top of the wavelet coherence plot exhibits weak coherent co-movement at low and high frequencies.

As a general overview for the Wavelet coherency of all cryptocurrencies with stocks as well as COVID-19 indicators is significant high degree co-movement for the first three months of the period across 64 to 256 days frequency band. As well as we find a higher coherence for the rest of the period with significance at more than 128 days frequency band but with different range of time starting from six months until the rest of the period.

The directional arrows give insights the lead-lag relationship as well as the sign of the dependence. If the arrow points downward, the second lead the other. And respectively if the arrow points upwards, the first series leads the other. If the arrow points to the right the two series are positively correlated. And if the arrow points to the left the two series are negatively correlated.

The arrows → indicate ← the phase difference between the Bitcoin and the growth rate of the COVID-19 new death. For example, and indicate that both Bitcoin and the growth rate of COVID-19 new death rate are in phase and out of phase, respectively.

↗ and ↙ indicate Bitcoin returns are leading those of the growth rate of the COVID-19 new death rate, while ↘ and ↖ indicate Bitcoin returns are lagging those the growth rate of the COVID-19 new death rate. The result is stable across the potential safe haven investment between cryptocurrencies and stocks with a little diversion towards the perception of COVID19 health crisis in terms of new death and new cases.

We apply Wavelet coherence between Bitcoin and COVID-19 indicator as well as the stocks, using row time series at each application for the studying the variance and the co-movement of the Bitcoin with each selected variable (Figure 11 and Appendix 2-1). It captures the co-movement between the commodities such as the Bitcoin and the stock market and the COVID-19 indicators.

The maximum scale for Bitcoin is 128 days. The majority of the arrows are ↘ for all stock markets which means that the Bitcoin are lagging those commodities as well as the COVID-19 pandemic. We observe a high degree of co-movement between Bitcoin and the stocks at the scale of 128 days frequencies for the first three months for the case of all stocks except the S&P who was keeping a high significant co-movement in the long run.

The low frequencies and high power of coherence in the co-movement signals implies higher return from the diversification of the portfolio in short horizon. A powerful co-movement at high frequencies suggests higher diversification levels in the long-run horizon. We find a low frequency and insignificant co-movement in the second half of the period for the case of stocks as well as COVID19 indicators. The causality and phase difference of Bitcoin with stocks is concluded through the arrow point → at the scale ranging from 64 to 256 days which means phase in relationship, indicating the positive correlation between the Bitcoin and the stock market.

We observe the arrow ↗ the first half period, ranging in scale from 8 to 64 days which means that the Bitcoin lead the stocks market in the short run during the COVID -19 crisis and after that it becomes a positive relationship of causality. As we observe through the figure that the increasing rate of death was associated with a decrease in the value of Bitcoin in short term, within the first three months of the period, with high scale of 64 days reaching after that term a low coherency for the next nine months.

The phase difference and causality for the COVID-19 death and the COVID-19 new cases and Bitcoin. We see, the main significant period of coherence is from January to March, the first three months, with scale ranging between 0.5 a d 75 days, that arrows are in majority ↙ and ↘ which means that the BITCOIN and the COVID-19 indicators are an out-phase relationship and the COVID 19 indicators are leading the value of the Bitcoin.

The Bitcoin is the biggest cryptocurrency in terms of capitalization, and it has unprecedented interaction towards the COVID-19 shock in short run followed by a recuperation in terms of value and size in the middle and long run.

The most general color in Wavelet coherency for Bitcoin case with stocks as well as COVID-19 indicators is red with different scale range in the short and long term, which means that the Bitcoin is correlated with stocks and the COVID-19 indicators.

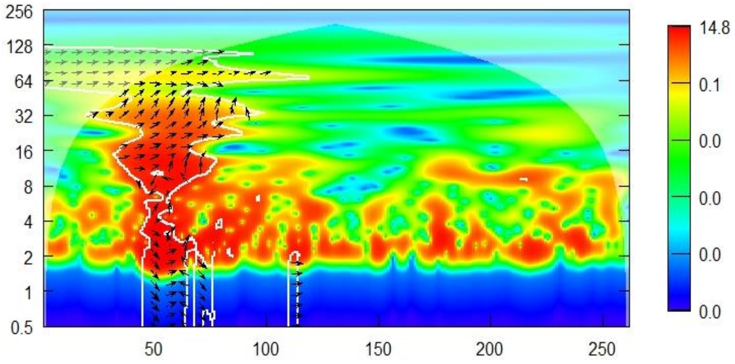
Economically the Bitcoin were influenced positively in terms of value within the shock of COVID-19 in the short term, and the shock were assimilated within the long horizon with less influence on the stability of the value of the Bitcoin.

Most of the significant parts are in the cone of influence which means that there is a significant connection between the Bitcoin and the stocks as well as the Bitcoin and the COVID- 19 indicators.

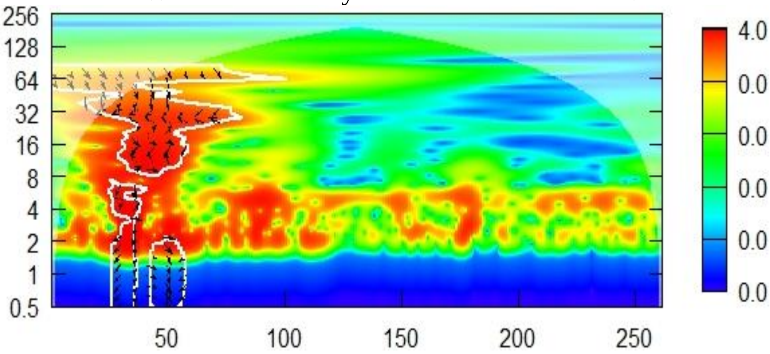
Therefore, Bitcoin is considered as strong safe haven asset from the perspective of Wavelet Coherency for the whole period and all analyzed stocks within the COVID-19 frame crisis.

Figure 11. *Wavelet Coherency for Bitcoin*

Panel 11-1 Wavelet Coherency between Bitcoin and DJGL world



Panel 11-2 Wavelet Coherency between Bitcoin and COVID-19 new death



Source: *Own study.*

Ethereum is the second largest cryptocurrency after the Bitcoin in terms of capitalization and size. Figure 12 is based on Wavelet coherency and phase difference for stocks and COVID-19 indicators, Ethereum show similar coherency, causality and correlation in the short horizon as well as the middle and the long run as Bitcoin.

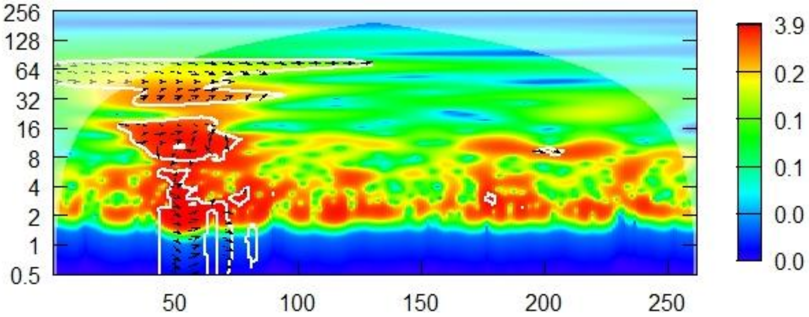
The range of scale of coherency in the short horizon between the Ethereum and the stock market is at 75 days with positive correlation, and in the long term with low coherence at the scale of 8 days.

The phase difference between the Ethereum and the stock market is in phase relationship and the stock market is leading the Ethereum during the COVID-19 crisis.

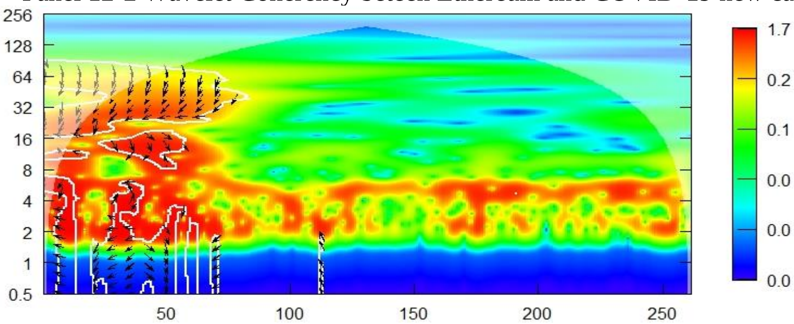
Ethereum is considered as strong safe haven asset based on the approach of Wavelet coherency for all analyzed stocks within the COVID-19 health crisis.

Figure 12. *Wavelet Coherency for Ethereum*

Panel 12-1 Wavelet Coherency Between Ethereum and MSCI world



Panel 12-2 Wavelet Coherency beteen Ethereum and COVID-19 new cases



Source: *Own study.*

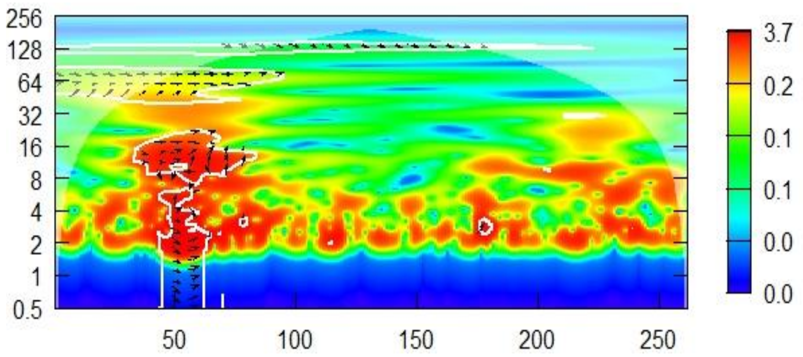
The Litecoin is a middle size of capitalization cryptocurrency comparing to the Bitcoin. The result of the Wavelet coherence approach is diverse for the Litecoin comparing to the Bitcoin. In Figure 13 there is high coherency between the Litecoin and the stock market which is synchronized only within the COVID-19 shock contagion in the third month of the studied period. The first two months was considered with weak coherence between Litecoin and the stock market, the rest of the period is considered with low coherency.

A positive correlation is considered between the Litecoin and the stocks at the scale frequencies ranging between 2 and 16 days. The majority of the significant region is in the cone of influence. The phase of difference between Litecoin and the stocks is categorized out of phase and the Litecoin is lagging the stocks at a range of frequencies of 128 days.

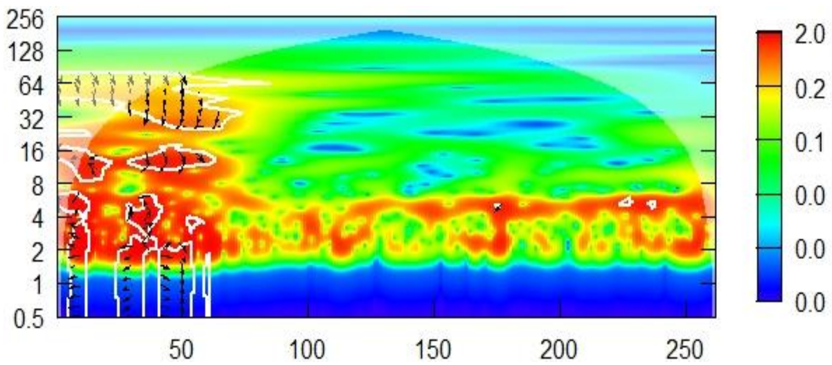
The COVID-19 indicators both the new death and the new cases have a high coherence with the value of the Litecoin at the first of three months, followed by a very low coherency for the rest of the period with rage scale of 4 days. Moreover, the COVID-19 crisis does not have any impact on the value of Litecoin in the long run. In general, and based on the approach of Wavelet coherence, Litecoin is a weak safe haven asset for all the analyzed stocks during the COVID-19 pandemic.

Figure 13. *Wavelet Coherency of Litecoin*

Panel 13-1 Wavelet Coherency between Litecoin and FTSE world



Panel 13-2 Wavelet Coherency between Litecoin and COVID-19 new cases



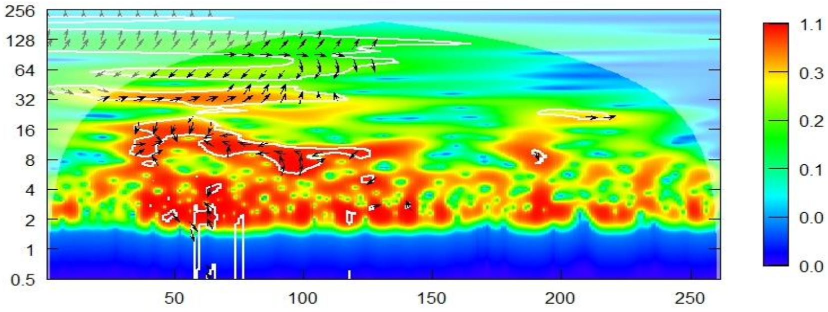
Source: *Own study.*

XRP is a small size cryptocurrency in terms of capitalization and in terms of integration in the financial market. In Figure 14, within the application of the Wavelet coherency approach for XRP with the studied stock market within the COVID-19 framework, we find that XRP is the lowest potential of safe haven assets comparing to the Bitcoin, Ethereum, and Litecoin. XRP show high coherence with the stock market just within the peak phase of contagion effect of the pandemic, in the third month of the studied period (Figure 14).

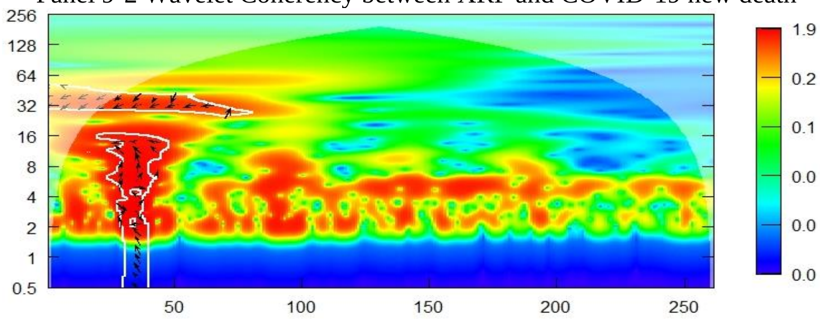
The rest of the period was categorized as low coherency between the XRP and the stock market. The significant region in the cone of influence is very small. The phase of difference and the causality of the XRP with stocks is concluded through the arrow point ↖ and ↘ at the scale frequencies ranging between 32 and 256 days, which means that the XRP value is lagging by the stocks returns. There is a weak coherency between the XRP and the COVID-19 indicators in short horizon and the long run with range scale of frequencies between 2 and 8 days.

Figure 14. *Wavelet Coherency of the XRP*

Panel 9-1 Wavelet Coherency between XRP and S&P world hedged



Panel 9-2 Wavelet Coherency between XRP and COVID-19 new death



Source: *Own study.*

5. Discussion and Conclusion

The COVID-19 pandemic provides a framework for the economic system to overcome crises through measures related to various fields, such as labor, fiscal policy, investment, capital markets, and international trade. The reframing of the investment system, coupled with rising uncertainty within the economy, underscores the need to search for safe haven assets as a crucial and timely issue during this health crisis.

The role of traditional commodities as safe haven assets must be reevaluated. Cryptocurrencies can serve as sources of portfolio diversification and hedging against cycles caused by economic and extraneous shocks. Using daily data from January 2020 to December 2020, this article investigates the safe haven properties of four cryptocurrencies—Bitcoin, Ethereum, Litecoin, and XRP—and four stock indices: FTSE, MSCI, DJGL, and S&P.

To measure variability and co-movement and examine the safe haven properties of cryptocurrencies compared to stocks during the COVID-19 period, we apply both the DCC-GARCH and Wavelet methods to extract data regarding the time-varying and time-frequency structures of correlation and co-movement between cryptocurrencies and the stock market. In the first part, we use Vector Autoregressive Dynamic Conditional Correlations to detect the dynamic variability of commodities in the capital market amid the COVID-19 circumstances.

This approach can illustrate changes in the capital market by incorporating safe haven assets into the variance portfolio. Our empirical results suggest that Bitcoin and Ethereum are safe haven investments in both the short and long run for all the studied stocks. However, Litecoin was only a safe haven investment for the MSCI, while XRP did not qualify as a safe haven investment for any of the selected stocks.

In the second part, we employ Wavelet Transformation and Wavelet Coherence models to measure the time series variance for each time point and scale. These findings support other empirical studies regarding the diversification of hedge funds through the complementarity between the stock market and cryptocurrencies as safe haven investments.

Based on the Wavelet Transform, the market capitalization of cryptocurrencies acts as a catalyst for variability during the COVID-19 health crisis. Bitcoin and Ethereum exhibit significant influence during the studied period, particularly pronounced in the third month. Litecoin shows a less pronounced effect in the third period with a low scale, while XRP demonstrates the weakest influence with a similar low scale throughout the entire period.

The selected stocks exhibit high power throughout the COVID-19 period, showing a similar response to the initial COVID-19 shock in the short and medium run during the first half of 2020. New case counts demonstrate less variability at the beginning of the health crisis compared to the variability of new deaths, with a stable trend for both indicators for the remainder of the period, reflecting the international measures taken in response to the COVID-19 health crisis.

Based on Wavelet Coherence, Bitcoin and Ethereum are strong safe haven investment assets for all the selected stocks, while Litecoin has weak potential as a safe haven investment, and XRP has the lowest potential as a safe haven for all the studied stocks during the COVID-19 health crisis.

Our findings on the emergence of cryptocurrencies as safe haven investments during this health crisis—impacting various economic and extraneous dimensions—provide new insights for investors seeking certainty in their investments and refuge for their portfolios. Specifically, Bitcoin and Ethereum can act as strong hedges and safe haven investments in the capital market.

Moreover, our analysis of the safe haven investment properties of cryptocurrencies and the capital market may offer significant enhancements for regulatory agencies and policymakers, guiding the introduction of new cryptocurrencies into the economy and the development of targeted policies for the monetary and financial system.

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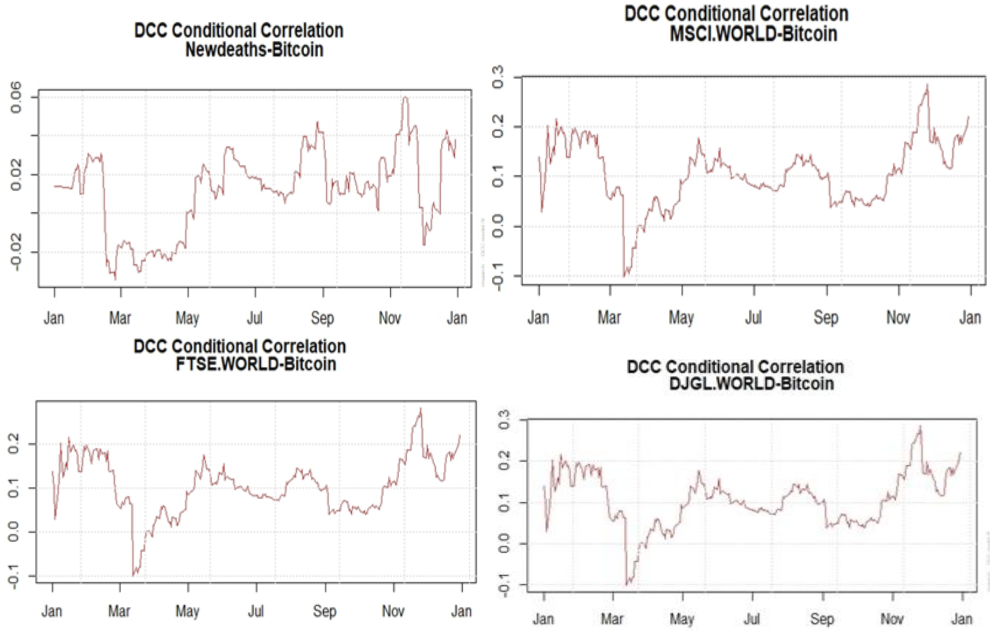
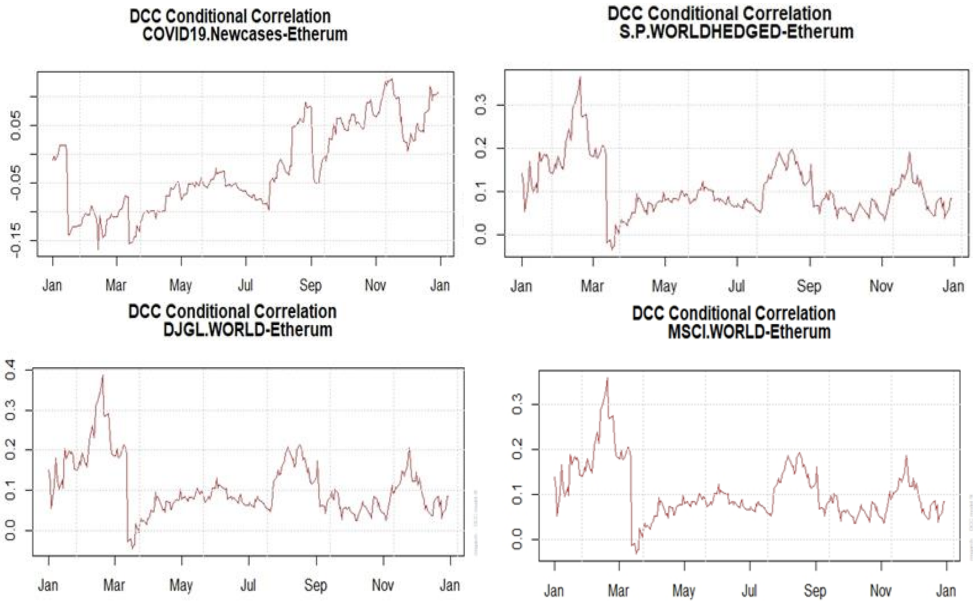
Appendix 1. *VAR-DCC-GARCH Results*

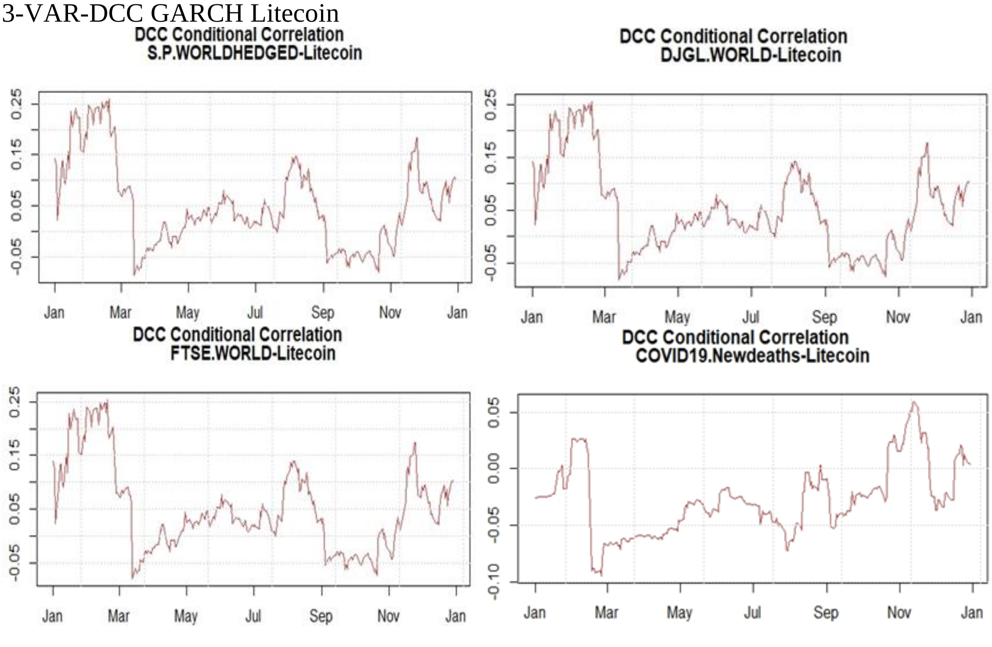
1-VAR-DCC GARCH Bitcoin



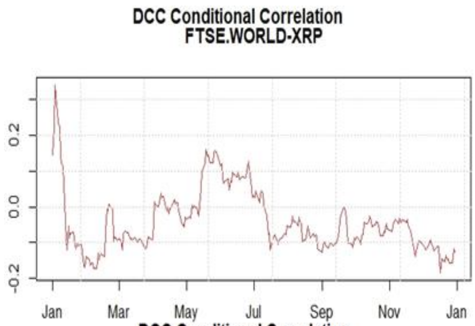
2-VAR-DCC GARCH Ethereum

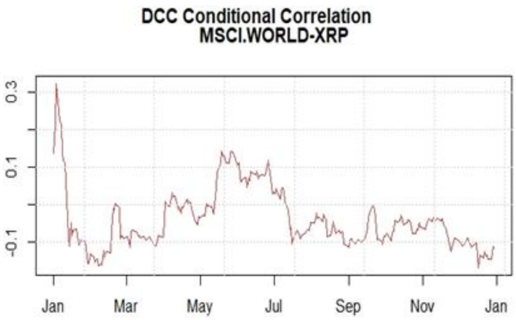


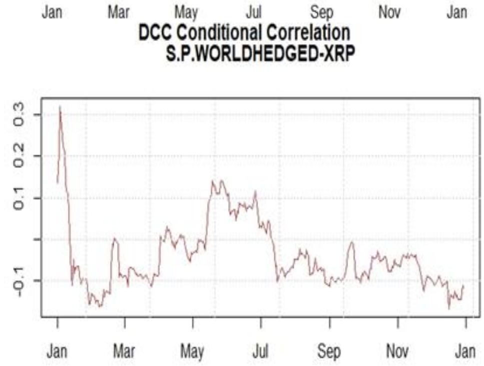
3-VAR-DCC GARCH Litecoin

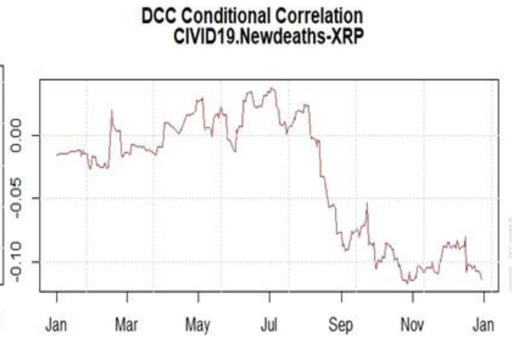


4-VAR-DCC GARCH XRP





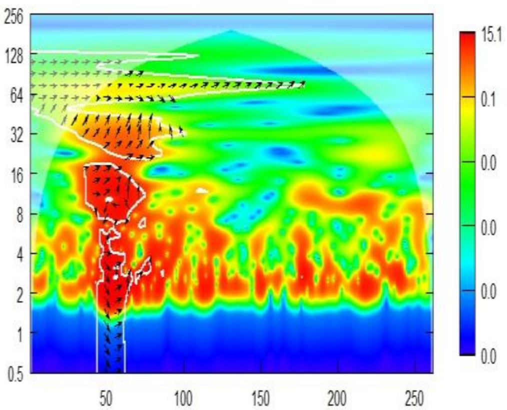




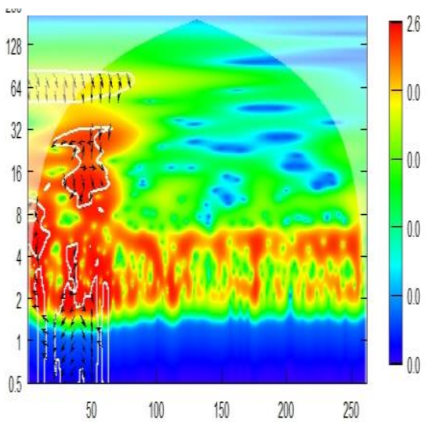
Appendix 2. *Wavelet Coherency Results*

1-Bitcoin

Wavelet Coherency between Bitcoin and FTE World

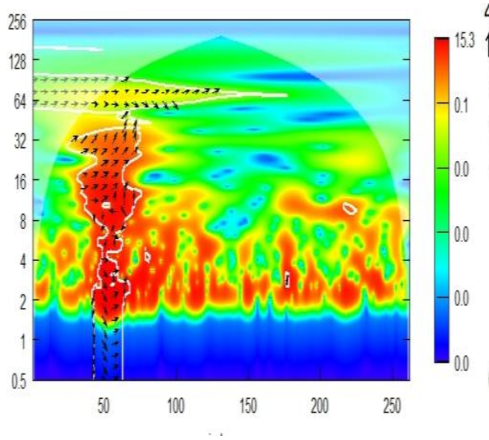


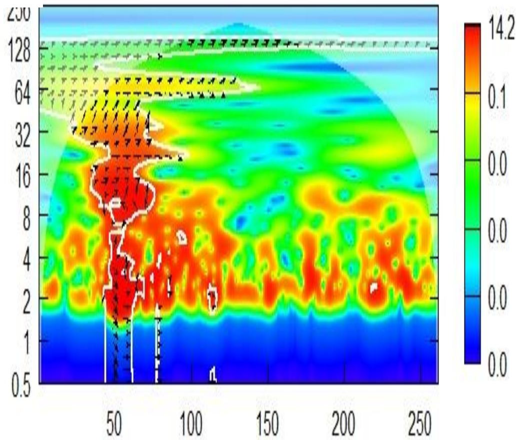
Wavelet Coherency between Bitcoin and COVID-19 new cases



Wavelet Coherency between Bitcoin and S&P World hedged

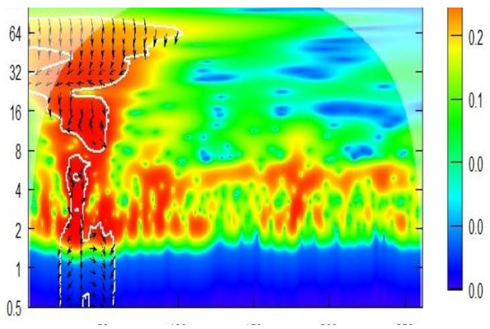
Wavelet Coherency between Bitcoin and MSCI



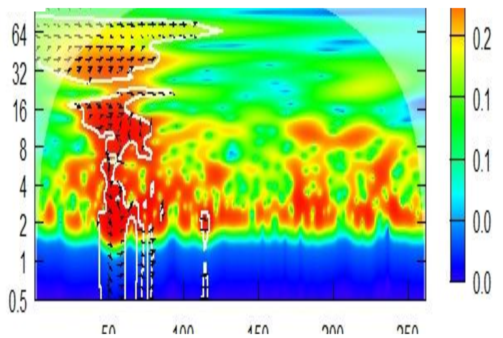


2-Etherum

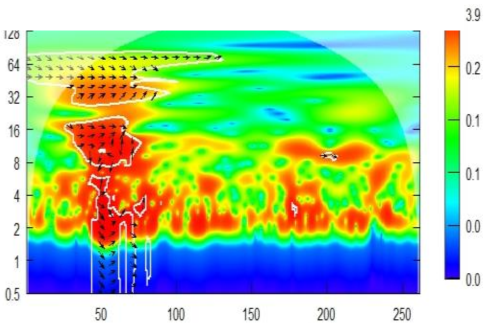
Wavelet Coherency between Etherum and COVID-19 new deaths



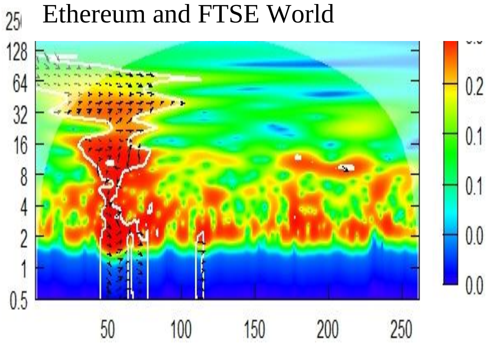
Wavelet Coherency between Etherum and S&P world hedged



Wavelet Coherency between Ethereum and DJGL World



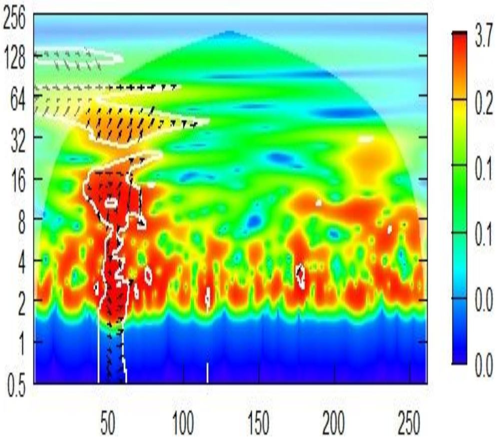
Wavelet Coherency between Ethereum and FTSE World



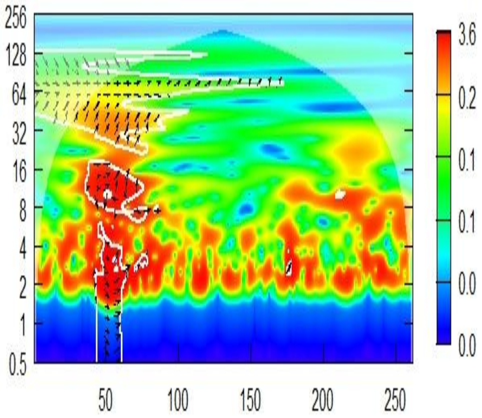
3-Litecoin

Wavelet Coherency between Litecoin and MSCI World

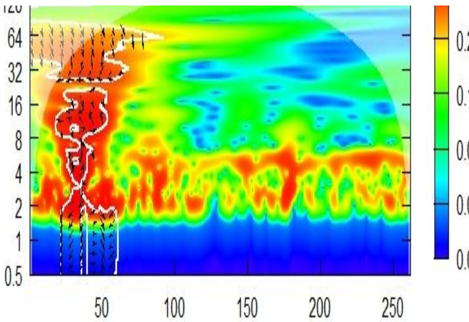
Wavelet Coherency between Litecoin and DJGL World

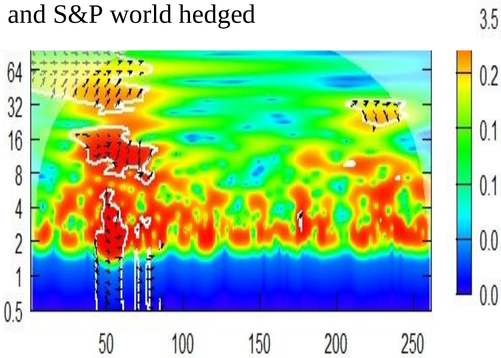


Wavelet Coherency between Litecoin and COVID19 new deaths



Wavelet Coherency between Litecoin and S&P world hedged

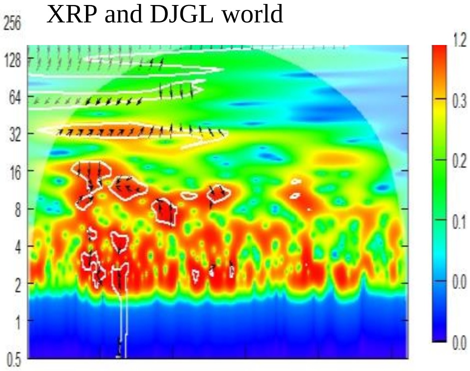




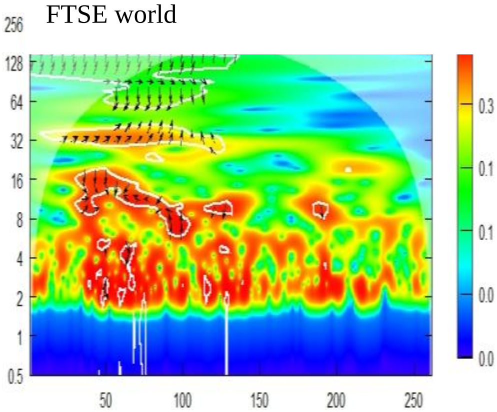
4-XRP

Wavelet Coherency between XRP and DJGL world

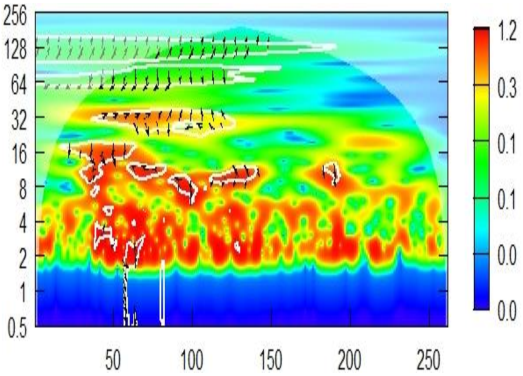
Wavelet Coherency between XRP and FTSE world

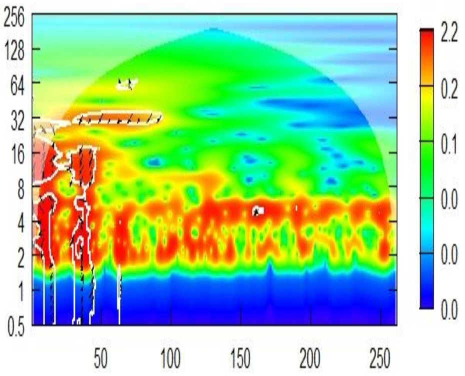


Wavelet Coherency between XRP and MSCI World



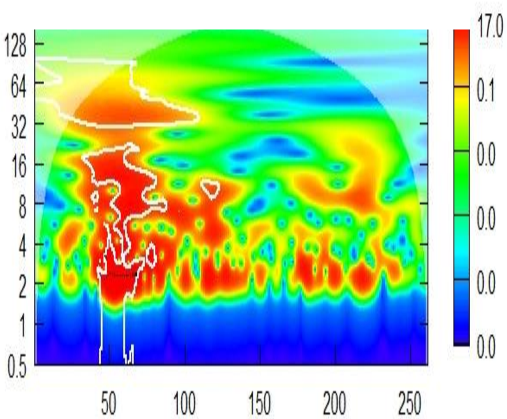
Wavelet Coherency between XRP and COVID-19 new cases



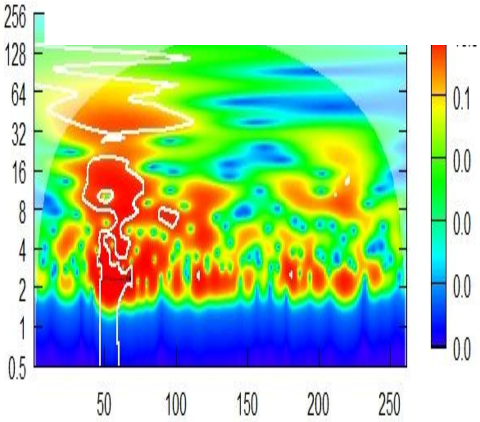


Appendix 3. *Wavelet Transformation Results*

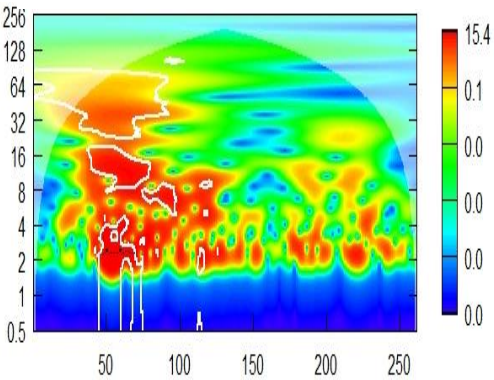
Wavelet Transformation FTSE world



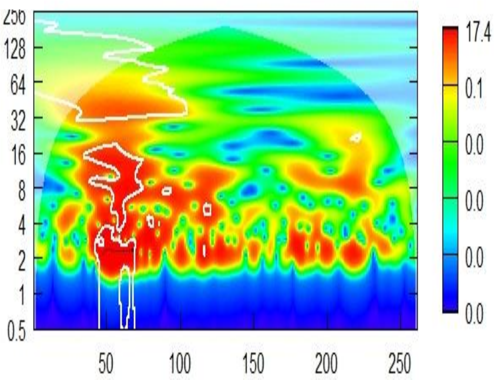
Wavelet Transformation DJGL world



Wavelet Transformation SP World Hedged



Wavelet Transformation MSCI



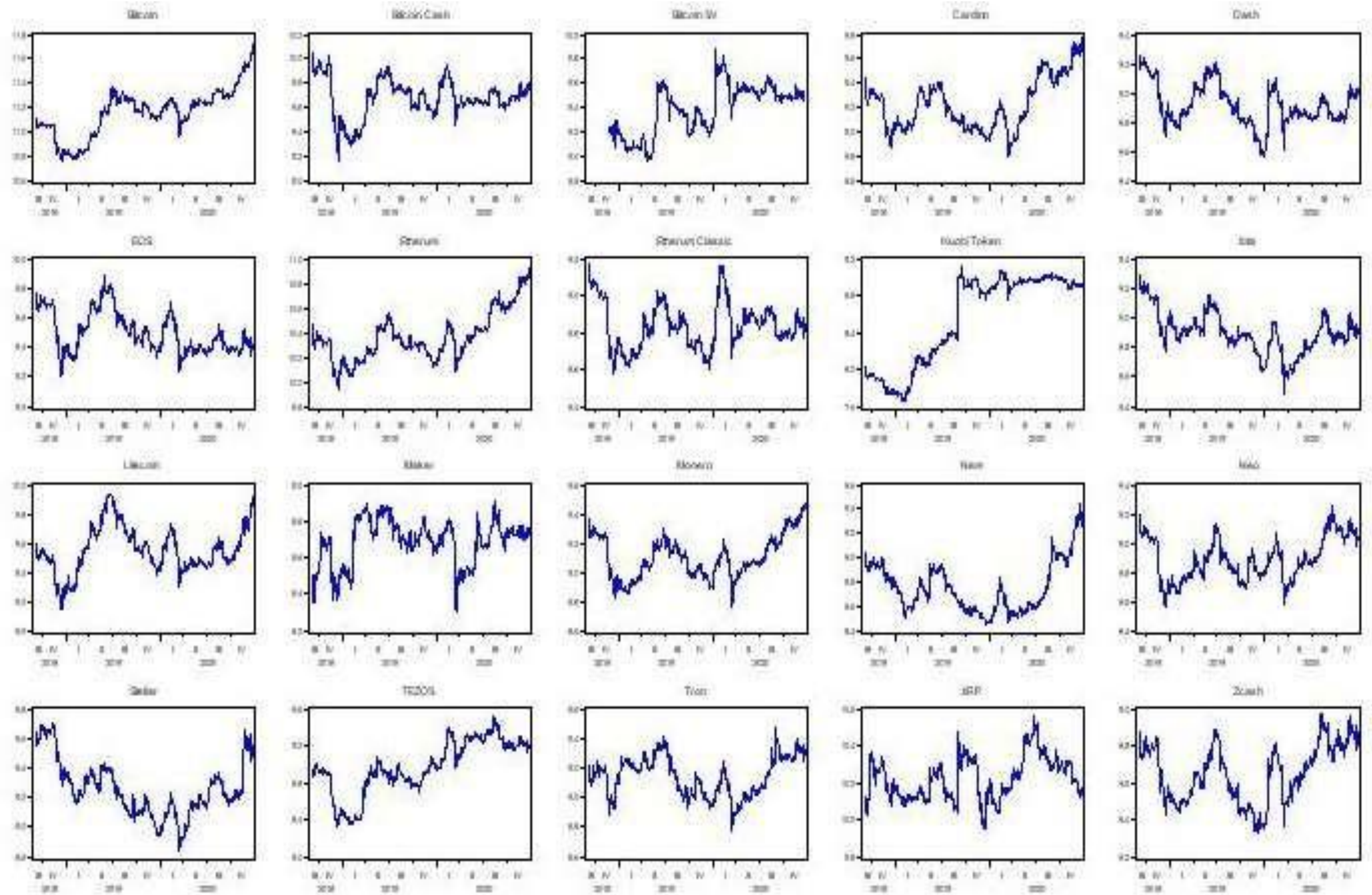


Table 1. *Descriptive Statistics for Wide range of cryptocurrencies for two Sub period Pre-COVID-19 and PostCOVID-19*

	PostCOVID 19											
	Min	1st Qu	Median	Mean	3rd Qu	Max	Std.Dev	ADF	ARCH	Kurtosis	Jarque-Bera	Skewness
Bitcoin	-0.46501	-0.00956	0.002541	0.005517	0.021107	0.165772	0.0443475	-6.4665	4.2657	47.46899	25688	-4.209104
Etherum	-0.55005	-0.01566	0.003716	0.005557	0.031471	0.173444	0.0557963	-6.9564	4.0022	36.58489	15343	-3.514246
XRP	-0.18286	-0.02135	-0.00348	-0.00272	0.017301	0.144923	0.0442121	-6.8589	11.458	3.034323	117.99	-0.5793017
Litecoin	-0.44881	-0.01756	0.002472	0.003328	0.024995	0.188752	0.0559964	-5.7381	10.752	16.43344	3144.6	-1.870529
S.P.WORLD	0.9814	0.9992	1.0002	1.0001	1.0014	1.0131	0.0031441	-5.305	47.666	9.911706	1200.4	-1.584432
MSCI World	0.9862	0.9994	1.0002	1.0001	1.001	1.0114	0.0024016	-5.1831	58.109	10.13762	1202.8	-1.193446
DJGI World	0.9831	0.9992	1.0002	1.0001	1.0012	1.014	0.0029072	-5.1918	54.896	10.7689	1365.6	-1.343664
FTSE	0.9837	0.9993	1.0002	1.0001	1.0012	1.0135	0.0028027	-5.178	56.547	10.47085	1283.6	-1.238498
New Cases	-4	-0.08855	0.024898	0.008816	0.121115	1	0.4144078	-6.5604	20.388	47.21804	25954	-5.453089
New Death	-18.6923	-0.06875	0.0303	-0.0454	0.15029	1	1.182291	-5.8924	0.045565	234.1049	615300	-15.0397
	PreCOVID19											
	Min	1st Qu.	Median	Mean	3rd Qu	Max.	Std.Dev	ADF	ARCH	Kurtosis	Jarque-Bera	Skewness
Bitcoin	-0.15189	-0.0156	-0.00043	-0.00059	0.014416	0.160346	0.0375464	-6.2676	12.178	3.568552	188.37	0.07197
Etherum	-0.20801	-0.02298	-0.00342	-0.0034	0.016416	0.163395	0.0489513	-5.8646	10.215	2.886396	130.93	-0.3611
XRP	-0.20801	-0.02497	-0.00418	-0.00334	0.016215	0.320902	0.0559733	-5.7217	36.455	5.382889	448.09	0.60802
Litecoin	-0.18017	-0.0276	-0.00441	-0.00314	0.019769	0.268087	0.0507959	-6.6652	5.1031	3.989177	256.49	0.6101
S.P.WORLD	0.9953	0.9994	1.0001	1	1.0008	1.0047	0.0012338	-5.6772	11.7	1.523063	42.086	-0.3558
MSCI World	0.9968	0.9996	1.0001	1	1.0006	1.0041	0.0009713	-6.0166	13.805	2.100639	73.544	-0.3689
DJGI World	0.9958	0.9994	1.0001	1	1.0008	1.0044	0.001187	-5.8146	15.708	1.630829	48.419	-0.386
FTSE	0.9961	0.9995	1.0001	1	1.0007	1.0044	0.0011292	-5.9367	14.882	1.836789	59.842	-0.4049

Source: *Created by the authors using the results from the study.*

*Note: The table is limited for a wide range of currencies from the dataset of 4 cryptocurrencies, we are limited within the descriptive analysis for the 20 cryptocurrencies, for the price return of crypto, daily data from 09/2018 through 12/2020. Within this period the main extra-economic shock occurred is COVID 19, the period studies is classified into two period from 09/2018 to 12/2019, and the second from 01/2020 to 12/202. The Arch refers to the LM-ARCH test of Engel(1982), ADF refers to the Augmented Dicky Fuller test with constant, Jarque Bera refers to the test of normality.

Table 2. *Correlation Matrix for the dataset before and during the Pandemic*

	Bitcoin	Etherum	XRP	Litecoin	S.P.WORLD	MSCI.WORLD	DJGL.WORLD	FTSE.WORLD	New_cases	New_deaths
Post-COVID19 Period										
Bitcoin	1									
Etherum	0.883493	1								
XRP	0.064332	0.046643	1							
Litecoin	0.861134	0.877619	0.019993	1						
S.P.WORLD	0.426971	0.423789	0.00751	0.388062	1					
MSCI.WORLD	0.455064	0.460891	0.041583	0.414247	0.957017	1				
DJGL.WORLD	0.443168	0.44521	0.037213	0.401393	0.963749	0.995357	1			
FTSE.WORLD	0.449002	0.453422	0.039509	0.40801	0.9593	0.998819	0.998447	1		
New_cases	-0.05863	-0.09355	-0.08028	-0.0815	-0.04021	-0.01987	0.02694	0.023522	1	
New_deaths	-0.00481	-0.05454	-0.00942	-0.03038	-0.01851	-0.01665	-0.01704	-0.01679	0.439601	1
Pre-COVID19 Period										
	Bitcoin	Etherum	XRP	Litecoin	S.P.WORLD	MSCI.WORLD	DJGL.WORLD	FTSE.WORLD		
Bitcoin	1									
Etherum	0.835839	1								
XRP	0.484652	0.60349	1							
Litecoin	0.786054	0.850677	0.531003	1						
S.P.WORLD	0.003792	0.070417	0.058606	0.068761	1					
MSCI.WORLD	0.02	0.084639	0.080901	0.080296	0.945489	1				
DJGL.WORLD	0.015258	0.085993	0.088233	0.084059	0.950479	0.992395	1			
FTSE.WORLD	0.016718	0.084669	0.085083	0.080798	0.944955	0.99756	0.997642	1		

Source: *Created by the authors using the results from the study.*
Note: *Within this study, we are trying to give just descriptive statistics for the Pre-COVID period (starting from 09/2018 to 12/2019) in terms of comparison of the data and the trend of the evolution. The econometric part, the DCC-GARCH model, as well as the Wavelet analysis will be focused on the period of the Post COVID (starting from 01/2020 to 12/2020).*

Table 3. *Estimation of multivariate VAR-DCC-GARCH model for Bitcoin, Etherum, XRP, and Litecoin result*

		Bitcoin		XRP		Litecoin		Etherum	
		Coef	P-value	Coef	P-value	Coef	P-value	Coef	P-value
	Ω	-0.52586	0	-3.22211	0.007693	-0.22798	0.381499	-4.51815	0
	α1	-0.17198	0.047393	-0.08772	0.375392	-0.12324	0.144265	-0.52469	0.036697
	β1	0.915766	0	0.484252	0.013249	0.956034	0	0.22703	0.070032
	γ1	-0.05055	0.365184	0.349759	0.012725	0.176618	0.000037	-0.07059	0.699011
S.P.WORLDHEDGED	Ω	-0.0374	0.995407	-0.0374	0.997661	-0.0374	0.996114	-0.0374	0.996664
	α1	0.017747	0.99775	0.017747	0.998205	0.017747	0.99916	0.017747	0.989101
	β1	0.899893	0.023568	0.899893	0.068088	0.899893	0.375215	0.899893	0.000033
	γ1	0.097332	0.981782	0.097332	0.994983	0.097332	0.994247	0.097332	0.99412
MSCI.WORLD	Ω	-0.03728	0.998812	-0.03728	0.998742	-0.03728	0.99884	-0.03728	0.998888
	α1	0.01765	0.999579	0.01765	0.999603	0.01765	0.999572	0.01765	0.99957
	β1	0.899774	0.912719	0.899774	0.912103	0.899774	0.90717	0.899774	0.911331
	γ1	0.097177	0.999106	0.097177	0.999336	0.097177	0.999441	0.097177	0.999346
DJGL.WORLD	Ω	-0.03731	0.999684	-0.03731	0.999701	-0.03731	0.999706	-0.03731	0.999707
	α1	0.017689	0.999757	0.017689	0.999768	0.017689	0.999759	0.017689	0.999772
	β1	0.899782	0.919964	0.899782	0.923039	0.899782	0.910583	0.899774	0.924402
	γ1	0.097156	0.999542	0.097156	0.999584	0.097156	0.999645	0.097177	0.999589
FTSE.WORLD	Ω	-0.03724	0.999742	-0.03724	0.999759	-0.03724	0.999759	-0.03724	0.999761
	α1	0.017635	0.99975	0.017635	0.999776	0.017635	0.999757	0.017635	0.999777
	β1	0.89973	0.927756	0.89973	0.930147	0.89973	0.923175	0.89973	0.930425
	γ1	0.097097	0.999635	0.097097	0.999676	0.097097	0.99973	0.097097	0.999681
COVID19.Newdeaths	Ω	-5.83138	0.753238	-5.6716	0.940932	-5.60113	0.199372	-0.06556	0.743953
	α1	0.137591	0.917836	0.133544	0.946303	0.150849	0.753658	0.307361	0.103186
	β1	-0.94645	0.000022	-0.9463	0.293071	-0.9478	0	0.981452	0
	γ1	0.183189	0.52905	0.174444	0.924285	0.193237	0.383799	0.642266	0.01413
COVID19.Newcases	Ω	-0.06556	0.744478	-0.06556	0.744048	-0.06556	0.744825	-5.89528	0.403812
	α1	0.307361	0.098156	0.307361	0.089505	0.307361	0.097531	0.168446	0.46136
	β1	0.981452	0	0.981452	0	0.981452	0	-0.9495	0.310167
	γ1	0.642266	0.0149	0.642266	0.016071	0.642266	0.015339	0.218242	0.395469
DCCa1		0.017356	0.355255	0.018425	0.592009	0.018654	0.431299	0.017826	0.950745
DCCb1		0.982644	0	0.981575	0	0.981346	0	0.982174	0