Diversifying with cryptocurrencies during COVID-19

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Abstract

Literature suggests assets become more correlated during economic downturns. The current COVID-19 crisis provides an unprecedented opportunity to investigate this considerably further. Further, whether cryptocurrencies provide a diversification for equities is still an unsettled issue. Additionally, the question of whether cryptocurrency futures are safe havens has received very little attention. We employ several econometric procedures, including wavelet coherence, copula principal component, and neural network analyses to rigorously examine the role of COVID-19 on the paired co-movements of six cryptocurrencies, as well as bitcoin futures, with fourteen equity indices and the VIX. We find co-movements between cryptocurrencies and equity indices gradually increased as COVID-19 progressed. However, most of these co-movements are positively correlated, suggesting that cryptocurrencies do not provide a diversification benefit during downturns. Exceptions, however, are the co-movements of bitcoin futures and tether being negative with equities. Results are consistent with investment vehicles that attract either more informed or more speculative investors differentiating themselves as safe havens.

Keywords: Co-movement; COVID-19; Bitcoin; Wavelet; Safe haven

JEL classification: C58; F37; G14; G15; Q31

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1 Introduction and motivations

As noted by Goodell (2020), the COVID-19 pandemic will impact financial systems, institutions, and markets to an unprecedented extent. There are ample reasons to suspect COVID-19 will change the dynamics of financial markets, both during the pandemic, and in terms of future attitudes and behaviors. Some even suggest that COVID-19 will alter entire research streams. For instance, Yarovaya et al. (2020) outline how COVID-19 will necessitate a large-scale reexamination of research into financial market contagion. It is likely that even well-researched topics will warrant updating in light of COVID-19. This includes papers that examine the movements of asset classes with both COVID-19 and each other.

Indeed, a reexamination of financial market dynamics in the context of COVID-19 and post COVID-19 is already underway. Very recent papers examine the impact of COVID-19 across industries (Goodell and Huynh, 2020). Others are examining the impact of COVID-19 on herding behavior (Yarovaya, Matkovskyy, and Jalan, 2020) and examining co-movements across commodities, equities, and economic policy uncertainty (Aloui et al., 2020; Sharif, Aloui, and Yarovaya, 2020). Of particular relevance to this paper, others are examining the correlations, hedging, diversifying and safe haven properties of cryptocurrencies with respect to how previously identified relations have changed during the COVID-19 crisis (Conlon and McGee, 2020; Conlon, Corbet, and McGee, 2020; Goodell and Goutte, 2020).

We employ several econometric procedures including wavelet coherence analysis (Kang, McIver, and Hernandez, 2019; Goodell and Goutte, 2020), principal component analysis (PCA), and neural network analysis to examine the role of COVID-19 on the paired co-movements of six cryptocurrencies, with fourteen equity indices, as well as bitcoin futures and the VIX. To provide clarity of comparison, we use the same combinations of cryptocurrencies and equity indices as the very recent (Conlon, Corbet, and McGee, 2020). Cryptocurrencies examined include bitcoin, ethereum, tether, XRP, and EOS. Equity indices include MSCI World, FTSE China, TA 35 Israel, NIFTY India, Jakkarta Phillipine, KOSPI Korea, FTSE Italy, IBEX 35 Spain, CAC 40 France, DAX All, Bovespa Brazil, SP500 US, EUROSTOXX, and FTSE RU. In addition, we also include bitcoin futures and the VIX.

We find that bitcoin and the MSCI World Index had increasing co-movement corresponding with the start of the pandemic, with bitcoin leading the MSCI index with positive correlation. All co-movements with cryptocurrencies and equity indices got progressively larger, as COVID-19 progressed, and are economically meaningful. Generally, co-movements are positively correlated, arguing against cryptocurrencies being safe havens. Notable exceptions, however, are the co-movements of bitcoin futures, and the particular cryptocurrency tether, which were negatively correlated with equity indices. Additionally, consistent with not being safe havoens, we find equity indices to negatively co-move with the VIX. However, again, we find that bitcoin futures and tether move positively with the VIX, affirming their value as safe havens. Overall, co-movements of the cryptocurrencies and bitcoin futures with VIX corroborate that most cryptocurrencies are not safe havens (consistent with Conlon, Corbet, and McGee, 2020), but tether is as safe haven; as are bitcoin futures.

Within the context of COVID-19, this article is motivated in several ways. First, it is known at least since Hartmann, Straetmans, and de Vries (2004), that assets and asset classes become more correlated during economic downturns (see also Bekaert, Hodrick, and Zhang, 2009; Lee, Lin, and Yang, 2011). Certainly COVID-19 presents an unprecedented opportunity to investigate this further.

Second, there is a great deal of literature interest in whether bitcoin, and cryptocurrencies in general, have gold-like safe-haven properties. Since Dyhrberg (2016a) and Dyhrberg (2016b), there has been interest in whether bitcoin might share some of the same hedging properties as gold (Baur and Lucey, 2010; Baur and McDermott, 2010; Bouri, Lucey, and Roubaud, 2019; Bredin, Conlon, and Potì, 2015; Gil-Alana, Abakah, and Rojo, 2020; Goodell and Goutte, 2020; Klein, Pham Thu, and Walther, 2018; O'Connor et al., 2015; Raza, Shah, and Shahbaz, 2018; Smales, 2019). The issue of whether cryptocurrencies are coupled with traditional asset classes is also not settled. Corbet, Meegan, et al. (2018); Feng, Wang, and Zhang (2018); Mensi et al. (2020); Shahzad et al. (2019) and many others find nuanced evidence correlation of cryptocurrencies with other assets. However, this issue begs reconsideration for the period of COVID-19.

Third, there is ongoing interest in how asset classes behave under uncertainty generally (e.g. Goodell, McGee, and McGroarty, 2020), and more particularly how cryptocurrencies behave under shocks to uncertainty (Kurka, 2019; Matkovskyy and Jalan, 2019; Wu et al., 2019; Wang et al., 2019). There is considerable early interest in how all of these relationships and characteristics of cryptocurrencies might be impacted by the COVID-19 crisis, both during the pandemic and extending into the future (Goodell and Goutte, 2020).

Fourth, the properties of bitcoin futures have comparatively received much less attention (for important exceptions see Akyildirim et al., 2019; Baur and Dimpfl, 2019; Corbet, Lucey, et al., 2018; Fassas, Papadamou, and Koulis, 2020; Kapar and Olmo, 2019; Kim, Lee, and Kang, 2019; Liu et al., 2019; Sebastião and Godinho, 2019). As theorized by Hale et al. (2018), bitcoin futures capture speculative demand, in contrast to bitcoin, which, in addition to investment demand, also supplies transactional demand[1].People use bitcoins to purchase goods and services (or for storage of funds following investment withdrawals), but bitcoin futures supply speculative demand, as they are bought in the hope that their value will increase. We also consider, following Hale et al. (2018), that investors in bitcoin futures are more specialized and informed traders than those investing in cryptocurrencies in general. We also consider this the case for those holding the particular cryptocurrency tether (da Gama Silva, Neto, and Klotzle, 2019; Wei, 2018). Wei (2018) finds that when bitcoin suffers a decline there is a subsequent increase in the volume of tether trading.

[1]Foley, Karlsen, and Putniņš (2019) estimate almost half of all bitcoin transactions are in illegal activities

Our finding that positive co-movements between cryptocurrencies and equity indices got progressively larger, as COVID-19 progressed, is consistent with cryptocurrencies correlating with other assets during downturns. In other words, not being safe havens. On the other hand, our finding of a progressing negative co-movement during the increase of COVID-19 between equity indices and bitcoin futures and tether is consistent with both bitcoin futures and tether acting as genuine safe havens.

As discussed further in the paper, we interpret our findings of bitcoin futures and tether acting differently from cryptocurrencies in general from several perspective. These results could be reflective of different investor types (Grinblatt and Keloharju, 2000). Or they could be reflective of bitcoin futures representing market speculation rather than vehicles for storage and transaction. Additionally, the results for tether[2] could be reflective of investors moving from other cryptocurrencies toward the noted stability of tether . Our results should be of great interest to a broad spectrum of academics, and investors.

2 Data and statistics

The data covers the period of 01 May 2019 to 11 May 2020. Data are from `https://www.investing.com/`. To provide clarity of comparison, we use the same combinations of cryptocurrencies and equity indices as the very recent (Conlon, Corbet, and McGee, 2020). Cryptocurrencies examined include bitcoin, ethereum, litecoin, tether, XRP, and EOS. Equity indices include MSCI World, FTSE China, TA 35 Israel, NIFTY India, Jakkarta Phillipine, KOSPI Korea, FTSE Italy, IBEX 35 Spain, CAC 40 France, DAX All, Bovespa Brazil, SP500 US, EUROSTOXX, and FTSE RU. In addition, we also include bitcoin futures and the VIX.

Complete descriptive statistics can be found in the following Tables 1 to 4.

[2]We acknowledge that the stability of tether is an unsettled issue (Chohan, 2019); however there is also the issue here of whether tether is simply perceived as stable.

Table 1: Descriptive Statistics (Part 1)

	Bitcoin	Bitcoin Future	Ethereum	Theter	XRP	Litecoin	EOS
Mean	-11.828	-19.182	-0.082	-3.717e-5	2.974e-4	0.116	0.009
Std. Deviation	461.614	444.232	12.048	0.002	0.015	4.167	0.292
Skewness	1.210	1.011	1.751	-0.301	-0.262	0.382	0.713
Std. Error of Skewness	0.149	0.149	0.149	0.149	0.149	0.149	0.149
Kurtosis	8.697	7.694	10.786	18.038	6.846	4.027	11.681
Std. Error of Kurtosis	0.296	0.296	0.296	0.296	0.296	0.296	0.296
Shapiro-Wilk	0.877	0.878	0.870	0.268	0.862	0.915	0.808
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	-1314.500	-2040.000	-29.920	-0.010	-0.090	-16.420	-1.580
Maximum	3042.600	2525.000	86.070	0.010	0.070	18.710	1.860

Table 2: Descriptive Statistics (Part 2)

	MSCI WORLD	CBOE VIX	FTSE China	TA 35 Israel	NIFTY India	Jakkarta Phillipine
Mean	0.505	-0.068	0.518	0.596	9.485	6.939
Std. Deviation	32.383	3.287	153.921	20.251	170.766	69.612
Skewness	1.420	-2.375	0.036	0.804	1.595	0.690
Std. Error of Skewness	0.149	0.149	0.149	0.149	0.149	0.149
Kurtosis	11.328	22.055	1.065	5.451	10.938	4.055
Std. Error of Kurtosis	0.296	0.296	0.296	0.296	0.296	0.296
Shapiro-Wilk	0.799	0.702	0.980	0.884	0.840	0.933
P-value of Shapiro-Wilk	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$
Minimum	-140.500	-24.860	-456.180	-83.150	-569.400	-206.670
Maximum	195.520	17.640	497.870	95.700	1135.200	361.730

Table 3: Descriptive Statistics (Part 3)

	KOSPI KOREA	FTSE Italy	IBEX 35 Spain	CAC 40 France	DAX ALL	BOVESPA Brazil
Mean	1.094	16.067	9.835	4.141	5.678	57.297
Std. Deviation	27.224	372.738	132.574	83.016	188.275	2210.225
Skewness	-0.015	2.959	2.418	1.853	1.416	1.708
Std. Error of Skewness	0.149	0.149	0.149	0.149	0.149	0.149
Kurtosis	3.858	21.561	16.752	11.008	11.766	11.333
Std. Error of Kurtosis	0.296	0.296	0.296	0.296	0.296	0.296
Shapiro-Wilk	0.919	0.774	0.812	0.839	0.841	0.802
P-value of Shapiro-Wilk	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$
Minimum	-127.510	-1388.800	-487.100	-328.390	-959.420	-10095.380
Maximum	85.450	3034.200	1045.500	565.990	1277.550	12588.600

Table 4: Descriptive Statistics (Part 4)

	SP500	EUROSTOXX	FTSE RU
Mean	0.208	2.342	5.169
Std. Deviation	53.818	52.109	96.463
Skewness	0.915	1.870	1.576
Std. Error of Skewness	0.149	0.149	0.149
Kurtosis	9.932	11.940	10.821
Std. Error of Kurtosis	0.296	0.296	0.296
Shapiro-Wilk	0.807	0.827	0.843
P-value of Shapiro-Wilk	$< .001$	$< .001$	$< .001$
Minimum	-230.380	-229.570	-452.120
Maximum	324.890	360.330	639.040

Figure 1 shows the correlation matrix between each variables with a heat map representation. A dark red color indicates that a respective two variables are extremely negatively correlated, while dark blue indicates an extremely positive correlation. For instance, we can see in Figure 1 that the VIX is generally negatively correlated with with the stock indices in our sample. This, of course, it expected as the VIX is a volatility market index. A result of greater interest is that in our panel of cryptocurrencies and bitcoin futures, two series have a negative correlation with stocks, namely tether and bitcoin futures. This argues in favor of tether and bitcoin futures being safe haven assets.

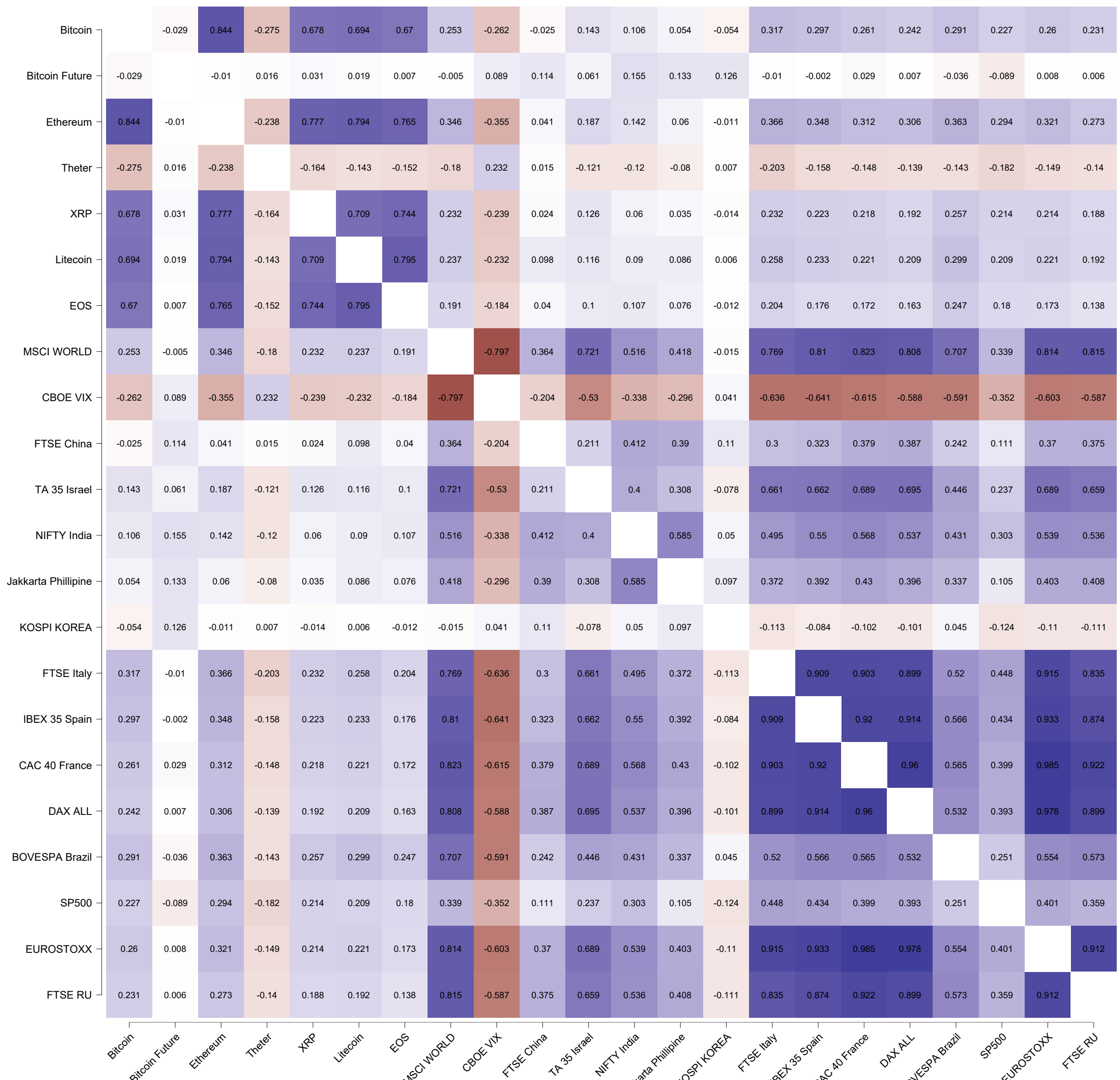

Figure 1: Heatmap of the return series

3 Principal Component Analysis

Regarding our principal component analysis, Table 5 displays the best projection in two dimensions of the variables in our study. The first axis RC1 is the segmentation that has the most information from the data. RC2 represents the next most important segment, and so on.

Examining Table 5, we see that the RCI axis captures the predominant portion of non-Asian equities. RC2 captures the cryptocurrencies other than tether and bitcoin futures. RC3 captures bitcoin futures and the Asian equities. Clearly tether has a very different relationships with equities than other cryptocurrencies. Bitcoin futures also behave very differently from cryptocurrencies, with the exception of tether.

Figure 2 displays a two-dimensional plot, in which RC1 is on the X axis and RC2 is on the Y axis. This illustrates in two dimensions the relationships between our data. In this way we see a projection of the variables with respect to the two main PCA axes, RC1 and RC2. We see that all variable are on the right hand side of the graph (x¿0) except bitcoin futures and Asian equities, which are on left (x¡0). Moreover, the cryptocurrencies are gathered in the upper in the upper portion of this graph. Figure 6, in Appendix, confirms these aggregations by plotting them in term of clusters.

Table 6 displays the component characteristics for this principal component analysis. As can be seen in the Cumulative column for RC2, the two-dimensional representation of Figure 2 reflects 58.6% of the total information. Overall, our principal component analysis strongly suggests that Tether and Bitcoin futures are potential diversifiers for equity. Our analysis, consistent with Conlon, Corbet, and McGee (2020), also suggests that cryptocurrencies, other than Thether, are not diversifiers or safe havens for equity investors.

Table 5: Component Loadings

	RC1	RC2	RC3	Uniqueness
Bitcoin		0.856		0.237
Bitcoin Future			0.576	0.689
Ethereum		0.916		0.112
Theter				0.896
XRP		0.886		0.242
Litecoin		0.910		0.204
EOS		0.920		0.210
MSCI WORLD	0.870			0.180
CBOE VIX	-0.722			0.447
FTSE China			0.576	0.543
TA 35 Israel	0.781			0.428
NIFTY India	0.481		0.498	0.410
Jakkarta Phillipine			0.610	0.448
KOSPI KOREA			0.578	0.668
FTSE Italy	0.928			0.139
IBEX 35 Spain	0.943			0.109
CAC 40 France	0.958			0.074
DAX ALL	0.958			0.097
BOVESPA Brazil	0.560			0.522
SP500	0.488			0.707
EUROSTOXX	0.967			0.075
FTSE RU	0.931			0.143

Table 6: Component Characteristics

	Eigenvalue	Proportion var.	Cumulative
RC1	9.340	0.425	0.425
RC2	3.550	0.161	0.586
RC3	1.529	0.069	0.655

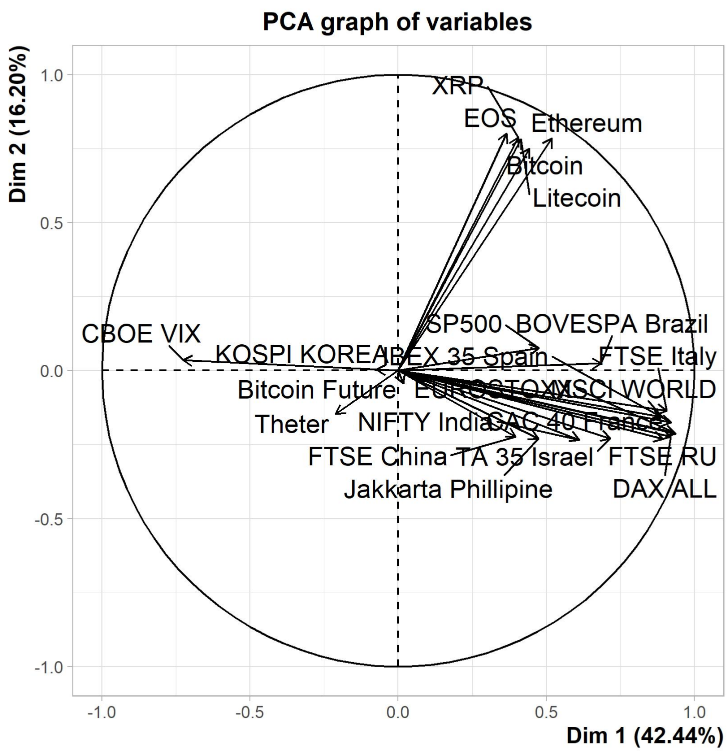

Figure 2: PCA Projection on the two first factor axis

Table 7: Component Correlations

	RC1	RC2	RC3
RC1	1.000	0.323	0.248
RC2	0.323	1.000	0.004
RC3	0.248	0.004	1.000

4 Neural network

We further investigate the co-movements of cryptocurrencies, bitcoin futures, and VIX and equities with neural network analysis. This methodology allows us to identify the connections and nodes between our variables. Our neural network analysis is shown in Figure 3. In these figures, a wider or thicker line between two variables indicates greater connection between them. This suggests higher dependency between these variables; and so greater potential impact and co-movements between them. Especially valuable, neural network analysis also captures the sign of the relationship and so the nature of the correlation. In our figures, a blue connecting line denotes a positive relationship (co-moving in the same direction; positively correlated). On the other hand, a red connecting line denotes a negative correlation. And so, in the context of our analysis, a red connecting line between a cryptocurrency (or bitcoin futures) and an equity index indicates that during COVID-19 this respective cryptocurrency has been a diversifier, or even a safe haven, with respect to this respective equity market.

Examining Figure 3, it is clear that all cryptocurrencies, with the exception of tether, are bunched together on the right-hand side of the network with positive (blue-colored) relationships. These results suggest that, with the exception of tether, cryptocurrencies are not diversifiers, much less safe havens, during extreme downturns.

Further, neural network analysis again confirms our results of wavelet coherence analysis and copula principal component analysis with regard to tether and bitcoin futures. Again, examining the figures for our neural network analysis, tether and bitcoin future have no direct connection nodes with the other cryptocurrencies. This indicates considerable differences in the specificities and characteristics of tether and bitcoin futures compared to other cryptocurrencies two cryptos against the others. Tether, and even more bitcoin futures (farther from bunching of most cryptocurrencies than tether) have a behavior, relationship, and impact on the other assets (in this case equities) that is different from other cryptocurrencies.

Additional examination of the color of the neural network links in Figure 4 allows other inferences. For instance, we see that bitcoin futures has a red connection with the SP 500. It also has a positive relationship with the VIX. Together these results suggest bitcoin futures has the role of a safe-haven asset with respect to US equities.

Interestingly, neural network analysis also shows a negative relationship between tether and bitcoin. This suggests that tether plays a different role in portfolio diversification than bitcoin, with tether as a diversifier for both equity and bitcoin investors. Similarly tether, is a diversifier for all the other cryptocurrencies (all of which have positive links with bitcoin). We also see that bitcoin plays a major role by leading the movements of other cryptocurrencies (tether and bitcoin futures excepted). Indeed, we can see that the main important connection in the cryptocurrency group comes from bitcoin on ethereum and then dispatching to the other cryptocurrencies. This evidences that bitcoin leads the other cryptocurrencies (other than tether). Finally, of additional interest, neural network analysis shows a red connection (negative correlation) between ethereum and FTSE China. This may suggest a particular value for ethereum for diversifying Asian portfolio investments.

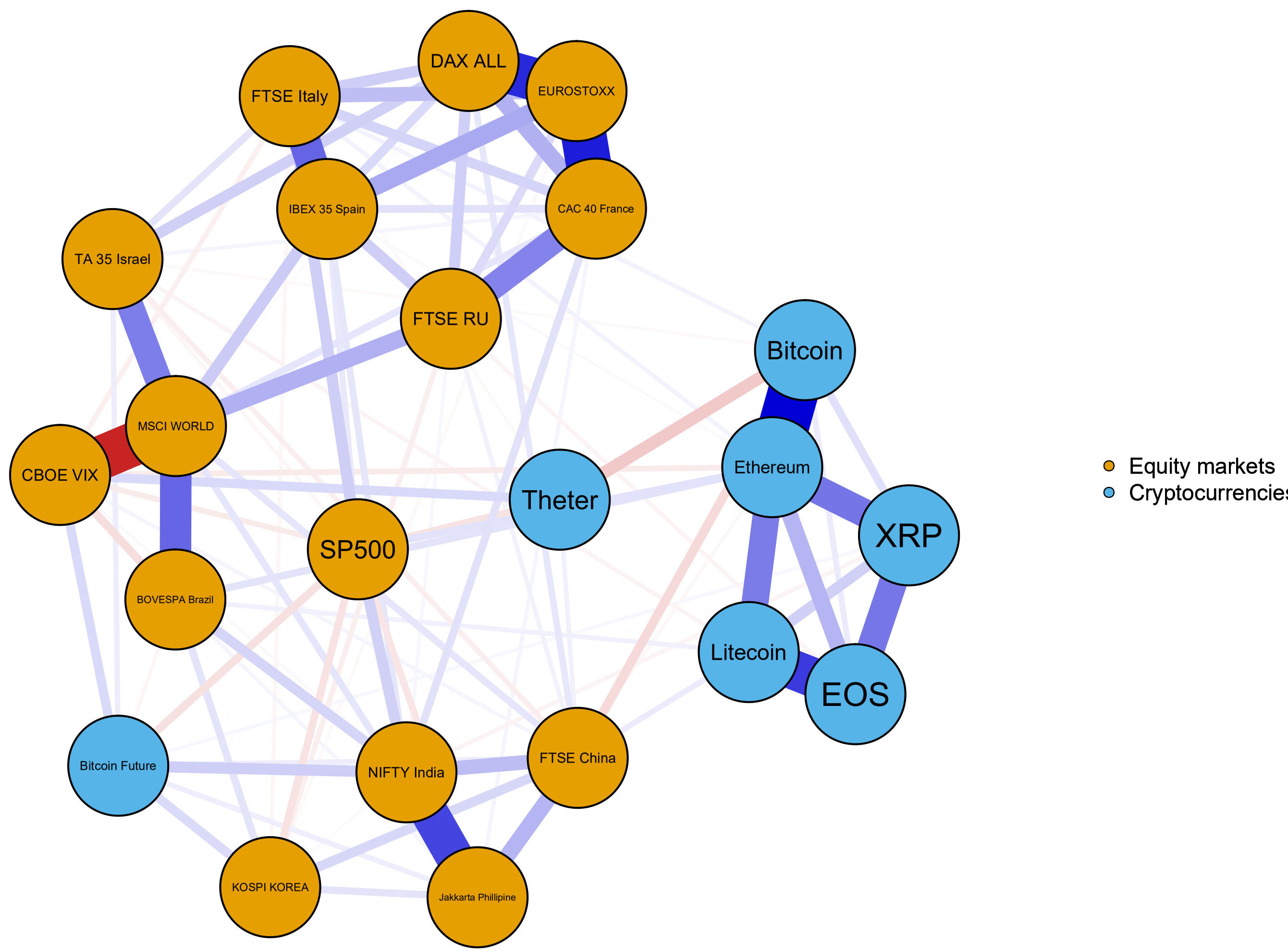

Figure 3: Neural Network Map

5 Wavelet approach

In this section, we further explore aspects of our findings with wavelet coherence analysis. This study applies the wavelet method of Grinsted et al. (2004) and recently used in Goodell and Goutte (2020) to study the relationship between COVID-19 world deaths and Bitcoin prices.

Figures 4 to 19 in the Appendix illustrate this analysis. In these illustrations, the coherency ranges from yellow (high coherency) to blue (low coherency) to designate the amount of co-movement. Therefore, a yellow color represents strong co-movement; whereas a blue color indicates weak co-movements.

Additionally, we discern causality and phase differences. Arrows indicate the phase differences between the two assets. For example, $\rightarrow$ and $\leftarrow$ indicate that the assets are in phase and out of phase. Being in phase (out of phase) indicates a positive (negative) correlation between both variables. Moreover, $\nearrow$ and $\swarrow$ indicate that the first asset are leading the second one, while $\searrow$ and $\nwarrow$ indicate the first asset values are lagging those of the second one.

In each of these figures, a vertical line in red denotes the starting of the COVID-19 pandemic.

5.1 Cryptocurrencies against VIX

It is useful to compare the co-movement of the cryptocurrencies in our sample with movements in the VIX, in order to better understand our findings regarding the co-movements of cryptocurrencies with equities during COVID-19. This is because it is generally considered that VIX is an index of market volatility, reflecting market stress and uncertainty. An initial expectation would be that equities would negatively co-move with an index of market uncertainty. Or, from a different perspective, examining our results alternatively with regard to VIX, rather than levels of COVID-19, allows for inferences that it is indeed market uncertainty that is driving co-movements.

We can see by examining the figures that the start of the pandemic is associated with increasing VIX values. The first series of graphs plot the co-movements of each cryptocurrency with VIX. In in all cases, the co-movements appear only after the start of the pandemic. Further, with the exception of thether and bitcoin futures, all co-movements of cryptocurrencies with VIX are out of phase (left arrow), suggesting negative correlation. These results, of a negative correlation with VIX, argue against the efficacy of cryptocurrencies as diversifiers during economic downturns.

5.2 Tether and bitcoin futures against VIX

Figure 5 illustrates specifically the co-movement of theter with VIX during COVID-19. Examining Figure 5, we see that during the COVID-19 pandemic (i.e., on the right side of line red) the co-movements are significant with lag of two weeks to one month and always positively correlated (right arrows) with the VIX. Figure 4 illustrates a similar situation for bitcoin futures. These results strongly suggest a role for both tether and bitcoin futures as diversifiers or safe havens during extreme economic downturns.

6 Conclusions

As noted by Goodell (2020) and others (e.g., Yarovaya et al., 2020), COVID-19, because of its scope and magnitude, calls for a reexamination of most aspects of financial market dynamics. It is generally accepted that most assets and asset classes become more correlated during economic downturns (e.g., Bekaert, Hodrick, and Zhang, 2009). COVID-19 presents an unprecedented opportunity to investigate this further. Along with this, there is a great deal of interest in whether cryptocurrencies, have gold-like safe-haven properties. Further, there is considerable interest in how asset classes behave under uncertainty generally and, in particular, how cryptocurrencies behave under shocks to uncertainty. Additionally, the potentially diversifying properties of bitcoin futures have as yet received less attention.

We employ several econometric procedures including wavelet coherence copula principal component, and neural network analyses to examine the paired co-movements of six cryptocurrencies as well as bitcoin futures with fourteen equity indices, and the VIX during COVID-19. We find that all co-movements with cryptocurrencies and equity indices got progressively larger, as COVID-19 progressed, and are economically meaningful. Generally, co-movements are positively correlated, arguing against cryptocurrencies being safe havens. Notable exceptions, however, are the co-movements of bitcoin futures, and tether, which are negatively correlated with equity indices. We also find equity indices co-moving negatively with the VIX.

However, in contrast to most cryptocurrencies, we find that bitcoin futures and tether move positively with COVID-19 and the VIX, affirming their value as safe havens. In summary, while most cryptocurrencies are not safe havens, tether and bitcoin futures are safe havens during extreme downturns We interpret our findings as consistent with bitcoin futures and tether acting differently from cryptocurrencies in general because of differing investor types. Bitcoin futures reflect market speculation rather than use as vehicles for storage and transaction, while investors in tether are attracted toward its noted stability and structural connection to the US dollar. Our results should be of great interest to a broad spectrum of academics, and investors.

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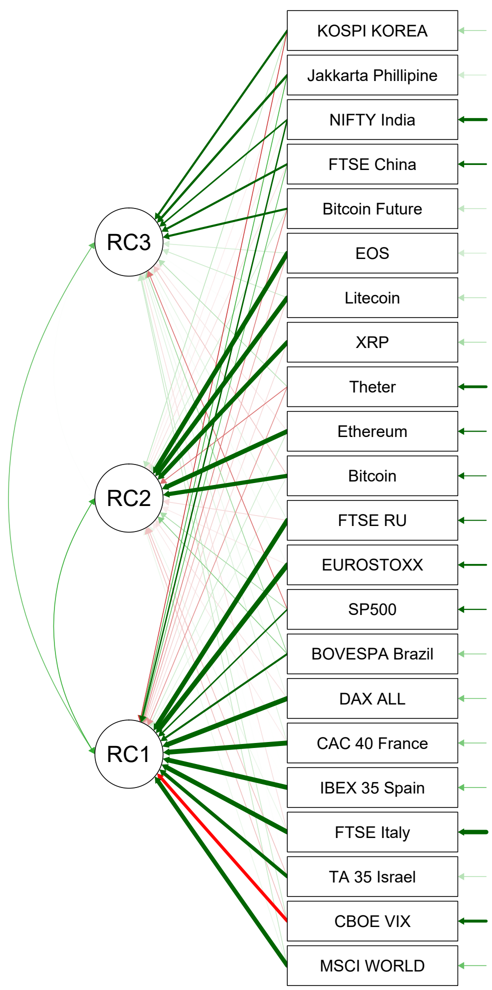
Appendix



PCA Paths

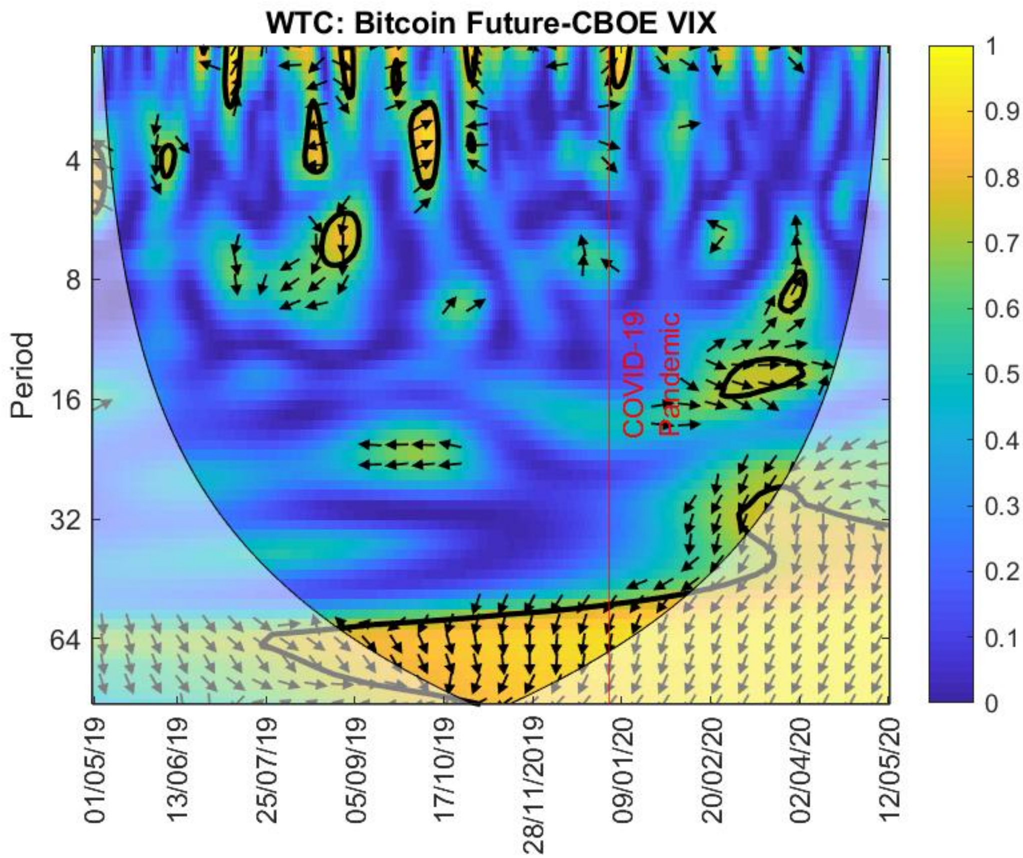


Figure 4: Wavelet coherency (WTC) between Bitcoin future and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

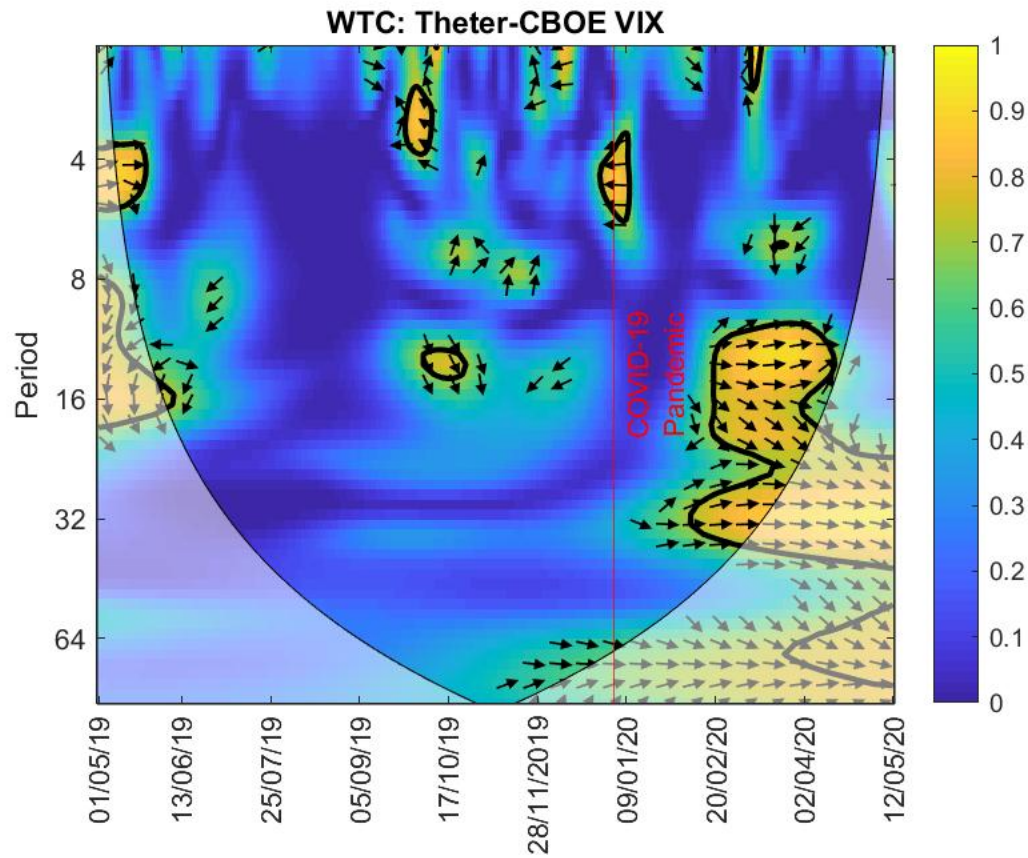


Figure 5: Wavelet coherency (WTC) between Tether and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

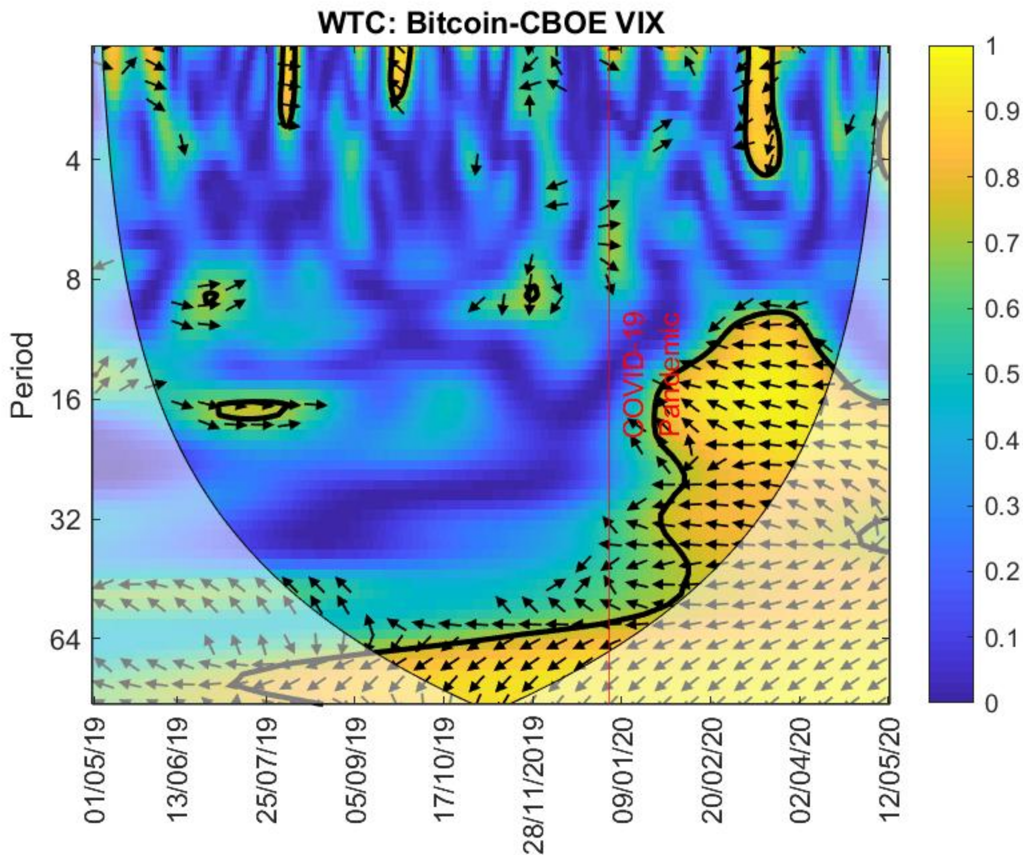


Figure 6: Wavelet coherency (WTC) between Bitcoin and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

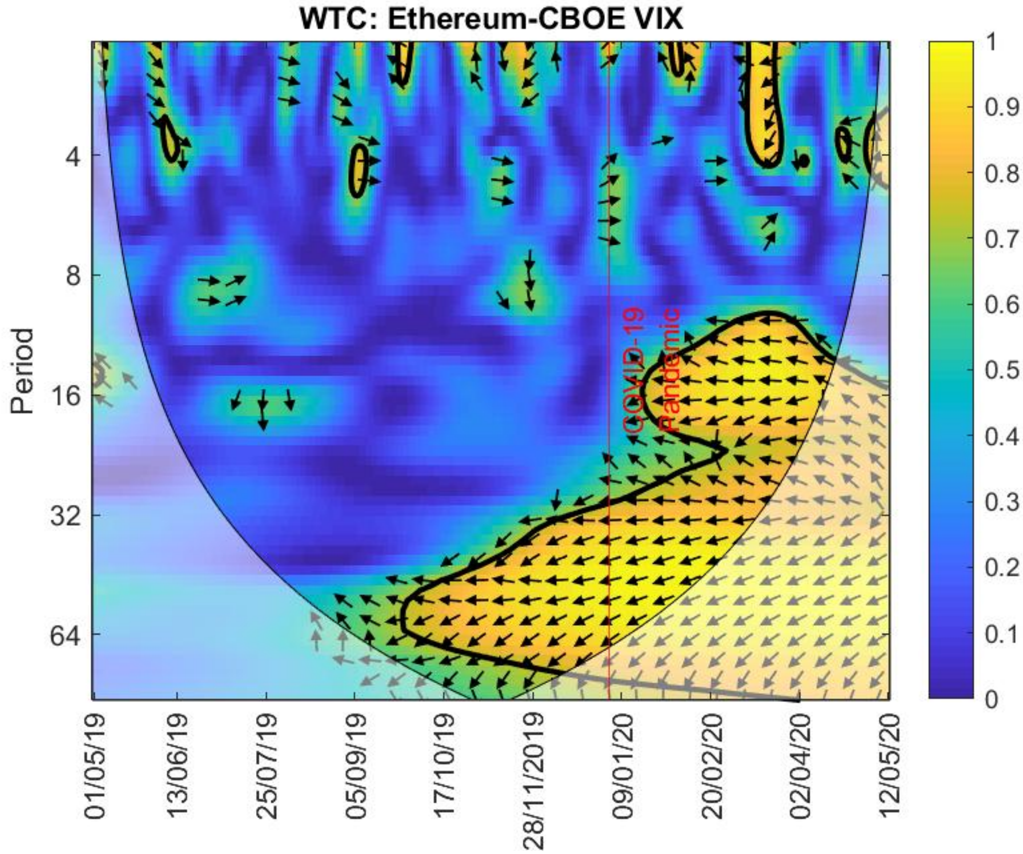


Figure 7: Wavelet coherency (WTC) between Ethereum and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

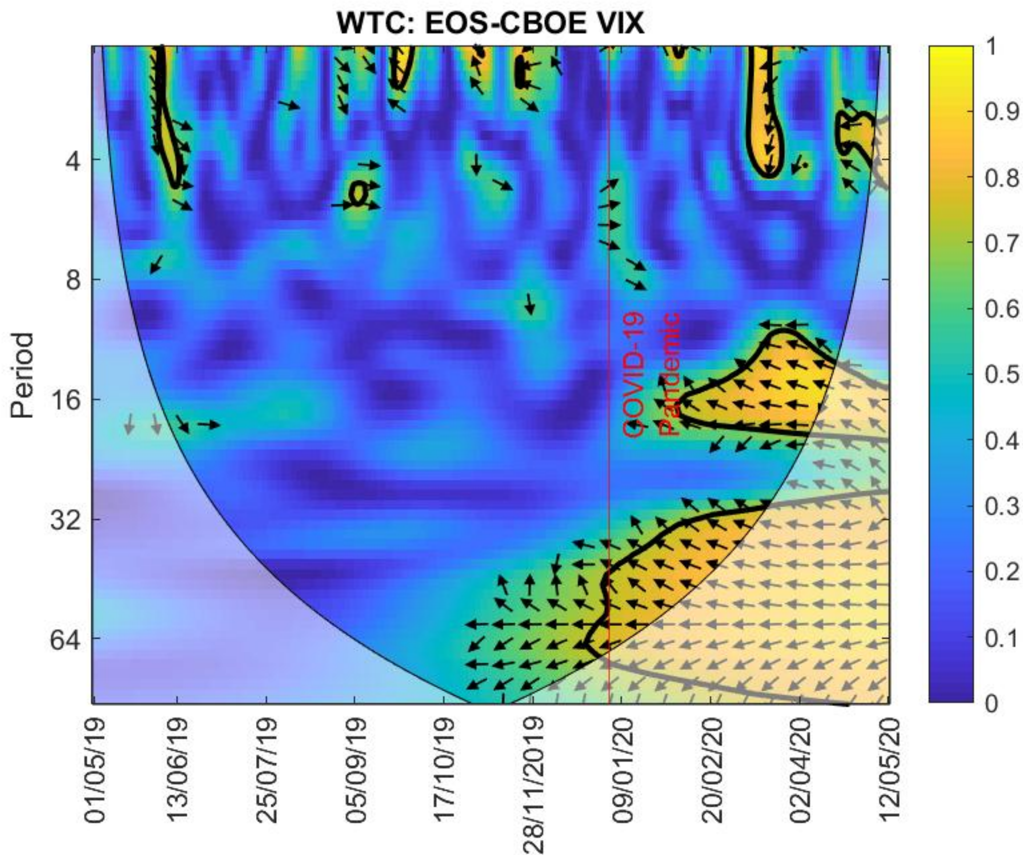


Figure 8: Wavelet coherency (WTC) between EOS and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

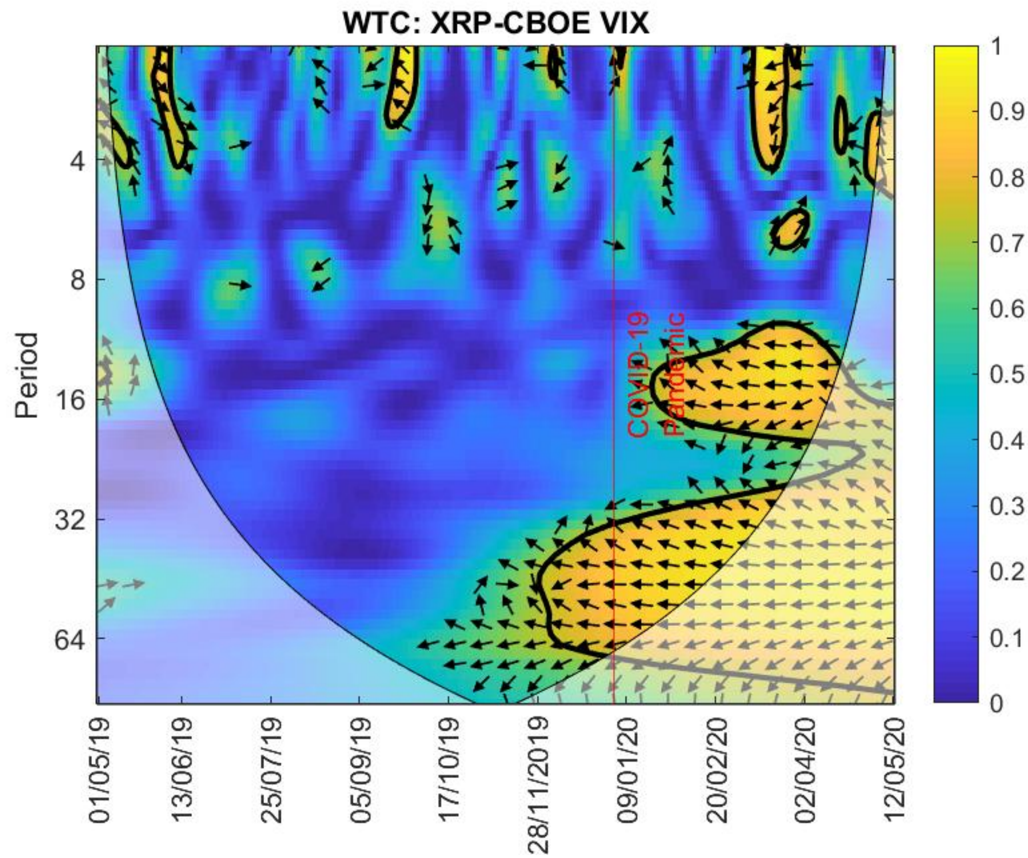


Figure 9: Wavelet coherency (WTC) between XRP and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

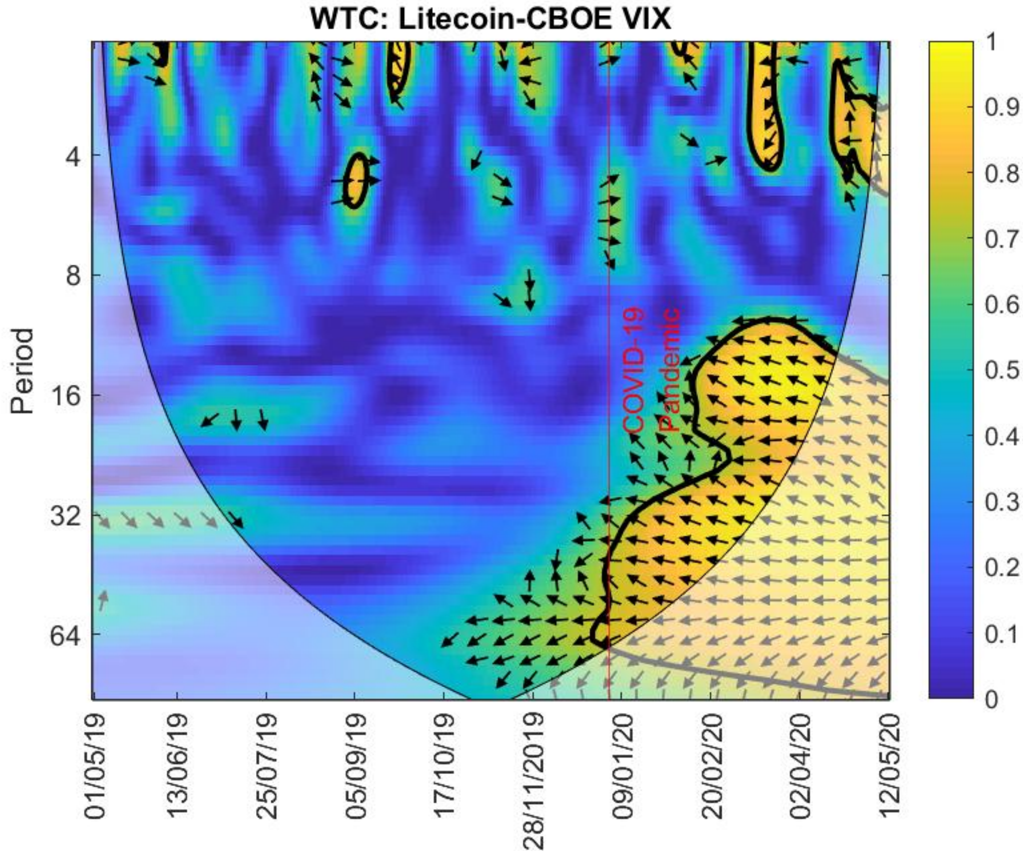


Figure 10: Wavelet coherency (WTC) between Litecoin and VIX. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

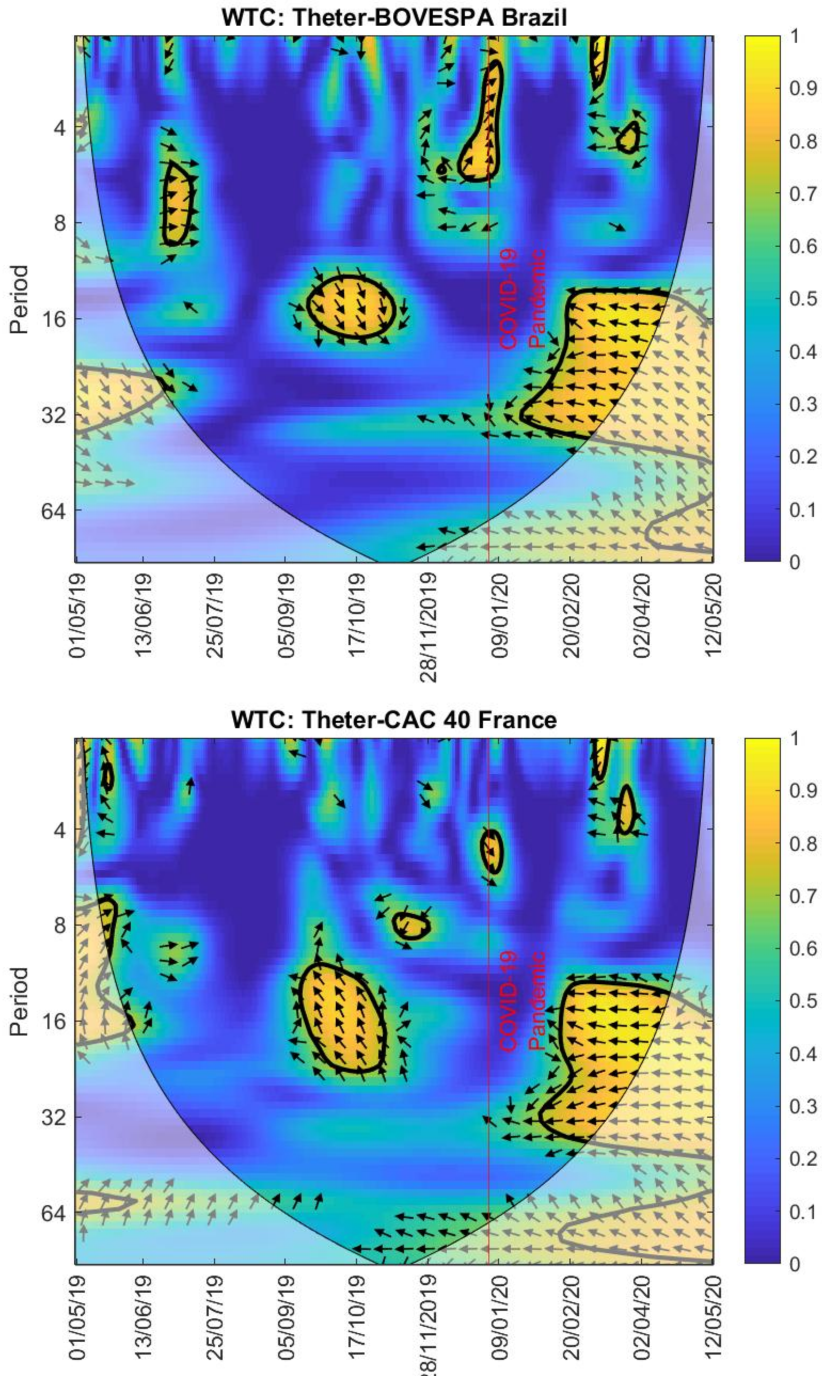


Figure 11: Wavelet coherency (WTC) between Tether and Bovespa (up) and CAC 40 (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

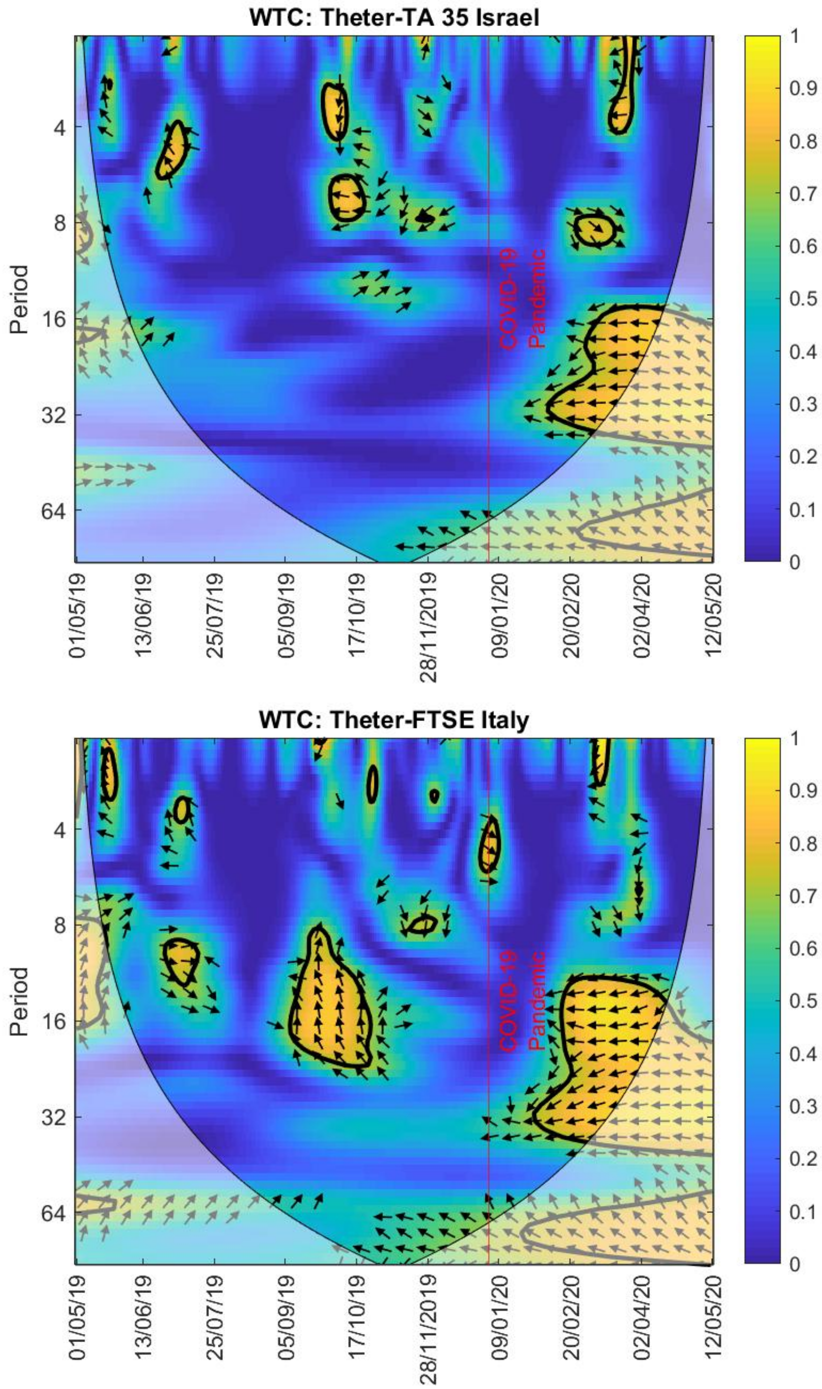


Figure 12: Wavelet coherency (WTC) between Tether and TA 35 (up) and FTSE Italy (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

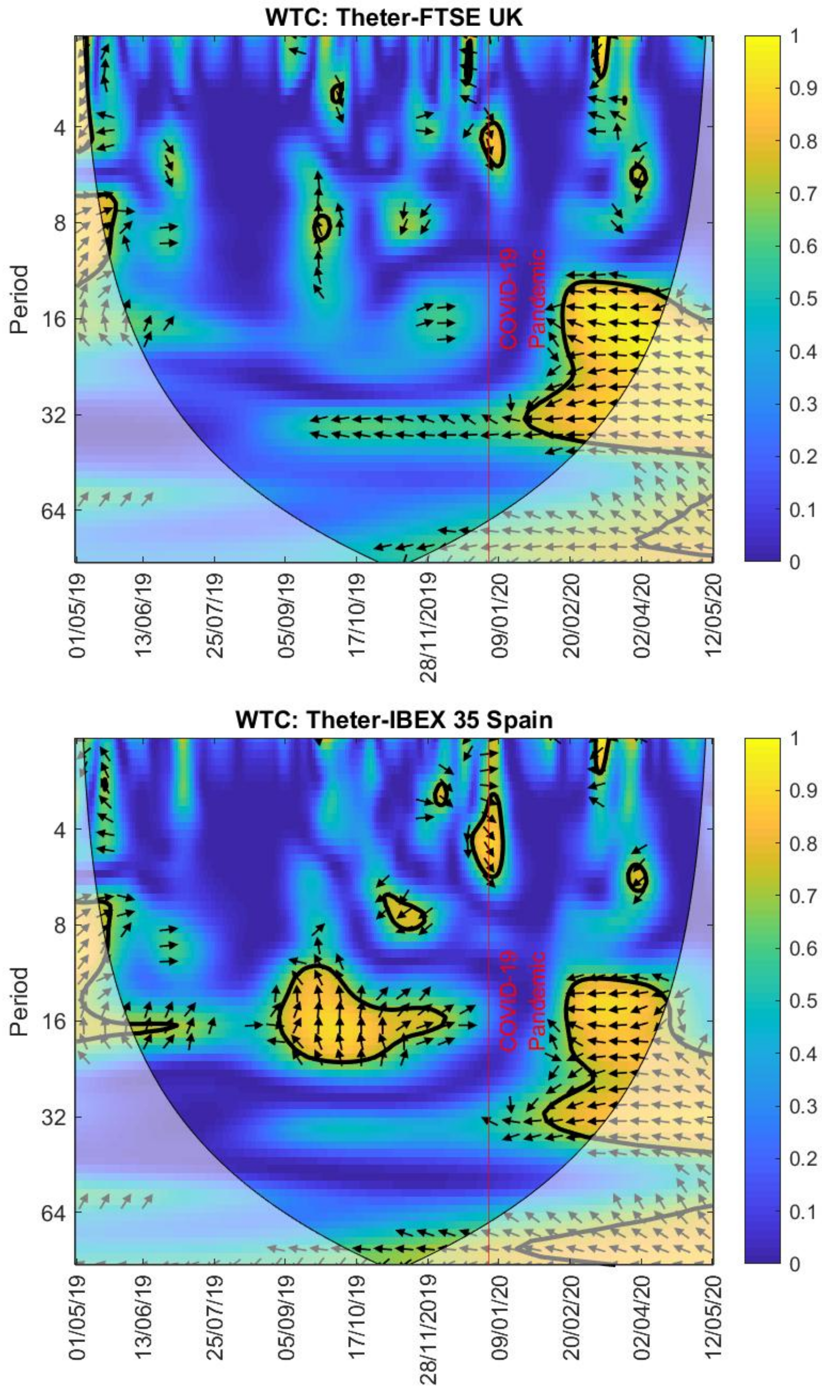


Figure 13: Wavelet coherency (WTC) between Tether and FTSE UK (up) and IBEX 35 (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

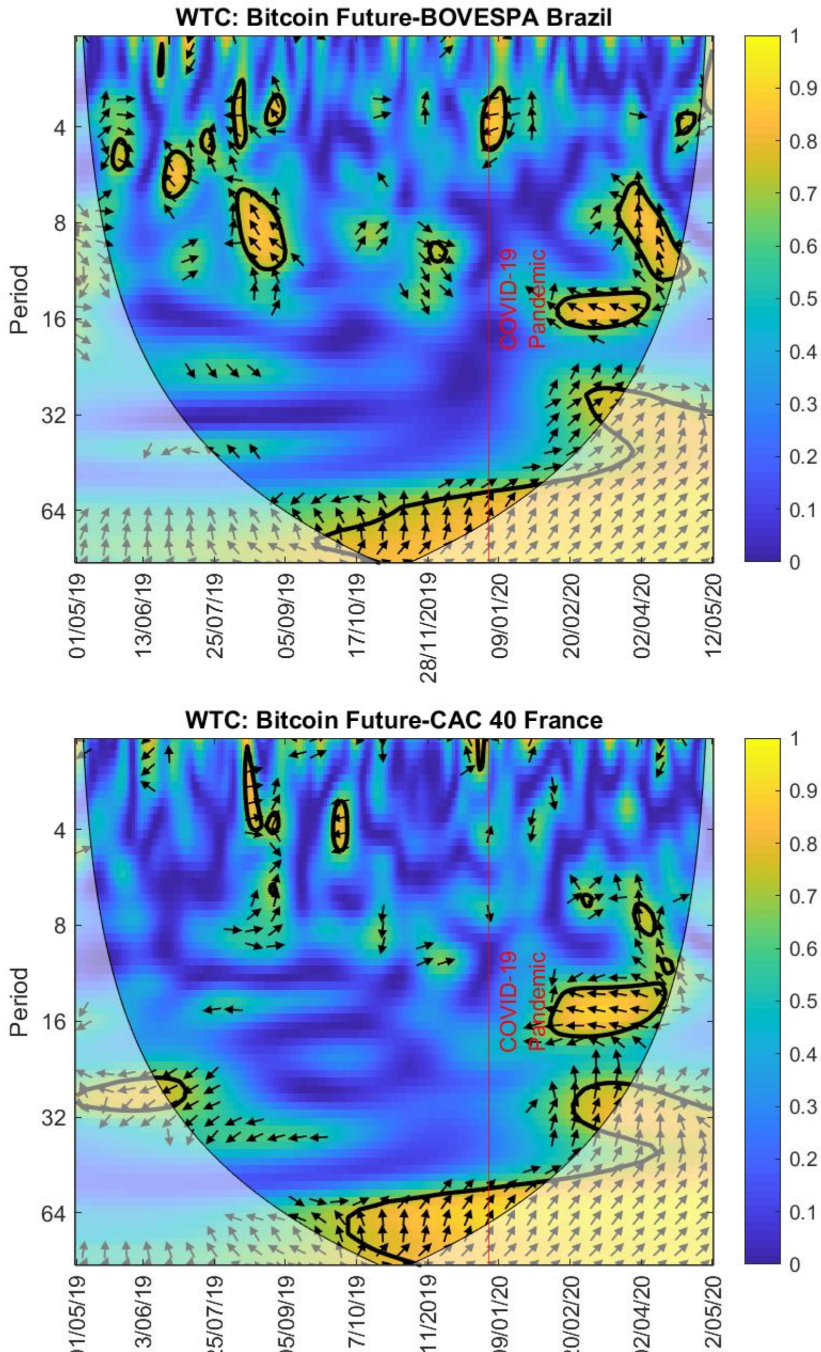


Figure 14: Wavelet coherency (WTC) Bitcoin future and Bovespa (up) qnd CAC 40 (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

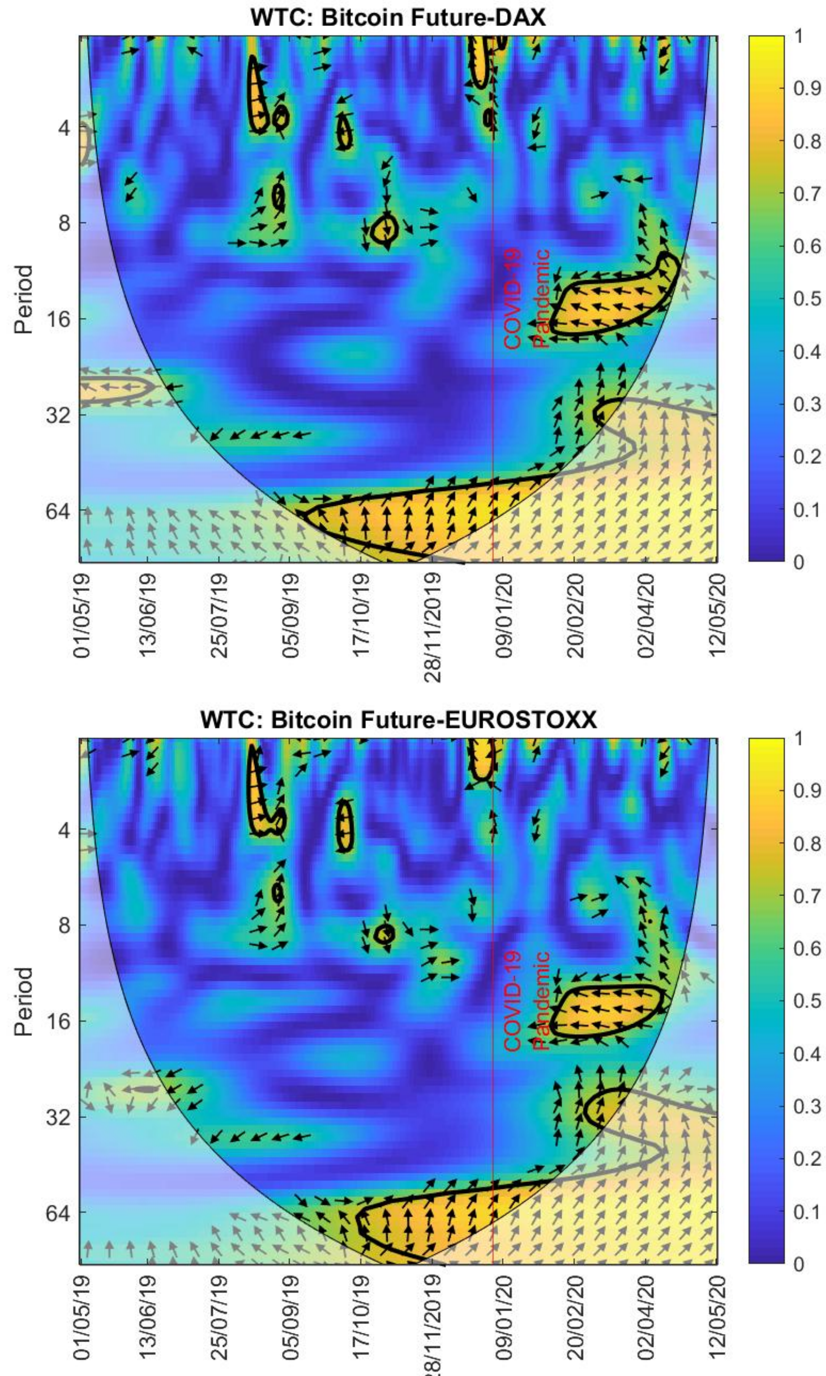


Figure 15: Wavelet coherency (WTC) between Bitcoin future and DAX (up) and EUROSTOXX (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u,s)$.

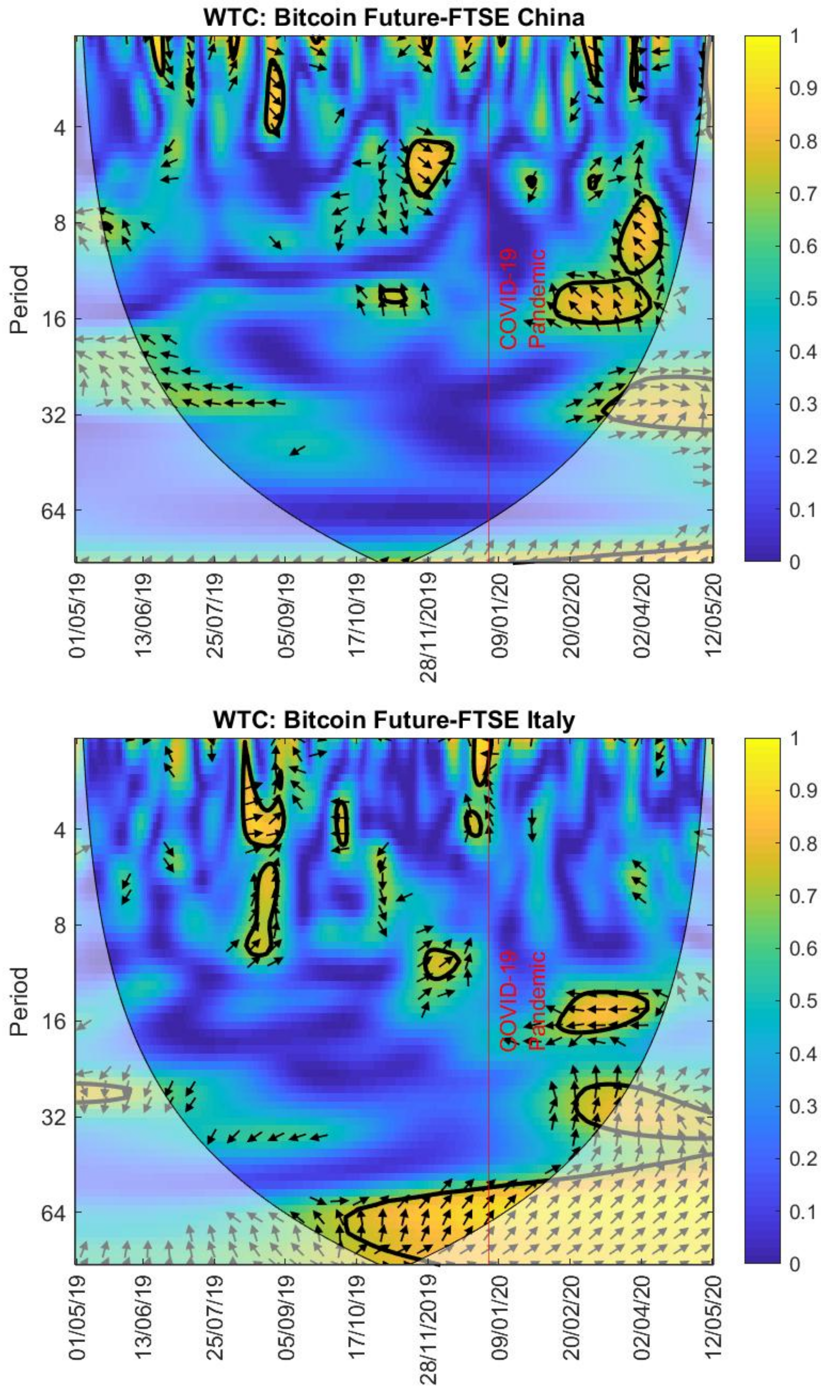


Figure 16: Wavelet coherency (WTC) between Bitcoin future and FTSE Chinq (up) and FTSE Italy (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

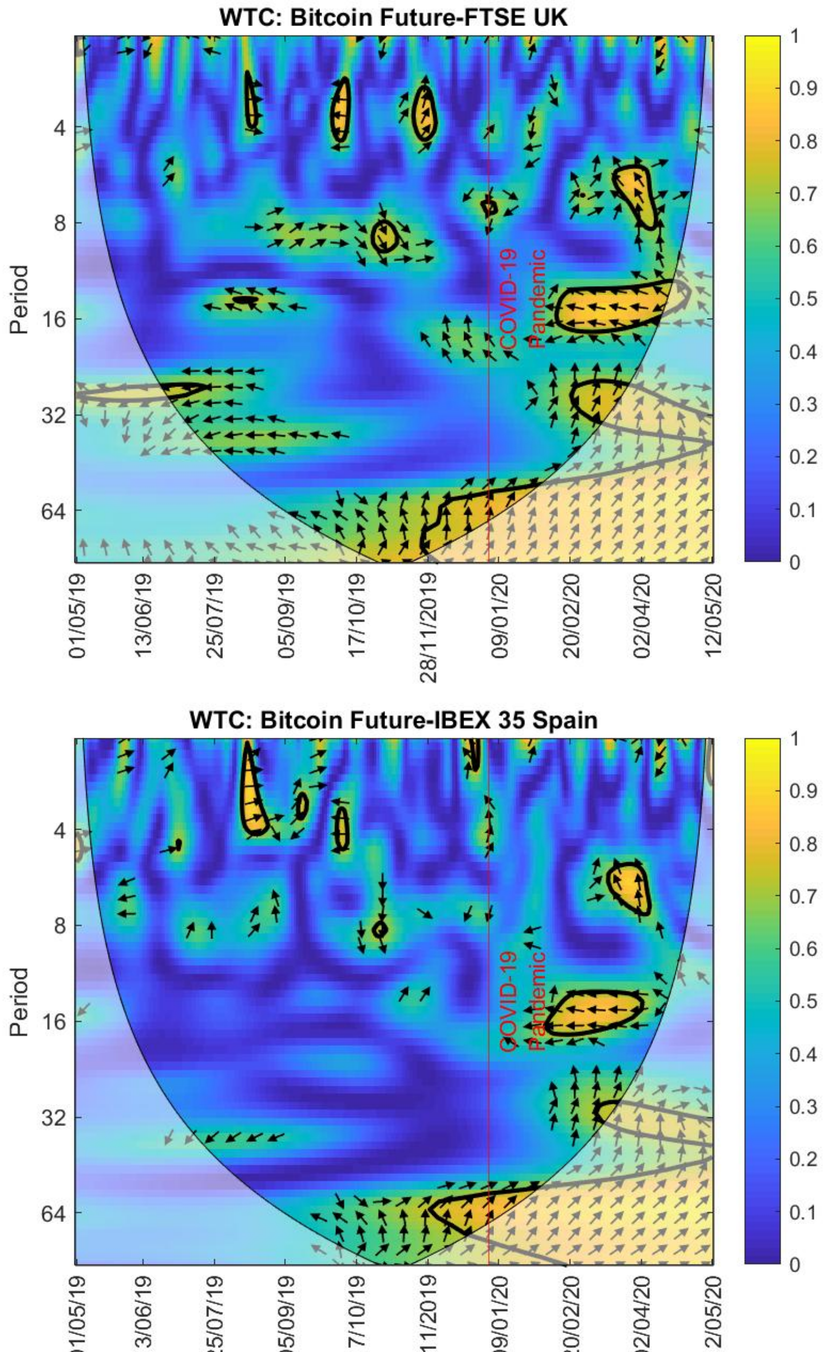


Figure 17: Wavelet coherency (WTC) between Bitcoin future and FTSE UK (up) and IBEX 35 Spain (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

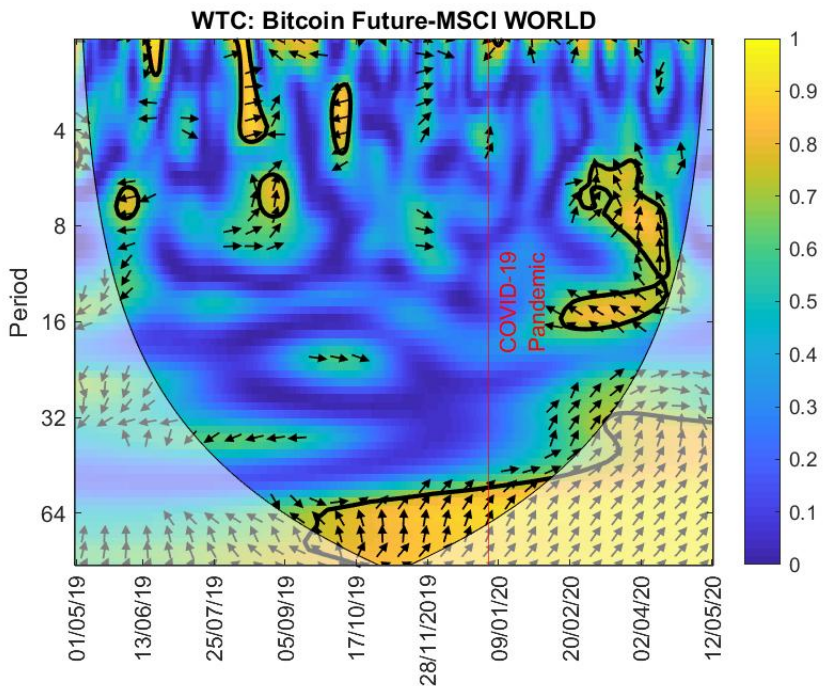


Figure 18: Wavelet coherency (WTC) between Bitcoin future and MSCI World Index. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.

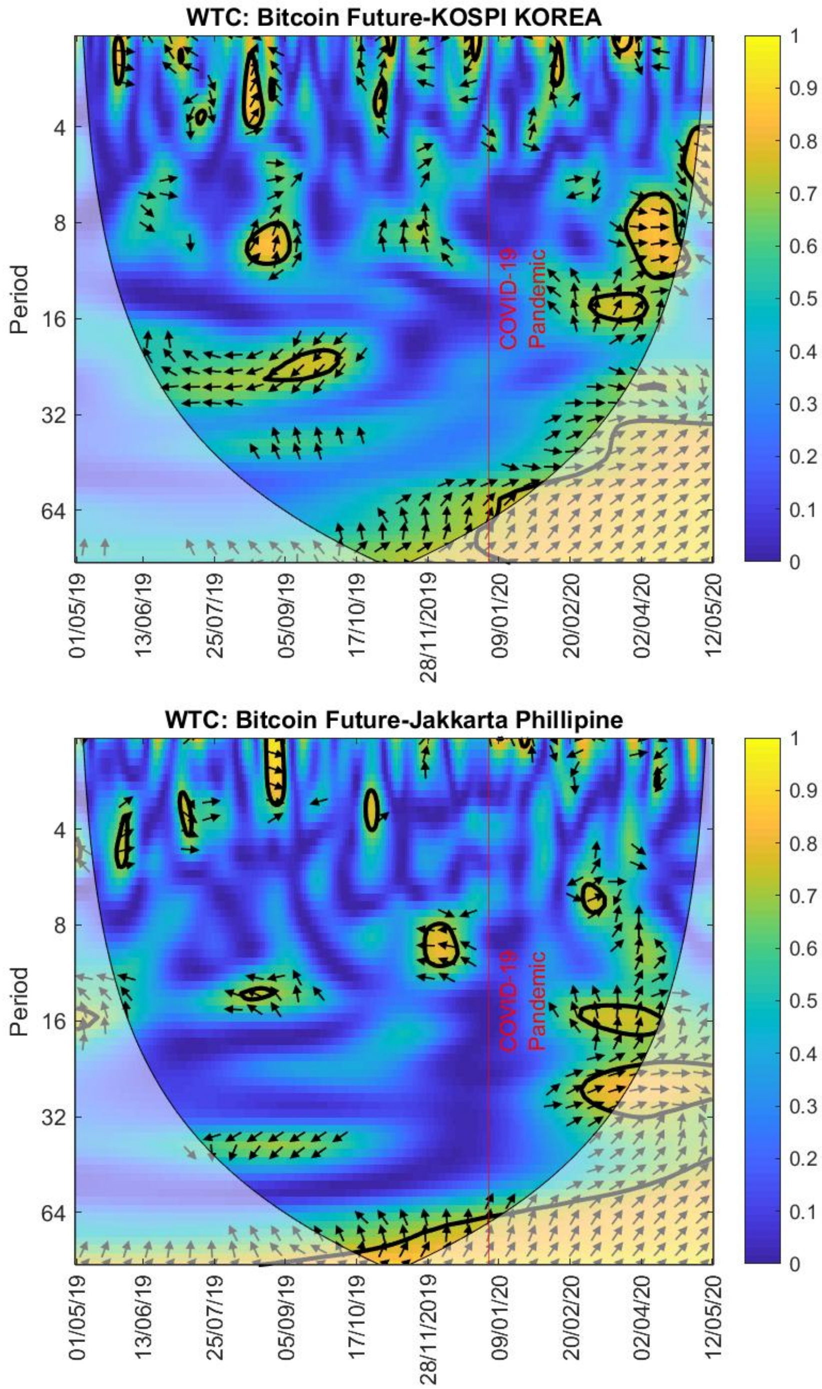


Figure 19: Wavelet coherency (WTC) betweenBitcoin future and KOSPI (up) and Jakkarta (down). The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (yellow)) the higher the absolute correlation value with respect to $R^2(u, s)$.