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# Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic

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## ABSTRACT

This research examines the behaviour of cryptocurrencies and stock markets during the COVID-19 pandemic through the wavelet coherence approach and Markov switching autoregressive model. Our results show a financial contagion in March, since both cryptocurrency and stock prices fell steeply. Despite this turn-down, cryptocurrencies promptly rebounded, while stock markets are trapped in the bear phase. In other words, we observe that the price dynamics during the pandemic depends on the type of the market. These findings are relevant for investors since some hedging properties can be found in the cryptocurrency response to such a drastic event.

## 1. Introduction

Cryptocurrencies have attracted the attention of many scholars and policy-makers since the creation of the first digital currency, Bitcoin. Compared to the fiat currencies, this disruptive payment method does not require any bank intermediation, given that digital currencies are based on cryptographic technologies, i.e. they are decentralized in production and circulation. As a consequence, cryptocurrencies (i) cannot be controlled by any government or central bank, and (ii) are not connected with the real economy.

Given these particular features, cryptocurrencies could be considered as perfect diversifiers during downturns or periods of high uncertainty, since public companies and fiat currencies are strictly connected with the state of the economy. For instance, public companies could suffer from a decrease in their stock prices due to multiple reasons that do not affect cryptocurrencies, such as poor management decisions, financial constraints, client loss and shifts in consumer preferences. In the same vein, the future of fiat currencies is related to their corresponding countries, thus they are vulnerable to any macroeconomic and political factor that destabilise the proper growth of the economy. However, the price evolution of cryptocurrencies is mainly connected with the behaviour of the traders and separated from any economic fundamental value, such as unemployment, production or consumption. This fact was demonstrated by Baek and Elbeck (2015), who contended that “Bitcoin market returns are mostly internally driven by market participants” (Baek and Elbeck, 2015, p. 33). The only connection of cryptocurrencies with the real economy is the fiat currency in which

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they are expressed.<sup>1</sup> This connection would be relevant if cryptocurrencies were related to central bank policies or other exchange rates.<sup>2</sup> Nevertheless, cryptocurrencies seem not to be correlated to international exchange rates (Baur et al., 2018; Corbet et al., 2018) and scholars are not able to find significant relations between the cryptocurrency behaviour and monetary policies (see Feng et al., 2018; Vidal-Tomás and Ibañez, 2018; Nguyen et al., 2019; Lyócsa et al., 2020).<sup>3,4</sup> Therefore, digital currencies are ideal candidates to reduce financial risks during periods of financial instability.

As highlighted by Goodell (2020), the ongoing COVID-19 pandemic represents a serious event affecting the worldwide economy.<sup>5</sup> In this unprecedented situation, scholars studied whether cryptocurrencies could be used as optimal instruments to diversify investors' portfolio.<sup>6</sup> More specifically, Conlon and McGee (2020) showed that Bitcoin cannot be used as a safe-haven for the SP 500; and Corbet et al. (2020) observed an increase in the dynamic correlations between Bitcoin and traditional markets. Given these results, cryptocurrencies should not be considered as suitable alternatives for diversifying portfolios. However, given that cryptocurrencies are not related to the real economy by design, one question arises: Why cryptocurrencies should be affected by the COVID-19 pandemic in the same way as (or more than) the traditional stock markets? Publicly companies will suffer a decrease in stock prices due to the effect of the lock-downs and mobility restrictions on their future sales and profits. Nevertheless, cryptocurrencies could be only affected by the panic and fear of investors.

In the empirical section of this paper, we hypothesise that cryptocurrencies only suffered a short period of financial panic during the COVID-19 pandemic, whose effect disappeared faster than in the traditional stock markets due to the absence of a connection between digital currencies and the real economy.

To support this hypothesis, we analyse the behaviour of Bitcoin and Ethereum, as main cryptocurrencies, and SP500 and Euro Stoxx 50, as main stock indices, focusing on the returns dynamics by means of the wavelet coherence approach (Kang et al., 2019, Sharif et al., 2020 and Goodell and Goutte, 2020) and Markov switching autoregressive model (Krolzig, 2013). With these two methods, we study the (de)synchronization between cryptocurrencies and stock markets time series by comparing (i) their correlation in time-frequency domain and (ii) the transitions of their market regimes. Our contribution to the literature is twofold. On the one hand, the wavelet approach underlines that the main correlation between these assets is only found in the three first weeks of March, both at high and low frequencies (daily and monthly). On the other hand, the Markov switching autoregressive model highlights the robustness of cryptocurrencies in front of the pandemic due to their fast recovery, i.e. Bitcoin and Ethereum are most of the time found in a bull market. These results are relevant for scholars and investors since it demonstrates the absence of a relationship between cryptocurrencies and the real economy as long as the hedging properties of cryptocurrencies.

## 2. Literature review

Before moving to the empirical analysis, it is interesting to discuss how cryptocurrencies can be used in a global financial system that, even in the past, has shown its own flaws.

### 2.1. Hedging the equity risk during financial crises

The analysis of the correlation among different asset returns has traditionally been employed to define portfolio systematic risk (Chua et al., 1990) and different investment diversification strategies due to the benefits of using uncorrelated financial instruments (Abanomey and Mathur, 1999). However, the international propagation of the financial crisis during the Great Recession underlined the difficulties of risk managers in an interconnected world. In particular, during this period, risk managers and investors could not benefit from the international diversification (Melvin and Taylor, 2009) since market crashes gave rise to high market correlations because of the loss aversion of traders (Tversky and Kahneman, 1986). Such drastic event exhibited the flaws of a global financial economy and the difficulties of describing properly a complex and interconnected system (Sinclair, 2010; Preis et al., 2012). The best example of this global financial interconnectedness is found on the outburst of the United States sub-prime mortgage crisis -where it all began-, which could lead to the European sovereign debt crisis (Moro, 2014; Gruppe et al., 2017; Wegener et al., 2019). In other words, the collapse of the housing bubble in US could give rise to the collapse of the banking system in several Eurozone member states (Greece, Portugal, Ireland, Spain and Cyprus). Interestingly, in both cases, the macroeconomic conditions of *one area* affected the

<sup>1</sup> For instance, BTC/USD (e.g., the Bitstamp exchange platform), BTC/JPY (e.g., the Zaif exchange platform) and BTC/KRW (e.g., the Bithumb exchange platform). Please, note here that USD, JPY and KRW refer to US dollar, Japanese yen and South Korean won, respectively. Investors can use different exchange platforms according to the fiat currency.

<sup>2</sup> For instance, this connection would be important if cryptocurrencies reacted to the devaluation or revaluation of any fiat currency.

<sup>3</sup> Considering the direct relationship between country-specific monetary policies and their fiat currencies, (Kurov and Stan, 2018), Bitcoin (e.g. BTC/USD) should be affected by the monetary policies of United States given that it is expressed in USD. However, and interestingly, scholars have not been able to observe this result. The absence of this logical relationship could be related to unknown Bitcoin properties that neutralise the effects of these policies. Therefore, scholars should address this point in future research in order to shed more light on this field.

<sup>4</sup> Roughly speaking, international exchange rates compare the economic strength between two economies (e.g., USD/EUR). However, in the case of cryptocurrencies, the exchange rate only expresses the value of the digital currencies in terms of an alternative fiat currency (e.g., BTC/USD). Hence, digital currencies are more similar to commodities (e.g., gold, silver, crude oil, or natural gas) than fiat currencies.

<sup>5</sup> See Yarovaya et al. (2020) for a recent review related to COVID-19 research.

<sup>6</sup> The following section briefly outlines key studies regarding this aspect, highlighting how cryptocurrencies could be potential alternative investments in a risk-sharing interconnected world.

behaviour of *all the stock markets* with no exception, giving rise to a synchronised decrease in prices during the previous two crises (Vidal-Tomás and Alfarano, 2020).<sup>7</sup>

Within this framework, in an ever-evolving world, the risk of a new systemic collapse is always present and COVID-19 introduced an unprecedented crisis that immediately infected the entire economic and financial structure. During the previous crises, asset managers could not consider the role of cryptocurrencies in portfolio diversification, as their use in the international financial scenario was marginal due to the lack of knowledge about the cryptocurrency market. However, given the increasing number of cryptocurrency studies, the impact of the digital currencies on international finance is now far from being negligible. Indeed, the emergence of some hedging properties is still a recurrent object of research. For instance, Chan et al. (2019) found that Bitcoin is a strong hedge for several stock market indices using monthly data, while Pal and Mitra (2019) observed that gold provides investors with a better hedge against Bitcoin. Therefore, the COVID-19 pandemic is an important event that allows us to (i) shed some light on the strengths and weaknesses of cryptocurrencies and (ii) to analyse their ability to reduce losses when using as a diversifier in a synchronized international system.

### 3. Data

The data that has been used for this study is sourced from Yahoo Finance in daily frequency. In particular, to analyse the different behaviour of cryptocurrencies and stock indices during the spread of the pandemic, we use SP500, Euro Stoxx 50<sup>8</sup>, Bitcoin and Ethereum.<sup>9</sup> We consider the first two indices as proxies of the western financial markets' dynamics, namely, USA and Europe. Moreover, we analyse the exchange rate of Bitcoin and Ethereum as proxies of cryptocurrencies' behaviour since they are the largest cryptocurrencies of the market. In relation to the sample period, we are focused on the period 1/11/2019 – 01/06/2020, thus we can assess the evolution of these assets before and during the pandemic. Finally, for the empirical analysis of this letter, we compute returns as the log price difference.

In Table 1, we show the descriptive statistics of returns. As expected, the cryptocurrency market is characterised by a higher standard deviation, skewness and kurtosis, given its well-known explosive behaviour (Corbet et al., 2019). However, we observe that the average return is lower in the stock markets than in the cryptocurrency market, which highlights the good performance of Bitcoin and Ethereum during this period compared to SP500 and Euro Stoxx 50.<sup>10</sup>

To analyse properly the diverse price dynamics, we report in Fig. 1 the normalised price of each index, in which we divide the time series by the maximum price of the sample period. We observe on March 12th (grey vertical line) the minimum return in Bitcoin (– 46.47%), Ethereum (– 55.07%) and Euro Stoxx 50 (– 13.24%), while SP500 suffered its second worst day with a return equal to – 9.99% (see Table 1).<sup>11</sup> On this day, the financial panic was spread in most of the markets, probably, as a consequence of the insufficient measures taken by the European Central Bank (ECB hereafter) in response to the COVID-19 pandemic (Inman, 2020). Computing the average price before March 12th (dotted lines), we note that Bitcoin and Ethereum prices easily recovered from the financial panic period, while stock market prices continue to be affected by the restrictive measures adopted to tackle the health emergency, highlighting only a timid recovery. In other words, cryptocurrencies prices went up above their average price computed before March 12th (dotted lines) while, as can be observed in Fig. 1, stock markets are stuck below their average.

### 4. Methodology

As anticipated in the introduction, to analyse the behaviour of cryptocurrencies and stock markets we employ the wavelet coherence approach and the Markov switching autoregressive model.

#### 4.1. Wavelet coherence approach

We use the wavelet coherence approach by means of the continuous wavelet transform, in order to analyse the co-movement between time series, both in time and frequency domain (see Kang et al., 2019, Sharif et al., 2020 and Goodell and Goutte, 2020).

According to Torrence and Compo (1998), the cross wavelet transform of two time-series  $x_t$  and  $y_t$  is defined by means of the continuous wavelet transform  $W_n^x(u, s)$  and  $W_n^y(u, s)$ , as follows:

$$W_n^{xy}(u, s) = W_n^x(u, s) * W_n^y(u, s) \quad (1)$$

<sup>7</sup> This international scenario underlines the concept *global financial village* proposed by Kenett et al. (2012).

<sup>8</sup> We use the Euro Stoxx 50 index since (i) it is the most used in the literature (e.g., Brechmann and Czado, 2013; Chen et al., 2018) and (ii) it represents the largest companies in the Eurozone. At any rate, using the Euro Stoxx index that includes 295 constituents, according to the official website ([www.stoxx.com](http://www.stoxx.com)), we observe very similar results. Thus, we obtain consistent outcomes even when using an alternative index that represents large, mid and small capitalisation companies of the Eurozone (material upon request).

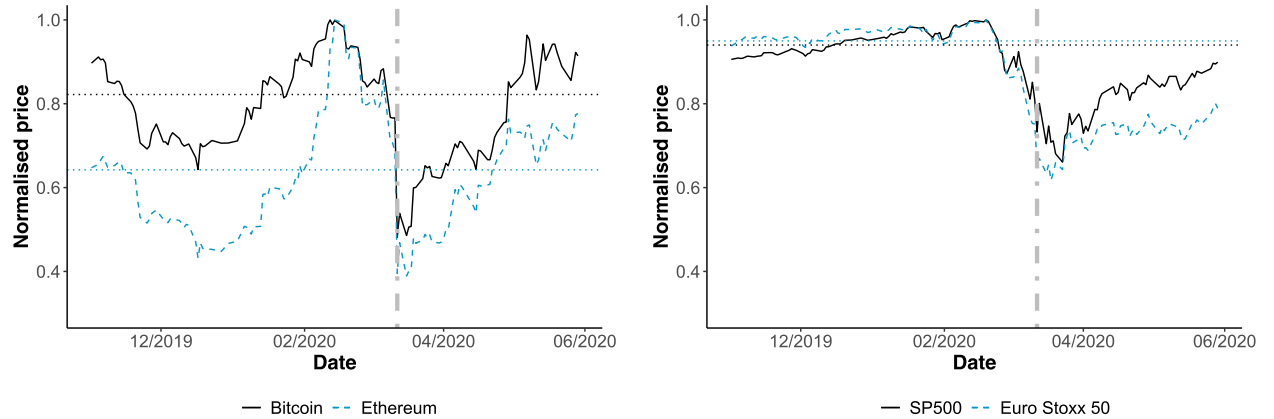
<sup>9</sup> With regard to the SP500 and Euro Stoxx 50 indices, we use adjusted prices in order to include the dividends that are paid to investors.

<sup>10</sup> Within the framework of the efficient market hypothesis proposed by Fama (1965), returns include all the public and private information regarding the equity value and performance of the firms in the economy. Thus, the low average return in the stock markets represents the low expectations of the traders in the economy, since investors anticipate a decrease in firm sales and profits due to the government measures to face COVID-19.

<sup>11</sup> In the case of SP500, the minimum return is found on March 14th (– 12.77%).

**Table 1**  
Descriptive statistics.

Financial market	Mean	S.D.	Skewness	Kurtosis	Minimum	Maximum
Bitcoin	0.0001	0.0568	- 3.9133	32.8238	- 0.4647	0.1671
Ethereum	0.0013	0.0710	- 3.3960	26.8767	- 0.5507	0.1742
SP500	- 0.0001	0.0269	- 0.6737	6.0920	- 0.1277	0.0897
Euro Stoxx 50	- 0.0013	0.0238	- 1.3798	8.2889	- 0.1324	0.0883



**Fig. 1.** Normalised price of cryptocurrencies (Bitcoin and Ethereum) on the left panel, and stock markets (SP500 and Euro Stoxx 50) on the right panel. The vertical grey line indicates the most negative day of the sample: March 12th. The dotted line refers to the average return computed before March 12th.

where  $u$  is associated to the location,  $s$  to the scale and  $*$  denotes the complex conjugate. This measure identifies areas in the time-frequency domain where prices show a high common power. In other words, it shows the local covariance between the time series at each scale.

Having computed the cross wavelet transform, the wavelet coherence, which captures the co-movement between two time series in the time-frequency domain, is defined as:

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

where  $S$  is a smoothing operator over time as well as scale, and  $0 \leq R^2(u, s) \leq 1$  (Rua and Nunes, 2009). Values close to 0 indicate the absence of correlation, while values close to 1 indicates a high correlation. Nevertheless, unlike the standard correlation coefficient, the wavelet squared coherence is restricted to positive values. As a consequence, it is not possible to identify positive and negative co-movements properly. To overcome this issue, we employ the phase difference proposed by Torrence and Compo (1998) that allows us not only to distinguish between positive and negative co-movements but also to shed some light on the causal relationships between time series. Wavelet coherence phase difference is defined as:

$$\psi_{xy}(u, s) = \tan^{-1} \left( \frac{\Im\{S(s^{-1}W^{xy}(u, s))\}}{\Re\{S(s^{-1}W^{xy}(u, s))\}} \right) \tag{3}$$

where,  $\Im$  and  $\Re$  are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. In the figures that report the wavelet coherence analysis, arrows indicate phase differences, which underlines the synchronization between the two series. On the one hand, arrows pointing to the right (left) indicate time series that are in-phase (out of phase), i.e. they are positively (negatively) correlated. On the other hand, arrows pointing upward indicate that the first time series leads the second; whereas downward pointing arrows indicate that the second time series is leading the first.<sup>12</sup>

<sup>12</sup> For the sake of space, and given the purpose of this study focused on co-movements between time series, we only report the wavelet coherence results, omitting the cross wavelet transform (material upon request).

## 4.2. Markov switching autoregressive model

Following Krolzig (2013), we use the Markov switching autoregressive model of asset returns to examine the hidden regimes of each time series, which is defined as follows:

$$r_t = \mu(S_t) + \sum_{l=1}^L \phi_l(S_t)r_{t-l} + \sigma(S_t)\nu_t \quad (4)$$

$$\nu_t \sim \text{NID}(0, 1), S_t = 1, 2$$

where the unobserved state is governed by a state variable  $S_t$  ( $S_t = 1$  or  $S_t = 2$ ) that denotes the corresponding regime: bull ( $S_t = 1$ ) and bear<sup>13</sup> ( $S_t = 2$ ) market;  $L$  is the number of lags;  $\mu(S_t)$  and  $\sigma(S_t)$  are the conditional mean and variance; and  $\nu_t \sim i.i.d(0, 1)$ .<sup>14</sup> By maximizing the log likelihood, we estimate the transition probabilities:  $P_{1,2}$  ( $P_{2,1}$ ) denotes the transition from a bull (bear) market to a bear (bull) market, while  $P_{1,1}$  ( $P_{2,2}$ ) is the probability of staying in a bull (bear) market. Thus, the probability transition matrix can be written as follows:

$$P \equiv \begin{bmatrix} P_{1,1} & P_{1,2} \\ P_{2,1} & P_{2,2} \end{bmatrix}$$

Finally, for the purpose of this letter, we report the smoothed state probabilities (Kim et al., 1999) that determines the transition between regimes.

## 5. Empirical results

### 5.1. Wavelet coherence approach

Figs. 2 and 3 show the main results of the wavelet coherence analysis. The x-axis indicates the time domain component while the y-axis indicates the frequency component, from lower levels of scale, which refer to high frequency variations (i.e. daily fluctuations), up to higher levels of scale, which refer to low frequency variations (i.e. weekly or monthly fluctuations). The black contours identify regions with a coherence statistically significance at the 5% percentage level. The cone of influence, represented by the grey curve, shows the areas affected by edge effects. Finally, the degree of coherence is related to different colours: from blue (low coherence/co-movement) to red (high coherence/co-movement).

As can be observed in Fig. 2, we can easily identify two zones in which there is a significant high degree of positive co-movement between cryptocurrencies and stock markets, given the red areas and the arrows pointing to the right. On the one hand, at daily frequencies (scale: 0–4), the wavelet coherence analysis underlines a high co-movement during March. In particular, Bitcoin/Ethereum and SP500 are correlated from March 6th to March 18th while Bitcoin/Ethereum and Euro Stoxx 50 co-move from March 3th to March 16th. These co-movements highlight the highest level of uncertainty caused by the COVID-19 pandemic in Europe given the lock-down in Italy (March 9th) and Spain (March 14th) along with the official announcement of the pandemic (March 11th) and ECB measures (March 12th). However, the co-movement at high frequencies disappears from March 18th underlying the different effects of the COVID-19 on cryptocurrencies and stock markets at high frequencies. On the other hand, we can also observe a second region of high co-movement at low-frequencies (scale: 16–36) that lasts over time since February.<sup>15</sup> This second region supports the results observed by Conlon and McGee (2020) and Corbet et al. (2020), in which they highlight the relation between cryptocurrencies and stock markets. Nevertheless, if we compare Figs. 2 to 3, in which we report the internal relation of each type of market (i.e. Bitcoin-Ethereum and Euro Stoxx 50-SP500), it is possible to note that, in Fig. 2, cryptocurrencies and stock markets are only related (over time) at lower frequencies while, in Fig. 3, Bitcoin-Ethereum and Euro Stoxx 50-SP500 are generally related regardless of the time-frequency domain. As we see in the next section, the fact that cryptocurrencies and stock markets are not related for all the time-frequency domain highlights, indeed, their different dynamics. As a consequence, they are not behaving in the same way during this unstable period.

### 5.2. Markov switching autoregressive model

In this section, we use the Markov switching autoregressive model introduced in Sec. (4.2). For the proper specification, we determine the optimum number of lags  $L$  by means of the Bayesian information criterion (BIC): lower BIC implies better fit. As can be observed in Table 2, the lower BIC is identified with one lag. The parameters estimated can be found in Table 3 while we report in Fig. 4 the smoothed transition probabilities from the Markov switching autoregressive model for each time series. The high degree of co-

<sup>13</sup> A bull phase is typically associated with rising prices, contrary to a bear phase that is associated to the decline or stalled period.

<sup>14</sup> For coherence with the methodology literature, we keep in both sections the nomenclature  $S$  to define the smoothing operator (wavelet coherence approach) and regime variable (Markov switching autoregressive model).

<sup>15</sup> In terms of causality, we observe that, at high frequencies, SP500 leads cryptocurrencies since arrows point downward highlighting a contagion from SP500 to cryptocurrencies. This result is less evident in the causal relations between cryptocurrencies and Euro Stoxx 50. On the other hand, at low frequencies, there is not a conclusive causal relation since Bitcoin and Ethereum lead SP500 while Euro Stoxx 50 slightly leads cryptocurrencies.

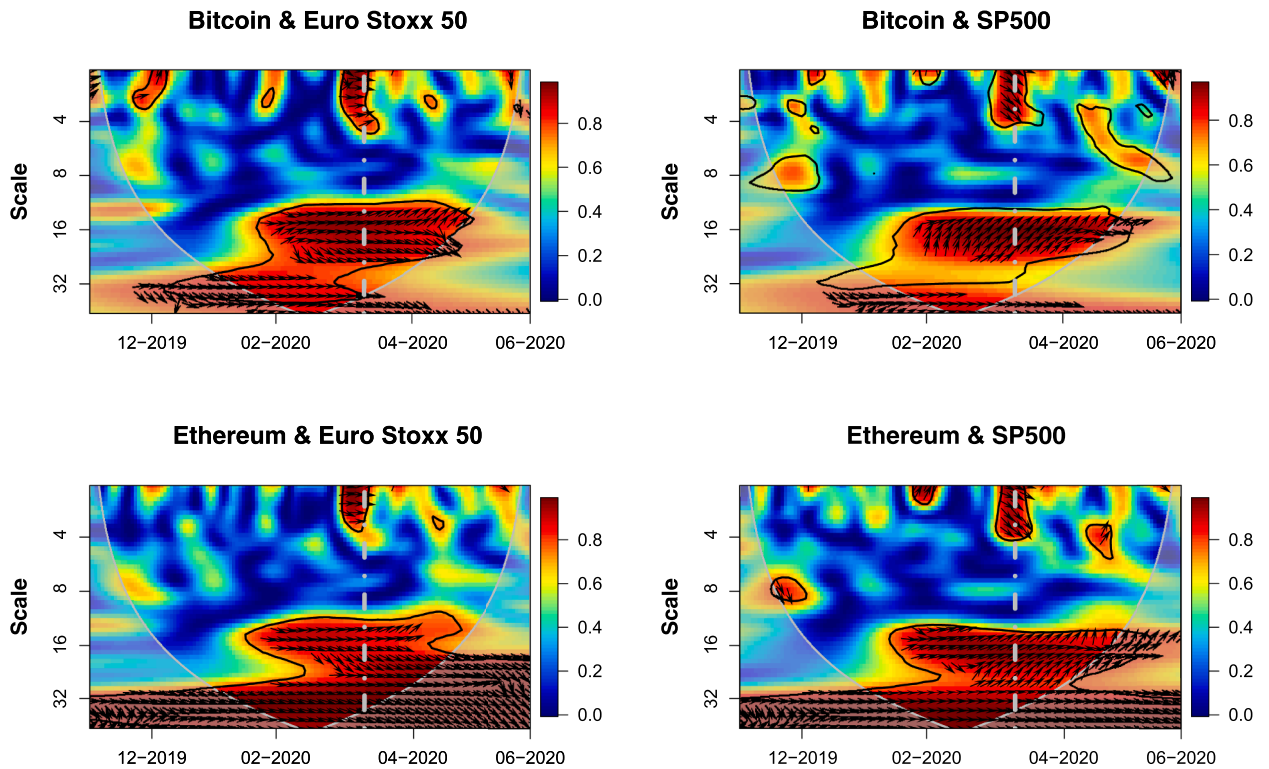


Fig. 2. Wavelet coherence between cryptocurrencies (Bitcoin and Ethereum) and stock markets (SP500 and Euro Stoxx 50). The vertical grey line indicates March 12th as a reference for the highest degree of financial panic.

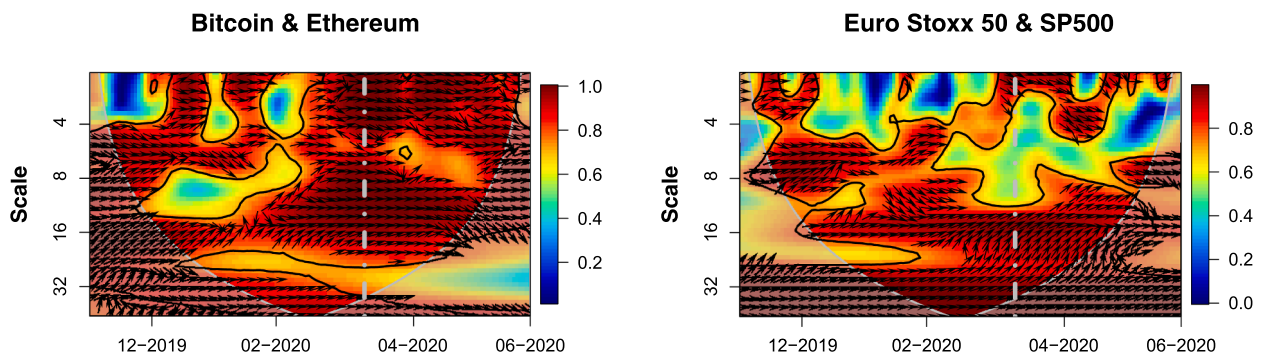


Fig. 3. Wavelet coherence between Bitcoin and Ethereum, on the left, and Euro Stoxx 50 and SP500, on the right. The vertical grey line indicates March 12th as a reference for the highest degree of financial panic.

Table 2

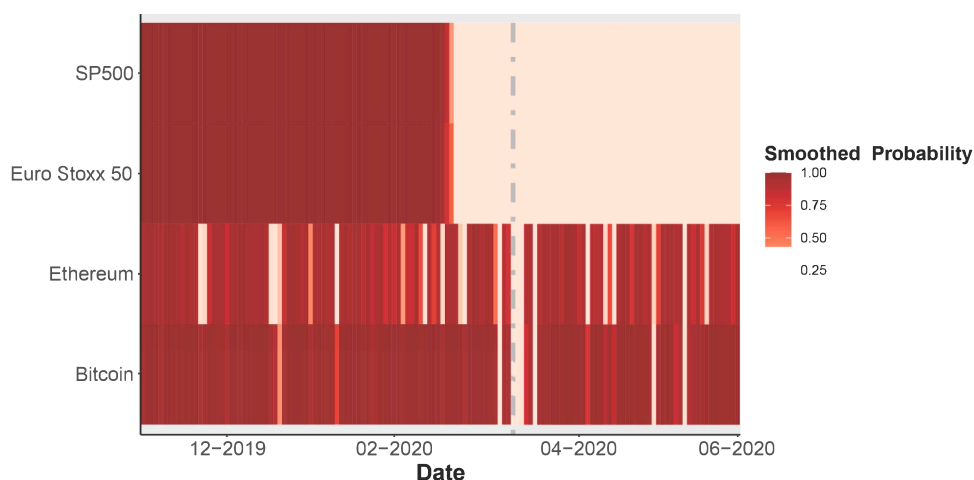
Computation of the Bayesian Information Criterion for lags selection.

Lags	Bitcoin	Ethereum	SP500	Euro Stoxx 50
1	- 449.51	- 392.29	- 725.96	- 691.58
2	- 439.62	- 384.30	- 715.22	- 684.19
3	- 432.89	- 379.26	- 716.38	- 658.40
4	- 425.28	- 357.71	- 660.09	- 662.93

movement observed in Fig. 3 for Bitcoin-Ethereum and Euro Stoxx 50-SP500, regardless of the time-frequency domain, is supported by the Markov switching autoregressive model given that cryptocurrencies and stock prices have their own specific (and different) regime. In other words, the dynamics during the COVID-19 pandemic depends on the type of the market, i.e. cryptocurrencies or

**Table 3**  
Parameters of the Markov switching autoregressive model.

Parameters	Bitcoin	Ethereum	SP500	Euro Stoxx 50
$\mu(S_t = 1)$	0.00054 (0.00142)	0.00538 (0.00150)	0.00150 (0.00043)	0.00069 (0.00046)
$\mu(S_t = 2)$	- 0.00023 (0.00316)	- 0.00344 (0.01265)	- 0.00264 (0.00230)	- 0.00358 (0.00207)
$\phi_1(S_t = 1)$	0.04777 (0.03502)	- 0.04904 (0.02591)	- 0.03877 (0.05412)	- 0.06351 (0.03985)
$\phi_1(S_t = 2)$	- 0.29065 (0.16726)	- 0.26599 (0.10913)	- 0.40504 (0.05774)	- 0.02549 (0.04138)
$\sigma(S_t = 1)$	0.00085 (0.00013)	0.00062 (0.00014)	0.00003 (0.00001)	0.00006 (0.00001)
$\sigma(S_t = 2)$	0.02694 (0.01344)	0.01843 (0.00548)	0.00127 (0.00025)	0.00111 (0.00019)
$P_{1,1}$	0.93169	0.80067	0.98541	0.98592
$P_{1,2}$	0.06831	0.19933	0.01459	0.01408
$P_{2,1}$	0.70842	0.64237	0.00000	0.00000
$P_{2,2}$	0.29158	0.35763	0.99999	0.99999



**Fig. 4.** Markov switching autoregressive model for each time series. The vertical grey line indicates March 12th as a reference for the highest degree of financial panic. A bull market is plotted as dark red (smoothed probability equal to 1) while a bear market is plotted as light red (smoothed probability equal to 0).

stocks.

Focusing on the phase transitions, stock markets changed their state from a bull market to a bear market on February 20th. However, we identify generally a bull market in the case of Bitcoin and Ethereum, with the exception of the period March 9th - March 19th, in which there is a bear market with some rebounds.<sup>16</sup> In other words, in terms of market regimes, the COVID-19 pandemic only affected cryptocurrencies for 10 days while stock markets have been affected since February, i.e. cryptocurrencies perform better in front of the pandemic. This result is supported by Fig. 1, in which the simple normalised price already underlines the fast recovery of cryptocurrencies. Moreover, the period in which Bitcoin and Ethereum changed to a bear market, according to the phase transitions in Fig. 4 (March 9th - March 19th), is similar to the one observed in the wavelet coherence analysis (Fig. 2), when Bitcoin and Ethereum are related to SP500 (March 6th - March 18th) and Euro Stoxx 50 (March 3th - March 16th) both at high and low frequencies. Therefore, to a greater or lesser extent, cryptocurrencies and stock prices are found in the same regime (Markov switching autoregressive model) when they are related both at high and low frequencies (wavelet coherence). In other words, co-movement at low frequencies is not enough to state that cryptocurrencies cannot be used as a hedge since they are characterised by a different dynamics.

<sup>16</sup> Note that Ethereum seems to fluctuate more between the two regimes. However, this period is the longest bear market shared by both cryptocurrencies.



## 6. Conclusion

The ongoing COVID-19 pandemic generated a global stock market crash that began on February 20th 2020, affecting all the financial markets without exceptions due to its effects on the real economy. In this context, scholars studied whether cryptocurrencies could be used as a hedge during the pandemic. However, they observed that cryptocurrencies do not reduce financial risk. Given that by design cryptocurrencies should not be affected by the real economy, we revised the co-movement and hidden regimes of Bitcoin, Ethereum, SP 500 and Euro Stoxx 50 during the pandemic by means of the wavelet coherence approach and the Markov switching autoregressive model. Our analysis highlighted interesting results for investors and scholars.

First, the wavelet coherence approach showed that cryptocurrencies and stock markets co-move over time at low frequencies, however, there was only evidence of co-movement at high frequencies (i.e. daily fluctuations) during the main period of financial panic in March. Second, the Markov switching autoregressive model underlined the fast recovery of the cryptocurrencies in front of the COVID-19 pandemic since their bull market was only interrupted during March 9th - March 19th, while stock markets were found on a bear market since February 20th. In other words, COVID-19 only caused a short-term impact on cryptocurrency dynamics. Therefore, although cryptocurrencies and stock markets are correlated at some specific scales/periods, investors can diversify their portfolios since (i) the co-movement is not observed for all the frequency-time domain and (ii) they are found on different market phases during the pandemic.

## CRedit authorship contribution statement

**Rocco Caferra:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing. **David Vidal-Tomás:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing.

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