On the dynamic equicorrelations in cryptocurrency market

Abstract

This paper investigates the time-varying co-movements in cryptocurrency market, employing a Dynamic Equicorrelation GARCH (DECO-GARCH) model, before and during the COVID-19 pandemic. Our results suggest that the equicorrelations are time-varying and highly responsive to major events, such as hacker attacks and government bans. The results lend support to the recent claim that interlinkages among cryptocurrencies have become stronger, particularly after mid-2017, with substantially increased trading activity in the market. The equicorrelations reach their peak in March 2020, after the official declaration of the World Health Organization (WHO) that novel coronavirus outbreak becomes a global pandemic, indicating potential contagion effects. We also examine the determinants of the market linkages and find that increased Bitcoin trading volume, attention-driven demand for Bitcoin and risk aversion significantly increase the equicorrelations during the COVID-19 bear market. Our results provide potential implications for investors, traders and policy makers and help improve their understanding of the cryptocurrency market's behavior during times of extreme market stress.

Keywords: Cryptocurrencies; DECO-GARCH; Trading volume; Investor attention

JEL Codes: C32; C58; G19

1. Introduction

Cryptocurrencies that were initially supposed to act as an open-source online payment system turned onto a new asset class with speculative features. As their popularity expands, questions arise relative to whether they constitute an alternative asset class that provides hedging or diversification benefits. The digital coins have become an important investment vehicle due to significant investor and media attention (Symitsi and Chalvatzis, 2019). The market has substantially grown over the past few years and its market value rose above 1 trillion US dollars for the first time in early January 2021 as the COVID-19 pandemic has prompted investors to seek out potential safe-haven assets. In this regard, understanding the cryptocurrency market interdependencies, particularly in times of heightened uncertainty, is of paramount importance for portfolio analysis and risk management as it helps investors develop profitable trading strategies.

Most of the existing studies analyze the co-movements between cryptocurrencies, particularly Bitcoin, and traditional assets, such as bonds and stocks (see among others, Dyhrberg, 2016a; Dyhrberg, 2016b; Bouri et al., 2017a; Corbet et al. 2018; Demir et. al., 2018; Bouri et al., 2019a; Guesmi et al., 2019). These studies document potential hedging ability and diversification benefits of Bitcoin and it is well understood that virtual currencies can add values to traditional asset portfolios. Despite their growing use for investment purposes, there is a limited understanding of how cryptocurrencies interact with each other. The literature on the dynamic linkages among virtual currencies is still in its infancy; only a few studies have recently explored the interdependence among cryptocurrencies and document increased interlinkages among cryptocurrencies over time (Yi et al., 2018; Antonakakis et al., 2019; Ji et al., 2019; Kumar and Anandarao, 2019; Katsiampa et al., 2019). This is the main motivation for our study.

The covid-19 pandemic, which was originated in Wuhan City of China on December 31, 2019, have destabilized the global economy and financial system. 83 million cases and more than 1.8 million deaths have been recorded around the globe until the end of 2020 (Worldometers, 2020). The extended lockdowns caused by the pandemic, triggered an unprecedented drop –on a post-world war context– of the economic activity and to subsequent government driven stimulus packages. The European Central Bank (ECB) on March 18, 2020 launched a new temporary asset purchase program of private and public sector securities of €750 billion, named as a Pandemic Emergency Purchase Programme (PEPP), with an explicit target to "*counter the serious risks to the monetary policy transmission mechanism and the outlook for the euro area posed by the outbreak and escalating diffusion of the coronavirus, COVID-19*".[1] The Federal Reserve of the USA, in its turn, announced a 2 USD trillion stimulus pack in March.[2] Along with the aforementioned, other policy measures were announced by the Central Banks, including policy changes that would sustain the interest rates close or around zero during and post the pandemic.

The extreme market volatility and deteriorated global economy have forced investors to seek shelter from the Covid-19 storm. Even though the COVID-19 and financial markets linkages are somewhat examined in the literature (Al-Awadhi et al., 2020; Ali et al. 2020; Göker et al., 2020; Goodell, 2020; Haroon and Rizvi, 2020; Iqbal et al., 2020; Sharif et al., 2020; Zhang et al., 2020, etc.), the cryptocurrencies dynamics through the Covid-19 outbreak is relatively under-researched (see Corbet et al., 2020; James et al., 2020; Umar and Gubareva, 2020; Shahzad et al., 2021) and most of the relevant academic work focus on Bitcoin rather than the other virtual currencies. Therefore, the existing literature lacks a clear understanding of cryptocurrency market dynamics in the wake of the COVID-19 pandemic. Our paper fills this gap by analyzing the cryptocurrency market integration and its determinants.

As suggested by Conlon et al. (2020), global market turbulence and recession resulting from COVID-19 pandemic represent the first widespread bear market since the trading of cryptocurrencies began. Therefore, the recent pandemic provides us an opportunity to analyze the behavior of cryptocurrencies in times of extreme financial and economic disruption. Given the increased trading volume in digital currencies hitting record highs during the pandemic, it is of particular importance to examine their interactions and market dynamics. More specifically, we attempt to answer the following research questions: (1) To what extent are the leading cryptocurrencies interconnected?, (2) How do the co-movements change over time and how responsive they are to the COVID-19 pandemic? and (3) What are the potential factors, including

[1] ECB announces €750 billion Pandemic Emergency Purchase Programme (PEPP) (europa.eu)
[2] Your Guide To The Federal Stimulus Package (forbes.com)

market microstructure, investor attention, and macro-financial variables, that can affect the degree of cryptocurrency market integration?

In order to address the above questions, we investigate the linkages among six cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Stellar (XLM) and Monero (XMR), using a dynamic equicorrelation GARCH (DECO-GARCH) model, which allows us to estimate higher dimensional systems with computational ease. The DECO model provides a single dynamic correlation coefficient that represents the correlation degree of assets (Yilmaz et al., 2015). Therefore, the DECO model enables us to analyze the market integration among the largest cryptocurrencies by a single number rather than examining each pairwise correlation to explore the market co-movements. Some papers, including Katsiampa (2019), Katsiampa et al. (2019) and Chan et al. (2019), investigate the time-varying co-movements in cryptocurrency market using various multivariate GARCH models such as BEKK-GARCH, DCC-GARCH and ADCC-GARCH. However, these studies explore the pairwise interdependencies while our goal in this study is to see the broader picture under the assumption that all pairwise correlations are equal on a given day but still remain time-varying over time. Thus, we can explore market integration and convergence/divergence of the six largest cryptocurrencies during the entire study period by using a single dynamic equicorrelation coefficient.

Following Ji et al. (2019), we further analyze the determinants of equicorrelations, by running different specifications of regressions, to identify the determinants of cryptocurrency market integration. Ji et al. (2019) investigate the determinants of volatility spillovers across the six largest cryptocurrencies using linear regression models and find that trading volume, financial uncertainties and gold prices are significant determinants of market spillovers. In this paper, we examine the potential factors that may drive the equicorrelation dynamics in cryptocurrency market. Following Ciaian et al. (2018), we also add investor attention measured by each cryptocurrencies' daily Wikipedia searches as an additional explanatory variable, along with trading volume and macro-financial variables. Additionally, making use of interaction variables, we analyze the effects of the variables on digital currency market linkages in the wake of COVID-19 pandemic.

Our main contribution is twofold. To the best of our knowledge, this is the first effort in the existing literature to examine the behavior of cryptocurrencies during the COVID-19 bear market using a single dynamic measure generated from the DECO-GARCH model. Second, our work adds to the growing literature of cryptocurrencies by exploring the potential determinants of intra-cryptocurrency co-movements. Our results show that the estimated equicorrelations are not only time-varying but also substantially responsive to major events, including hacker attacks (Bitfinex hack in August 2016, Coincheck hack in January 2018) and Chinese and Indian government bans on cryptocurrency operations. Mostly importantly, the equicorrelations reach their peak in March 2020 when the WHO declared coronavirus as a pandemic, which suggests potential contagion effects in cryptocurrency markets due to extreme global risk aversion and potential herding behavior of investors. By extending the analysis further, we find that increased investor attention to Bitcoin measured by Wikipedia search intensity, trading volume of Bitcoin and risk aversion (VIX) significantly increase the interlinkages across cryptocurrencies during the COVID-19 pandemic. Macro-financial factors, such as gold, oil exchange rate, stocks and corporate bonds, are not significant drivers of the cross-cryptocurrency co-movements, suggesting that cryptocurrency market integration is not explainable on the basis of fundamental macro-financial factors, even in times of extreme adverse market conditions.

The rest of the paper is organized as follows: Section 2 provides a literature review, Section 3 presents the data and summary statistics, Section 4 describes the methodology, Section 5 contains the empirical results, and finally Section 6 concludes.

2. Literature review

The literature on cryptocurrencies can be divided into two main streams. The first stream relates to the determinants of cryptocurrency prices, while the second one focuses on the return and volatility interactions. It is worth noting that there are also papers analyzing the portfolio performance of cryptocurrencies (see Brauneis et al., 2019; Platanakis and Urquhart 2019a; Platanakis and Urquhart, 2019b; Symitsi and Chalvatzis, 2019, etc.) and their uni-variate volatility dynamics (see indicatively, ; Katsiampa, 2017; Charles and Darné, 2019; Fakhfekh and Jeribi, 2019).

A voluminous body of the existing literature focuses on the determinants of cryptocurrency prices, and mostly on Bitcoin prices. Dyhrberg (2016a) and Dyhrberg (2016b) investigate the relation between Bitcoin, gold, and US dollar, using a GARCH volatility model. The results indicate that Bitcoin can be classified as “something” between gold and the dollar, and possibly provides advantages of a pure medium of exchange and a pure store of value as well. However, Baur et al. (2018) replicate and extend Dyhrberg’s (2016a) study claiming that most of the explanatory variables in the model are not stationary and hence the model is misspecified. Their more robust results show that Bitcoin behaves differently from other financial assets including gold and US dollar in terms of return volatility and correlation characteristics. Demir et al. (2018) explore the prediction power of the Economic Policy Uncertainty (EPU) on Bitcoin returns and conclude that Bitcoin can act as a hedge against the economic uncertainty. In a more recent study, Chan et al. (2019) investigate the hedging ability of Bitcoin and demonstrate that the hedging capacity changes with respect to data frequency. Daily and weekly returns do not show strong hedging performances while monthly frequency can produce effective strong hedging strategy.

Some researchers include different covariates measuring the investor attention. Li and Wang (2017), for example, examine the technology (mining difficulty and Google searches) and the economic determinants of Bitcoin prices using an Autoregressive Distributed Lag (ARDL) model. Their results suggest that prices adjust to changes in economic variables and market circumstances in the short run, while they are more sensitive to economic variables and less sensitive to technology factors in the long run. On the contrary, Ciaian and Rajcaniova (2016) and Ciaian et al. (2016) find that the attractiveness indicators, such as volume of daily Bitcoin views of Wikipedia, are the strongest drivers of Bitcoin price formation. They further note that macro-financial developments do not explain the Bitcoin prices. Similarly, Kristoufek (2013) provide evidence of significant connection between search queries in Google trends and Wikipedia, and Bitcoin prices.

The second main strand of the literature explores the dynamic co-movements among the digitial currencies by employing either multivariate GARCH-BEKK model or Diebold and Yilmaz (2012) spillover index methodology. Katsiampa et al. (2019) investigate the co-movement of eight cryptocurrencies and show that their pairwise price returns are strongly positively correlated. Kumar and Anandarao (2019) provide evidence of significantly increased interlinkages in cryptocurrency markets over time, implying the possibility of turbulence and herding behavior. Ji et al. (2019) analyze the dynamic connectedness and integration using the spillover index technique. Their results suggest the existence of significant interlinkages and volatility transmissions across cryptocurrencies. They further investigate the possible determinants of spillovers and find that trading volume and global financial uncertainty play an important role in explaining the spillovers. Yi et al. (2018) show that the cryptocurrencies are not only tightly interconnected but the "mega-cap" ones are more favourable in propagating volatility shocks to the rest. In a similar study, Antonakakis et al. (2019) show that the dynamic total connectedness across several cryptocurrencies exhibits large dynamic variability, suggesting a cyclical behavior in the transmission mechanism.

Recent literature studying the potential investment benefits of cryptocurrencies cites mixed results. Some recent papers provide evidence that the COVID-19 pandemic has negatively impacted the potential role of cryptocurrencies as diversifying investments; and thus, cryptocurrencies fail to act as a safe-haven during the pandemic. For example, Corbet et al. (2020a) analyze the dynamic correlations between Chinese stock exchanges, gold and Bitcoin, and indicate that investors preference towards gold raises concerns about the final status of cryptocurrencies. A similar conclusion has also been reached by some studies conducted before the pandemic (see, for example, Corbet et al., 2019 and Corbet et al., 2018). Conlon and McGee (2020) document that, in times of increased uncertainty, the digital assets act neither as hedges, nor as safe-havens, but probably as amplifiers of contagion. Conlon et al. (2020) demonstrate that, for the majority of international equity markets they examined, Bitcoin and Ethereum are not safe-haven assets, as opposed to Tether that maintained its peg to the US dollar during the pandemic. Furthermore, Ji et al. (2020) suggest that the validity of Bitcoin as a safe haven investment is weak, however gold and soybean commodity futures are strong safe haven assets during the pandemic.

Some recent studies, on the contrary, claims that cryptocurrencies still exhibit the properties of hedging and safe-haven assets. Corbet et al. (2020b) conclude that the digital assets act as a safe-haven and offer diversification benefits during the pandemic. Similarly, Iqbal et al. (2020) find that some cryptocurrencies, such as Bitcoin and Ethereum, have performed well and provided positive gains during the COVID-19 period. Employing wavelet coherences, Goodell and Goutte (2020) report that the levels of COVID-19 measured by the COVID-19 world deaths lead to an increase in Bitcoin prices. Mariana et al. (2020) suggest that Bitcoin and Ethereum exhibit short-term safe-haven properties with the latter being potentially a better one.

Apart from the studies investigating the hedging and diversification benefits of cryptocurrencies, some recent work analyzes the co-movement dynamics among the virtual assets, including the COVID-19 period in their study samples. Shahzad et al. (2021) examine, via a Markov regime-switching (MS) vector autoregressive with exogenous variables (VARX) model, the daily return spillover among 18 cryptocurrencies. Their results show that the total spillovers abruptly intensify following the outbreak of COVID-19, implying contagion effects. In a more recent study, King and Koutmos (2021) provide evidence of heterogeneity in herding behaviors and feedback effects in digital currency market. They further claim that herding behavior drive the price dynamics, even if cryptocurrencies can be treated as a segmented market. Our study mostly relates to the strand of the literature that examines intra-cryptocurrencies co-movements. Therefore, we contribute to the recent literature by analyzing how the connectedness dynamics across cryptocurrencies has evolved over time and what determines the interlinkages during a very stressful period.

3. Data and Summary Statistics

We use daily price data of six popular and the largest cryptocurrencies in terms of market value, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Stellar (XLM) and Monero (XMR), from August 25, 2015 to December 24, 2020. The selection of the sample period is based on the data availability. The price data are downloaded from coinmarketcap.com and converted into percentage logarithmic returns. All the price variables are denominated in US dollar. Table 1 presents the descriptive statistics and initial test results.

The highest (lowest) average returns are reported for ETH (XRP). The unconditional risk, as proxied by the values of standard deviations, is the highest (lowest) for XLM (BTC). Therefore, in terms of the risk-return profile, BTC provides lesser returns but possess the lowest risk compared to other cryptocurrencies. The skewness values are mostly positive, except for BTC and ETH, and the kurtosis statistics are all greater than three implied by the normal distribution, showing the leptokurtic behavior of the cryptocurrencies' return distributions. The non-normality is also confirmed by JB statistics that reject the null hypothesis of normality.

Table 1. Summary Statistics of Cryptocurrencies

	BTC	XLM	XRP	LTC	ETH	XMR
Mean	0.246	0.224	0.185	0.200	0.324	0.302
Median	0.226	-0.196	-0.234	-0.123	0.042	0.128
Maximum	22.512	72.310	102.736	51.035	30.277	58.464
Minimum	-46.473	-40.995	-61.627	-44.901	-55.071	-49.421
Std. Dev.	3.903	7.368	6.780	5.495	5.985	6.250

Skewness	-0.904	1.977	2.465	0.733	-0.193	0.721
Kurtosis	17.048	21.016	45.238	15.479	10.299	13.190
Jarque-Bera	16309.260 [a]	27655.540 [a]	147003.100 [a]	12834.290 [a]	4342.432 [a]	8609.385 [a]
$Q^2(10)$	71.023[a]	501.815 [a]	269.088 [a]	121.136 [a]	177.298 [a]	177.298 [a]
ARCH (10)	5.585 [a]	40.381 [a]	21.829 [a]	9.550 [a]	11.376 [a]	16.096 [a]
ADF	-45.040 [a]	-41.705 [a]	-27.980 [a]	-44.243 [a]	-43.918 [a]	-46.512 [a]

Notes: (a), (b) and (c) denote statistical significance at 1%, 5%, and 10% levels, respectively. JB stands for Jarque-Bera normality test. Q^2 (10) and ARCH (10) represent the Ljung-Box Q-statistics on the squared returns and ARCH Lagrange multiplier tests up to 10th lag, respectively. ADF denotes the Augmented Dickey Fuller unit-root tests which include both trend and intercept in the equation.

We further investigate whether cryptocurrency returns are suitable for volatility modelling. More specifically, we examine the existence of autocorrelation in squared returns and heteroskedastic (ARCH) effects in the raw return series. The Ljung-Box tests applied in squared returns up to ten lags, $Q^2(10)$, reject the null hypothesis of no serial correlation, providing evidence of significant autocorrelation. ARCH Lagrange Multiplier (LM) test statistics reject the null hypothesis of no ARCH effects, suggesting significant ARCH effects. We also check for the stationarity of the price returns by the unit root test of Dickey and Fuller (1979). The tests reject the null hypothesis of a unit root, suggesting that the price returns of all the cryptocurrencies are stationary.[3] Therefore, the return series are suitable for further modelling and a multivariate GARCH-class model is appropriate to analyze the conditional variances and correlations.

Figure 1 provides a visual representation of the six cryptocurrencies' price (black lines) and return (red lines) evolution over time. The plots demonstrate that the prices follow almost the same pattern. All the digital coins experience substantial price appreciations during late 2017 and significant price falls in early 2018. For example, after reaching its peak of almost $20,000 in late 2017, Bitcoin prices sharply decline to approximately $7,000 by February 2018. Other cryptocurrencies behave in a similar fashion, which gives an evidence of significant linkages, particularly under bullish and bearish market conditions. Furthermore, the patterns of price return series indicate volatility clustering; large (small) changes tend to be followed by large (small) changes, of either sign. The plots provide a visual evidence of heightened volatility in all the return series during 2017 and early 2018 when the trading volume peaked. In addition, a sharp decline in the prices and returns of all currencies is visible during March 2020, and then the market seems to quickly rebound. This suggests that cryptocurrencies move in tandem with global equity markets as their values significantly fall during 2020 stock market crash, known as Black Thursday, casting doubt on the safe haven property of cryptocurrencies.

[3] We further checked the stationarity using breakpoint unit root test of Vogelsang and Perron (1998). The results stay the same and the price returns are stationary.

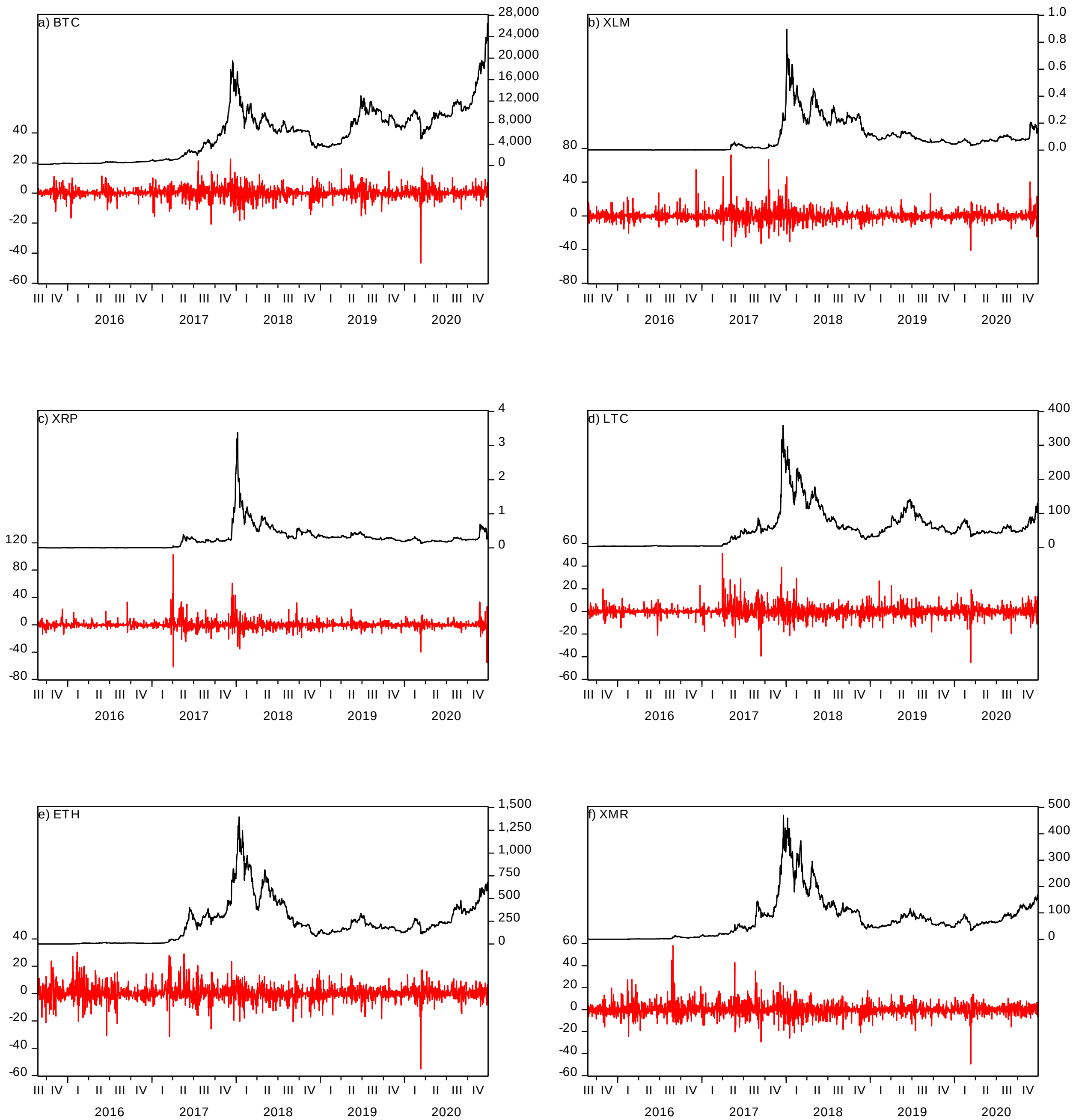

Figure 1. Prices and returns over time

4. Methodology

The Dynamic Equicorrelation (DECO) model of Engle and Kelly (2012) is a special case of the DCC model in which all pairs of cryptocurrencies have the same correlation cross-sectionally but the equicorrelations are dynamic. The DECO model has two stages in the estimation process. The first stage includes the univariate conditional volatility estimation and the second stage estimates the equicorrelations. Note that we employ the GJR-GARCH model of Glosten, Jagannathan, and

Runkle (1993) to capture the asymmetric effects in the first step.4 The return on cryptocurrency i at time t is assumed to have the following dynamic

$$\begin{aligned} r_{i,t} &= \mu_i + \phi r_{i,t-1} + \varepsilon_{i,t} \\ h^2_{i,t} &= \omega_i + \alpha\varepsilon^2_{i,t-1} + \beta h_{i,t-1} + \gamma\varepsilon^2_{i,t-1} I_{t-1} \end{aligned} \tag{1}$$

where $r_{i,t}$ is the cryptocurrency returns and $h^2_{i,t}$ represents the conditional variance. $I_{t-1}=1$ if $\varepsilon_{t-1} <0$ and zero otherwise, α measures the impacts of past squared errors in current level of conditional volatility, and β quantifies the effects of lagged volatility on the current volatility. The model coefficient γ captures the asymmetric effects of negative and positive shocks (news). If $\gamma > 0$, bad news have a greater impact on conditional volatility and if $\gamma < 0$, good news leads to higher volatility.

The conditional covariance matrix H_t can be written as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{2}$$

where $R_t=[\rho_{ij,t}]$ denotes the conditional correlation matrix and $D_t=diag(h_{1,t},\dots,h_{n,t})$ is the diagonal matrix of the conditional variances.

The DECO model is derived from the DCC model of Engle (2002) which has the form of the correlation matrix, Rt^{DCC} as given below:

$$\begin{aligned} R_t^{DCC} &= \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2} \\ Q_t &= (1-\psi-\zeta)K + \psi\eta_{t-1}\eta'_{t-1} + \zeta Q_{t-1} \end{aligned} \tag{3}$$

where ψ and ζ are non-negative scalars satisfying the condition $\psi + \zeta <1$, η_t represents the standardized residuals, i.e. $\eta_{i,t}=\varepsilon_{i,t}/h_{i,t}$ and K is the $n\times n$ unconditional covariance matrix of η_t. $Q_t^* = diag\left(\sqrt{q_{ii,t}}\right)$ represents a diagonal matrix composed of the square root of the diagonal elements of the covariance matrix Q. An element of R_t^{DCC} is:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{4}$$

Following Engle and Kelly (2012), we define the conditional correlation matrix R_t^{DECO} in the equicorrelation form as given below:

$$R_t^{DECO} = (1-\rho_t)I_n + \rho_t J_n \tag{5}$$

where ρ_t is the conditional equicorrelation, I_n represents the n-dimensional identity matrix and J_n is the nxn matrix of ones.

The DECO model sets ρ_t equal to the average DCC correlations and then can be simply written as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(J'_n R_t^{DCC} J_n - n\right) = \frac{2}{n(n-1)}\sum_{i \neq j} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{6}$$

The scalar version of the DECO model can be expressed as:

$$Q_t = (1-\lambda-\pi)K + \lambda \eta_{t-1}\eta'_{t-1} + \pi Q_{t-1} \tag{7}$$

Note that we estimate the model parameters using the quasi-maximum likelihood (QML) estimation, which allows us to obtain asymptomatically robust standard errors in the presence of non-Gaussian error processes. For further details, refer to Bollerslev and Wooldridge (1992).

5. Empirical results

5.1. DECO-GARCH findings

Table 2 presents the estimation results of the first-step univariate AR(1)-GJR-GARCH (1,1)-DECO (1, 1) model. The AR(1) term φ is statistically significant for BTC, ETH and XMR, showing that relevant market information is instantaneously reflected in the prices of these cryptocurrencies. The ARCH *(α)* and GARCH *(β)* parameters are all significant at conventional levels, suggesting strong effects of past shocks and volatilities on the current conditional volatility (Katsiampa, 2019; Fakhfekh and Jeribi, 2019). The asymmetry terms γ are all statistically insignificant, suggesting a symmetric return-volatility relationship. This finding is consistent with Charles and Darne (2019), who replicates the study of Katsiampa (2017), by using the robust QML estimator. In addition, our findings related to the asymmetry stand in stark contrast with the leverage effect and volatility feedback mechanism observed in equity markets.

Table 2 . GJR-GARCH Model Results

	BTC	XLM	XRP	LTC	ETH	XMR
Panel A. GJR-GARCH estimates						
μ	0.214[a]	0.014	-0.093	0.136	0.196[c]	0.219[b]
	(0.063)	(0.132)	(0.091)	(0.096)	(0.108)	(0.103)
φ	-0.019	0.021	0.011	-0.015	0.015	-0.093[a]
	(0.044)	(0.044)	(0.035)	(0.029)	(0.028)	(0.030)
ω	0.772[b]	3.027	3.711[b]	1.254	2.750[a]	1.583[b]

	(0.338)	(1.944)	(1.649)	(0.847)	(0.961)	(0.632)
α	0.156[a]	0.228[a]	0.457[b]	0.076[a]	0.177[a]	0.158[a]
	(0.037)	(0.085)	(0.206)	(0.022)	(0.038)	(0.045)
β	0.793[a]	0.765[a]	0.594[a]	0.894[a]	0.756[a]	0.847[a]
	(0.040)	(0.093)	(0.120)	(0.048)	(0.053)	(0.040)
γ	0.058	-0.063	-0.131	-0.023	0.008	-0.073
	(0.094)	(0.065)	(0.153)	(0.041)	(0.066)	(0.050)
Univariate Diagnostic Tests						
$Q^2(10)$	2.836	1.607	3.617	2.041	3.724	8.698
	[0.985]	[0.998]	[0.962]	[0.996]	[0.958]	[0.560]
ARCH (10)	0.351	0.187	0.440	0.142	0.874	0.913
	[0.966]	[0.997]	[0.927]	[0.999]	[0.557]	[0.520]
Panel B. DECO model estimates						
ρ_{DECO}	0.641[a]					
	(0.130)					
λ	0.093[a]					
	(0.021)					
π	0.899[a]					
	(0.025)					
Multivariate Diagnostic Tests						
Hosking (10)	342.438					
	[0.714]					
Li-McLeod (10)	342.631					
	[0.711]					

Notes: Robust standard errors are in parentheses and the p-values are in the brackets. (a), (b) and (c) denote statistical significance at 1%, 5%, and 10% levels, respectively. Q^2 (10) and ARCH (10) represent the Ljung-Box Q-statistics on the squared returns and ARCH Lagrange multiplier tests up to 10th lag, respectively. Hosking (10) and Li-McLeod (10) are the multivariate versions of Ljung–Box statistic of McLeod and Li (1983), up to 10 lags.

The diagnostic test results show that all the univariate models pass the relevant tests. The Ljung-Box tests fail to reject the null hypothesis of no serial correlation and the ARCH LM tests fail to reject the null hypothesis of homoscedasticity. Therefore, the standardized squared residuals do not exhibit any serial correlation and the ARCH LM tests do not give any evidence of remaining ARCH effects, indicating that the univariate models are well specified.

Table 2 also reports the parameters of the second step in the DECO model. All the DECO model estimates are statistically significant, suggesting a substantial time-varying co-movement across cryptocurrencies. The coefficient of average equicorrelation ρ_{DECO} is 0.641. The parameter λ of standardized residuals is positive and statistically significant at the 1% level, suggesting important effects of shocks on the equicorrelations. The lagged equicorrelation coefficient π is highly significant and around 0.9, showing strong persistence and slow mean-reversion in the time-varying equicorrelations. We also apply multivariate portmanteau tests to check the validity of the DECO model. The Hosking and Li-McLeod tests do not reject the null hypothesis of no serial correlation in the multivariate model, providing evidence of well-specification. Taken together, the statistical significance of the estimates and the diagnostics tests confirm our use of the DECO-GARCH model.

Figure 2 displays the time evolution of dynamic equicorrelations. The fitted equicorrelations vary approximately between 0.04 and 0.98. Starting at a value around 0.6 at the beginning of the sample period, the equicorrelations almost reach 0.98 towards the end of the study period. The equicorrelations have an upward trend over time; they significantly increase and remain very high after mid-2017. The surge in trading activity of the digital currencies, particularly from institutional investors after 2017, might lead to stronger interdependencies. As shown by the strengthened DECOs over time, cryptocurrencies have become more integrated, which supports the recent findings of Katsiampa et al. (2019), Ji et al. (2019), Kumar and Anandarao (2019) and Demiralay and Bayraci (2020). The heightened equicorrelations also highlight the diminished diversification benefits of cryptocurrencies through time.

The equicorrelations significantly strengthen in some sub-periods. Sudden increases in correlations coincide with significant incidents. Bitcoin-related news, such as the introduction of the new fork, increase the level of equicorrelations during late 2015. The equicorrelations display a slight but sudden increase with Brexit led to increased risk aversion. It seems that the biggest cryptocurrency heists, such as Bitfinex hack in August 2016 and Coincheck hack in January 2018, undermined public confidence and raised safety concerns, which in turn create closer linkages among cryptocurrencies. The equicorrelations also substantially upsurge when Chinese and Indian governments banned cryptocurrency operations. Cross-cryptocurrency correlations reach their peak (almost 0.98) early March when the WHO declared that COVID-19 can be characterized as a pandemic. The market seems to decouple after the first shock of the pandemic until two large cryptocurrency exchanges, Coinbase and Binance, experienced technical problems with their services in early September, leading to a market crash. At that time, Bitcoin saw the biggest price drop since Black Thursday.

To sum up, our findings provide evidence of contagion and potential herding behavior as the equicorrelations display significant increases during market turmoil, which confirms the findings of Kumar and Anandarao (2019) and Antonakakis et al. (2019). Ji et al. (2019) argue that the majority of the traders in the cryptocurrency market are young and inexperienced individual investors, who can mimic trading strategies of other investors, particularly under the periods characterized by uncertainty. Bouri et al. (2019b) also claim that dispersion of information, that makes cryptocurrency investors expect more likely extreme outcomes than moderate ones, characterizes the decision-making process in the market. In addition, the DECO measure of co-movements across the digital currencies reaches its highest point in the wake of COVID-19, showing that cryptocurrencies recoupled during the pandemic. This suggests that cryptocurrencies may provide diminished diversification benefits during COVID-19 bear market, which is somewhat in parallel with Corbet et al. (2020) and Conlon and McGee (2020) who find that cryptocurrencies, particularly Bitcoin, may not display characteristics of hedge or safe-haven assets but rather act as amplifiers of contagion in times of significant financial and economic disruption.

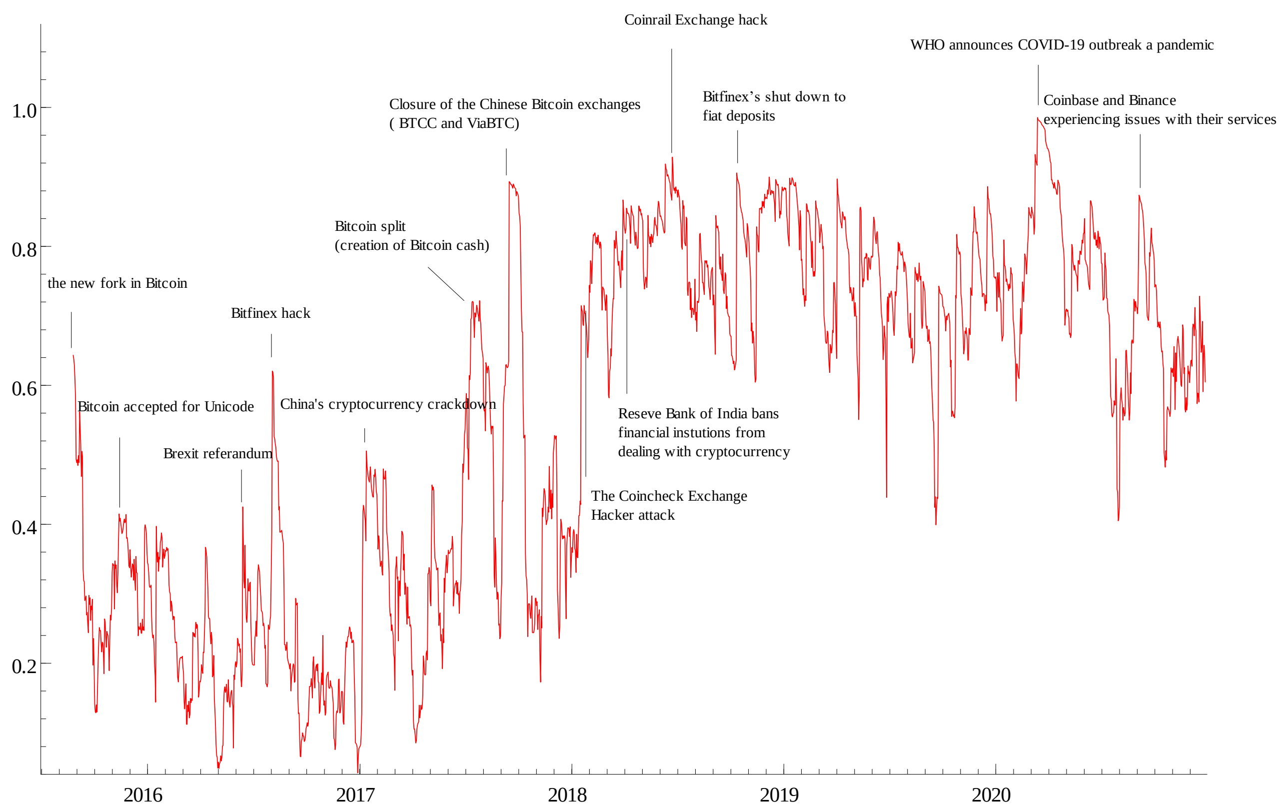

Figure 2. Dynamic Equicorrelations

5.2 Determinants of Equicorrelations

Having found time-varying linkages across cryptocurrencies, we further investigate what explains the evolution of the equicorrelations. To this end, we perform multiple linear regression analysis and run OLS regressions using Newey-West robust estimator. We apply a Fisher transformation on the estimated DECOs in order to ensure that the DECOs are not confined to the interval [−1,1].[4] We estimate the various specifications of the model given below:

$$\rho_t^{DECO} = \theta_0 + \theta_1\rho_{t-1}^{DECO} + \theta_2 Volume_{i,t} + \theta_3 Wiki_{i,t} + \theta_4 EPU_t + \theta_5 VIX_t + \theta_6 EXC_t + \theta_7 MSCI_t + \theta_8 Gold_t + \theta_9 Oil_t + \theta_{10} Bond_t + \eta_t \qquad (8)$$

where $Volume_i$ is the trading volume for each cryptocurrency, $Wiki_i$ represents Wikipedia search entries, *EPU* and *VIX* denote US economic policy uncertainty (EPU) and US Volatility Index, *EXC* is the spot dollar/euro exchange rate, *MSCI* is the MSCI World stock index, *GOLD*, *OIL* and *BOND* represent spot gold, spot oil prices and the Pimco Investment Grade Corporate Bond Exchange-Traded Fund index, respectively. The selection of the potential explanatory variables is based on the previous literature (see among others Dyhrberg, 2016a; Dyhrberg 2016b; Ciaian and Rajcaniova, 2016; Ciaian et al., 2016; Ji et al. 2019). Note that non-stationary explanatory variables are converted to the first differences to achieve stationarity.[5]

We also analyze how each predictor given above affects the dynamic equicorrelations. Accordingly, we use a dummy variable, $D_{COVID\text{-}19}$, which equals to one for the COVID-19 period between March 11, 2020 and December 24, 2020 and zero otherwise. Since we are interested in the impacts of predictors during the COVID-19 bear market, we run linear models containing the interaction terms with the dummy variables as given below:

$$\begin{aligned}\rho_t^{DECO} = \theta_0 + \theta_1\rho_{t-1}^{DECO} + \theta_2 Volume_{i,t} + \theta_3 Wiki_{i,t} + \theta_4 EPU_t + \theta_5 VIX_t + \theta_6 EXC_t + \theta_7 MSCI_t \\ + \theta_8 Gold_t + \theta_9 Oil_t + \theta_{10} Bond_t + \theta_{11} Volume_{i,t} D_{COVID-19} \\ + \theta_{12} Wiki_{i,t} D_{COVID-19} + \theta_{13} EPU_t D_{COVID-19} + \theta_{14} VIX_t D_{COVID-19} \\ + \theta_{15} EXC_t D_{COVID-19} + \theta_{16} MSCI_t D_{COVID-19} + \theta_{17} Gold_t D_{COVID-19} \\ + \theta_{18} Oil_t D_{COVID-19} + \theta_{19} Bond_t D_{COVID-19} + \eta_t\end{aligned}$$

Table 4 reports the estimated coefficients. Models I and II examine the impacts of each cryptocurrency's trading volume on the adjusted equicorrelations, excluding and including the interaction terms, respectively. The parameters are statistically significant in the cases of Bitcoin BTC_{Volume}, Monero XMR_{Volume} and Stellar XLM_{Volume}, with mixed signs. Specifically, it is positive for Bitcoin and Stellar and negative for Monero. The regression coefficients BTC_{Volume} are much larger in magnitude than the others, suggesting that the increased trading demand for Bitcoin significantly strengthens the market linkages and may lead to contagion in the cryptocurrency market. Capturing

[4] Fisher transformation is applied as: $adjusted\ DECO_t = log((1+\rho_t)/(1-\rho_t))$, where ρ_t is the dynamic equicorrelations.

[5] For the sake of brevity, we do not include the descriptive statistics and stationarity tests of the explanatory variables. It is worth-noting that Phillips-Perron unit-root tests with trend and intercept show that all the trading volumes, Wikipedia searches and EPU and VIX are stationary at levels, hence we take the logarithm of these variables. EXC, GOLD, MSCI, OIL and PIMCO are non-stationary and we use the first-difference of these variables accordingly. For interested readers, all the relevant results are available upon request.

the interactions, Model II shows that only the coefficient $BTC_{Volume}*D_{COVID\text{-}19}$ is statistically significant. The parameter is positive, showing that, during the COVID-19 pandemic, Bitcoin's trading volume has significantly increased the equicorrelations. The trading volumes of other digital currencies do not have any significant impact on the equicorrelations, implying that demand for cryptocurrencies, except for Bitcoin, does not drive the market interlinkages in the wake of COVID-19.

These findings support the results of Ji et al. (2019) who attribute the mixed impact of trading volume to volatility spillover effects and transaction costs. Ji et al. (2019) argue that the cryptocurrency market stability may increase, if transaction costs are lower as a result of higher algorithmic trading activity. However, as found in Yang (2018), particularly Bitcoin market is dominated by overconfident noise traders who create a risk for the fundamental traders, which partly relates to our findings too. Our results are also in line with Bouri et al. (2019c) who document the importance of trading volume to predict extreme negative and positive returns of cryptocurrencies. Last but not least, Koutmos (2018) further highlights that microstructure variables, such as number of Bitcoin transactions and number of unique addresses, can provide useful information to explain Bitcoin returns.

Models III and IV quantify the effects of daily Wikipedia views on the equicorrelations. It is worth-noting that Wikipedia searches reflect investor attention. The cryptocurrency market is largely dominated by uninformed noise traders who need basic information about the virtual currencies (Baur and Dimpfl, 2018). Therefore, the frequency of Wikipedia searches can be a good proxy for investor attention (Kristoufek 2013; Ciaian et al., 2016). The models produce positive (negative) statistically significant coefficients for Litecoin $LTC_{Wikipedia}$ (Bitcoin $BTC_{Wikipedia}$ and Stellar $XLM_{Wikipedia}$). Looking at the statistically significant interaction terms in Model IV, we observe that $BTC_{Wikipedia}*D_{COVID\text{-}19}$ and $XRP_{Wikipedia}*D_{COVID\text{-}19}$ are positive and $ETH_{Wikipedia}*D_{COVID\text{-}19}$ and $LTC_{Wikipedia}*D_{COVID\text{-}19}$ are negative. This suggests that increased investor attention to Bitcoin and Stellar leads to higher linkages across cryptocurrencies during COVID-19 bear market. On the other hand, Ethereum and Litecoin Wikipedia searches significantly reduce equicorrelations.

Based on the magnitude of the coefficients, the interaction term $BTC_{Wikipedia}*D_{COVID\text{-}19}$ has a much greater impact on the equicorrelations than the other variables, showing that the increased attention-driven demand for Bitcoin during the COVID-19 period significantly strengthens the connectedness among cryptocurrencies. As suggested by Ciaian and Rajcaniova (2016), the attention effect can be either positive or negative on cryptocurrencies price depending on the type of news. The positive (negative) interaction terms suggest that public attention on Bitcoin and Ripple (Ethereum and Litecoin) tend to increase (decrease) the cryptocurrency market interrelations in times of extreme market stress, reflecting differences in investors' characteristics and sentiments as the crypto markets either recouple or decouple following the searches. In other words, cryptocurrency traders may differ in interpretation of common information or news under the periods characterized by high uncertainty. Our results show that investor attention significantly affects the cross-cryptocurrency co-movements, particularly in the wake of the pandemic, however does not necessarily induce a contagion effect.

Under models V and VI, we investigate the effects of macro-financial variables on the equicorrelations. The results suggest that only EPU and VIX have a significant and positive effect in both models, indicating that uncertainties resulting from economic policy decisions and investors’ risk preferences significantly drive cryptocurrency market correlations. In times of high uncertainty, financial market participants can flee to cryptocurrencies from other assets to hedge any possible market losses; this collective action of traders and herding behavior can cause heightened linkages among cryptocurrencies. This is partly in line with Bouri et al. (2017b) and Ji et al. (2019). The rest of the macro-financial factors do not carry useful information to explain the cryptocurrency dynamics, supporting the findings of Baur et al. (2018) suggesting that various cryptocurrencies perform differently from other financial assets, in terms of return volatility and correlation characteristics. However, the results cast doubt on the potential hedging ability of cryptocurrencies against increased uncertainty, even if they seem to be detached from macro-financial factors, such as gold, oil and exchange rate.

Table 4. Determinants of the equicorrelations

	I		II		III		IV		V		VI	
Constant	-1.652[a]	(0.349)	-1.719[a]	(0.334)	3.182[a]	(0.036)	3.384	(0.288)	-0.645[a]	(0.198)	-0.839[a]	(0.271)
BTC_{Volume}	0.334[a]	(0.102)	0.316[a]	(0.098)								
ETH_{Volume}	0.035	(0.042)	0.037	(0.042)								
LTC_{Volume}	-0.077	(0.060)	-0.077	(0.062)								
XMR_{Volume}	-0.136[a]	(0.029)	-0.121[a]	(0.031)								
XRP_{Volume}	-0.011	(0.046)	0.026	(0.049)								
XLM_{Volume}	0.079[b]	(0.037)	0.063[c]	(0.036)								
$BTC_{Wikipedia}$					-0.710[a]	(0.108)	-0.857[a]	(0.110)				
$ETH_{Wikipedia}$					-0.165	(0.102)	-0.110	(0.109)				
$LTC_{Wikipedia}$					0.711[a]	(0.098)	0.790[a]	(0.099)				
$XMR_{Wikipedia}$					0.000	(0.000)	0.000	(0.001)				
$XRP_{Wikipedia}$					0.009	(0.089)	-0.062	(0.095)				
$XLM_{Wikipedia}$					-0.690[a]	(0.088)	-0.616[a]	(0.070)				
EPU									0.226[a]	(0.077)	0.344[a]	(0.085)
EXC									-2.332	(1.809)	-0.722	(1.925)
GOLD									0.000	(0.000)	0.000	(0.000)
MSCI									0.001	(0.002)	0.001	(0.004)
OIL									-0.009	(0.008)	-0.004	(0.010)
PIMCO									0.001	(0.026)	0.010	(0.047)
VIX									0.680[a]	(0.184)	0.662[a]	(0.216)
$BTC_{Volume}*D_{COVID-19}$			1.170[c]	(0.630)								
$ETH_{Volume}*D_{COVID-19}$			-0.885	(0.610)								
$LTC_{Volume}*D_{COVID-19}$			-0.023	(0.221)								
$XMR_{Volume}*D_{COVID-19}$			-0.056	(0.159)								
$XRP_{Volume}*D_{COVID-19}$			0.057	(0.04)								

$XLM_{Volume}*D_{COVID-19}$			-0.025	(0.029)								
$BTC_{Wikipedia}*D_{COVID-19}$							2.184[a]	(0.421)				
$ETH_{Wikipedia}*D_{COVID-19}$							-1.572[a]	(0.377)				
$LTC_{Wikipedia}*D_{COVID-19}$							-1.446[a]	(0.272)				
$XMR_{Wikipedia}*D_{COVID-19}$							0.000	(0.001)				
$XRP_{Wikipedia}*D_{COVID-19}$							0.399[c]	(0.221)				
$XLM_{Wikipedia}*D_{COVID-19}$							-0.010	(0.286)				
$EPU*D_{COVID-19}$											-0.964[a]	(0.212)
$EXC*D_{COVID-19}$											-4.934	(3.436)
$GOLD*D_{COVID-19}$											0.000	(0.000)
$MSCI*D_{COVID-19}$											0.006	(0.004)
$OIL*D_{COVID-19}$											-0.004	(0.014)
$PIMCO*D_{COVID-19}$											0.013	(0.051)
$VIX*D_{COVID-19}$											1.540[a]	(0.378)
Adjusted R^2	0.562		0.582		0.396		0.456		0.185		0.222	

Notes. (a), (b) and (c) denote statistical significance at 1%, 5%, and 10% levels, respectively.

Moving to the interaction terms in model VI, there is strong statistical evidence that EPU $EPU*D_{COVID-19}$ and VIX $VIX*D_{COVID-19}$ have a significant effects on the equicorrelations during the COVID-19 period. Interestingly, $EPU*D_{COVID-19}$ is negative, suggesting that the economic policy uncertainty during the pandemic does not induce contagion and leads to decoupling of cryptocurrency returns instead. This is somewhat in line with Demir et al. (2018) providing evidence of negative correlations between the U.S. EPU and Bitcoin returns. In addition, Ji et al. (2019) assert that Bitcoin may act as a hedging instrument against EPU. Looking at the size and sign of the interaction terms, $VIX*D_{COVID-19}$ has a positive and the largest impact on cryptocurrency market dynamics, showing that the increased risk aversion and shifts in investors' risk appetite have caused recoupling of virtual currency returns during the COVID-19 bear market. This is in parallel with Chen et al. (2020), showing that Bitcoin returns can be explained by fear sentiment in the time of the pandemic.

Our findings can contribute to a better understanding of the factors behind the dynamic linkages among cryptocurrencies. In overall, investor demand and public attention for Bitcoin and increased risk aversion play a greater role in driving the cryptocurrency markets integration than macro-financial factors in the wake of the COVID-19 pandemic. Our results support the findings from Ciaian and Rajcaniova (2016), Ciaian et al. (2016), and Koutmos (2018). The cryptocurrency market co-movements seem to be detached from main economic fundamentals, such as exchange rate, oil and gold prices, that traditionally have an explanatory power in conventional asset returns. However, as also suggested by King and Koutmos (2021), even if the virtual currencies are independent of the economic factors that typically affect conventional assets, herding behaviors, particularly in times of extreme uncertainty, may drive the price dynamics.

6. Conclusion and Potential Implications

This study contributes to the growing literature of cryptocurrencies by measuring the level of co-movements, using a dynamic equicorrelation GARCH (DECO-GARCH) model. We further analyze the potential determinants of intra-cryptocurrency interdependencies. More specifically, we investigate the linkages among six cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Stellar (XLM) and Monero (XMR). Our sample period covers the novel Coronavirus period, enabling us to analyze the virtual currency market dynamics in times of extreme market conditions.

Our empirical results reveal that DECOs are strengthened over time, suggesting increased cryptocurrency market integration. The estimated time-varying equicorrelations are substantially heightened during some dramatic events, including hacker attacks, such as the Bitfinex hack in August 2016, and the Coincheck hack in January 2018, and government bans on the cryptocurrency operations, imposed by the Chinese and the Indian governments. The correlations reach their maximum value around 0.98 in March 2020, right after the official declaration of the WHO that the novel coronavirus becomes a global pandemic.

Analyzing the determinants of the market co-movements, we find that trading volume and investor attention, captured by Wikipedia search intensities, are significant drivers of the variation of the dynamic equicorrelations. In terms of the macro-financial factors, only Economic Policy Uncertainty (EPU) and Volatility Index (VIX) are statistically significant. Therefore, our results add to the stream of the literature (Kristoufek, 2013; Ciaian and Rajcaniova, 2016; Ciaian et al., 2016; Koutmos, 2018) that supports that macro-financial variables are less important in explaining the cryptocurrency dynamics; on the contrary, market microstructure and investor attention are of greater importance in driving the market linkages. More specifically, we provide evidence of the explanatory power of Bitcoin trading volume, attention-driven demand for Bitcoin and risk aversion measured by the VIX on the equicorrelations during the COVID-19 period. In other words, increased trading volume, public attention and risk preferences have a great impact on the virtual currency market behavior in times of extreme market stress.

Our findings have potential implications for investors, policy-makers and academics. The highly volatile interdependencies across the digital currencies may have a significant impact in the decision-making process of various stakeholders. Firstly, the strengthened level of equicorrelations during certain events suggests the deteriorated diversification benefits when needed most, and a cryptocurrency-only portfolio would harm investors and traders, particularly after 2017, when the trading volume skyrocketed in the market. Our results further imply the possibility of contagion as the correlations at equilibrium are significantly increased; indicating that a loss in one cryptocurrency can be accompanied by a loss in another. Secondly, even if the cryptocurrency market dynamics seem to be independent of the macro-financial variables, higher trading volume and increased public attention on Bitcoin may induce contagion effects. Finally, comprehending what drives cryptocurrency market integration, particularly in such an extreme volatile period due to the COVID-19 crisis, is highly relevant for policy makers and authorities, in devising strategies to cope with financial contagion and to ensure financial market stability.

References

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID–19 crisis. *Finance Research Letters*, 101604.

Al-ahdal, W. M., Alsamhi, M. H., Tabash, M. I., & Farhan, N. H. (2020). The impact of corporate governance on financial performance of Indian and GCC listed firms: An empirical investigation. *Research in International Business and Finance*, 51, 101083.

Al-Awadhi, A. M., Al-Saifi, K., hAwadhi, A., & Alhamadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, 100326.

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19)–An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 100341.

Antonakakis, N., Chatziantoniou, I. Gabaue, D., (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *Journal of International Financial Markets, Institutions and Money*, 61, 37-51.

Baur, D. G., and Dimpfl, T., (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, *173*, 148-151.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance Research Letters*, *25*, 103-110.

Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric reviews*, *11*(2), 143-172.

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019a). Cryptocurrencies as hedges and safe-havens for US equity sectors. The Quarterly Review of Economics and Finance.

Bouri, E., Gupta, R., & Roubaud, D. (2019b). Herding behaviour in cryptocurrencies. *Finance Research Letters*, *29*, 216-221.

Bouri, E., Lau, C. K. M., Lucey, B., & Roubaud, D. (2019c). Trading volume and the predictability of return and volatility in the cryptocurrency market. *Finance Research Letters*, 29, 340-346.

Bouri, E., Jalkh, N., Molnar, P. Roubaud, D., (2017a). Bitcoin for energy commodities before and after the December 2013 crash: Diversifier, hedge or safe haven? *Applied Economics*, 49(50), 5063-5073.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017b). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87-95.

Brauneis, A., & Mestel, R. (2019). Cryptocurrency-portfolios in a mean-variance framework. *Finance Research Letters*, *28*, 259-264.

Canh, N. P., Wongchoti, U., Thanh, S. D., & Thong, N. T. (2019). Systematic risk in cryptocurrency market: Evidence from DCC-MGARCH model. *Finance Research Letters*, 29, 90-100.

Chan, W. H., Le, M., & Wu, Y. W. (2019). Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance,* 71, 107-113.

Charles, A., Darné, O., (2019). Volatility estimation for Bitcoin: Replication and robustness. *International Economics*, *157*, 23-32.

Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and bitcoin price dynamics: The case of COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2298-2309.

Ciaian, P., & Rajcaniova, M. (2016). The digital agenda of virtual currencies: Can BitCoin become a global currency?. *Information Systems and e-Business Management, 14*(4), 883-919.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied Economics*, *48*(19), 1799-1815.

Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters, 35*, 101607.

Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*, *54*, 101248.

Corbet , S., Meegan, A., Larkin, C., Lucey, B., and Yarovaya, L., (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economic Letters* 165, 28-34.

Corbet, S., Larkin, C., & Lucey, B. (2020a). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, 101554.

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., & Oxley, L. (2020b). Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. *Economics Letters*, *194*, 109377.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182-199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28-34.

Coronavirus Update (Live): 82,449,240 Cases and 1,799,596 Deaths from COVID-19 Virus Pandemic - Worldometer (worldometers.info)

Demir, E., Gozgor, G., Lau, C.K.M. and Vigne, S.A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters* 26, 145-149.

Demiralay, S., & Bayracı, S. (2020). Should stock investors include cryptocurrencies in their portfolios after all? Evidence from a conditional diversification benefits measure. *International Journal of Finance & Economics*.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57-66.

Dyhrberg, A.H., (2016a). Bitcoin, gold and the dollar - A GARCH volatility analysis. *Finance Research Letters* 16, 85-92.

Dyhrberg, A.H., (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters* 16, 139-144.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339-350.

Engle, R. and Kelly, B. (2012). Dynamic Equicorrelation. *Journal of Business and Economic Statistics* 30(2), 212-228.

Fakhfekh, M., & Jeribi, A. (2019). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, 101075.

Gil-Alana, L. A., Abakah, E. J. A., & Rojo, M. F. R. (2020). Cryptocurrencies and stock market indices. Are they related?. *Research in International Business and Finance*, *51*, 101063.

Glosten, L., Jagannathan, R., and Runkle, D. (1993). Relationship between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance*, 48, 1779-1801.

Göker, I. E. K., Eren, B. S., & Karaca, S. S. (2020). The Impact of the COVID-19 (Coronavirus) on The Borsa Istanbul Sector Index Returns: An Event Study. *Gaziantep Üniversitesi Sosyal Bilimler Dergisi*, *19*(COVID-19 Special Issue), 14-41.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 101512.

Goodell, J. W., & Goutte, S. (2020a). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters*, 101625.

Goodell, J. W., & Goutte, S. (2020b). Diversifying with cryptocurrencies during COVID-19. *Available at SSRN 3631971*.

Guesmi, K., Saadi, S., Abid, I. and Ftiti, Z., (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis* 63, 431-437.

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, 100343.

Iqbal, N., Fareed, Z., Wan, G., & Shahzad, F. (2020). Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. *International Review of Financial Analysis*, *73*, 101613.

James, N., Menzies, M., & Chan, J. (2020). Changes to the extreme and erratic behaviour of cryptocurrencies during COVID-19. *Physica A: Statistical Mechanics and its Applications*, 125581.

Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, *63*, 257-272.

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis, 71*, 101526.

Katsiampa, P. (2017). Volatility estimation for bitcoin: A comparison of GARCH models. *Economic Letters* 158, 3-6.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*.

King, T., & Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. *Annals of Operations Research*, 1-18.

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters*, *167*, 81-85.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports*, *3*, 3415.

Kumar, A.S. and Anandarao, S., (2019). Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. *Physica A*, 524, 448-458.

Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. *Decision Support Systems*, *95*, 49-60.

Mariana, C. D., Ekaputra, I. A., & Husodo, Z. A. (2020). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic?. *Finance research letters*, 101798.

Platanakis, E., & Urquhart, A. (2019a). Portfolio management with cryptocurrencies: The role of estimation risk. *Economics Letters*, *177*, 76-80.

Platanakis, E., & Urquhart, A. (2019b). Should investors include bitcoin in their portfolios? A portfolio theory approach. *The British Accounting Review*, 100837.

Shahzad, S. J. H., Bouri, E., Kang, S. H., & Saeed, T. (2021). Regime specific spillover across cryptocurrencies and the role of COVID-19. *Financial Innovation*, *7*(1), 1-24.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 101496.

Symitsi, E., & Chalvatzis, K. J. (2019). The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. *Research in International Business and Finance*, *48*, 97-110.

Umar, Z., & Gubareva, M. (2020). A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. *Journal of Behavioral and Experimental Finance*, *28*, 100404.

Vogelsang, T. J., & Perron, P. (1998). Additional tests for a unit root allowing for a break in the trend function at an unknown time. *International Economic Review*, 1073-1100.

Yang, H. (2018). Behavioral anomalies in cryptocurrency markets. *Available at SSRN 3174421*.

Yi, S., Xu, Z. And Wang, G-J., (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, 60, 98-114.

Yilmaz, M. K., Sensoy, A., Ozturk, K., & Hacihasanoglu, E. (2015). Cross-sectoral interactions in Islamic equity markets. *Pacific-Basin Finance Journal*, 32, 1-20.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528.