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Time Varying Dependence in the Cryptocurrency Market and COVID 19 Panic Index: An Empirical Investigation

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ABSTRACT

The aim of this paper is to study the interdependence between the coronavirus panic index (PI) and major cryptocurrencies throughout the period of the Covid-19 pandemic.We investigate the evolution of cryptocurrency's value following changes in the Covid panic index levels; then, we use the DCC-MIDAS specification to extract the long- and short-term volatility components of cryptocurrencies and study the responses of the cryptocurrencies to the pandemic panic index. The results show that the panic level metrics could be considered as a potential driver of cryptocurrencies volatility and has a significantly positive influence on the long-term cryptocurrencies correlation during stress levels. Our findings contribute to the existing literature in several ways. First,we provide specific evidence on the driving effect of Covid panic index on cryptocurrencies'correlation during a crisis. Second, our paper adds to the current literature on cryptocurrencies and fills in the existing gap related to the lack of academic research on the pandemic's impact on the cryptocurrency market. Third, the results offer interesting insights for future research and have important implications for investors, especially in understanding the cryptocurrencies'behavior and exploring whether cryptocurrencies can serve as a hedge against the COVID-19 crisis.

Keywords: Covid 19, Volatility, Digital currency, DCC-MIDAS, Causality, Kernel regression, Response-impulsion
JEL Classifications: C32, C58, G15, G17

1. INTRODUCTION

Since their introduction, cryptocurrencies had gained a lot of interest from researchers and investors as prospective speculative instruments regardless of the primary purpose of their use, as an instrument used for the purpose of decentralized peer-to-peer payments.

The cryptocurrency market had been steadily expanding until 2017. Investors'growing interest in crypto-assets and the exceptionally high volatility of their price conducted several recent empirical studies to focus on the dynamics of cryptocurrency returns.

Liu and Tsyvinski (2018) provided empirical evidence showing that cryptocurrency returns cannot be explained by traditional asset pricing models and standard risk factors. As there is no fundamental information, such as earnings, dividends and cash flows, cryptocurrencies'dynamic is unpredictable. The cryptocurrency markets represent a complex system in the domain of finance. Recent statistical analysis of cryptocurrency markets had identified features, such as very high volatility, long memory structures, and increased dependency of volatility.

On the other hand, financial markets worldwide have been severely affected by the recent COVID-19 pandemic that spread fear and anxiety among investors and had provided the first widespread bear market since the trading of cryptocurrencies began.

The pandemic of COVID-19 has caused havoc in the equity markets around the world through negative returns. The contagion has also affected the cryptocurrency market's increased uncertainty, and higher volatility because of the contagion. Historically, this pattern emerged during periods of financial turmoil, such as the 2008 crisis.

Ji et al. (2019) showed that periods of extreme financial stress could cause spillover effects in the cryptocurrency market. Matkovskyy and Jalan (2019) suggest in their study that the direction of contagion is from traditional to crypto-markets. Indeed, in case of financial disasters investors avoid crypto-assets.

Liu (2019) showed that the Covid-19 crisis had negatively affected the potential role of cryptocurrencies as diversifying investments.

The literature on the spillover, safe-haven and cross-market interdependence across assets and financial markets has attracted a lot of attraction since the global crisis of 2007. The covid-19 pandemic has managed to plunder and destabilize the world, putting in danger economic boundaries, global businesses, and the world's financial system. The covid-19 crisis inspired a new stream of literature focused on the pandemic's impact on currency markets to support the current market players and regulators in their attempts to forecast the currencies'behavior during the periods of financial distress.

Various studies indicate that investors are not always rational; they tend to make decisions based on various news whose reliability may easily be questioned. The investors'behavior affects cryptocurrency price. The psychological state may lead to behavioral biases in the cryptocurrency market.

David (2018) stated that "cryptocurrencies are less about technology than psychology," they showed that traders' humors and reactions could influence the dynamics of cryptocurrencies'market.

In this perspective, different papers offer additional insights into investors'sentiments by observing the currencies'herding behavior. As widely known, herding refers to the imitating investors'judgments while making decisions that lead to a synchronization of price co-movements of similar currencies.

Christie and Huang (1995) suggested that a reduction of the variability of the outcome could be observed, in case of the convergence of opinion, since beliefs converge to the prevailing market reaction.

In the present study, we analyze the relationship between Covid panic index and cryptocurrencies return over the period 2019-2021. For this purpose, we consider the most liquid cryptocurrencies namely: Bitcoin, litecoin, ripple, dash, ethereum, binance coin, stellar,cardano, thether, chainlink, and the coronavirus panic index (PI), the index used as a proxy for the panic created by Ravenpack.

As our sample period covers the most recent global crisis caused by the pandemic, we contribute to the contemporary literature on the cryptocurrencies market in three ways. Firstly, we identify how the major cryptocurrencies'returns respond to the changing of the Pandemic intensity. We study the differences in responses of the cryptocurrencies to the pandemic panic index.

Secondly, we investigate the evolution of cryptocurrencies'value over time. We apply different long-memory methods, namely R/S analysis, Hurst exponent and spectral density,to check for any differences in this association's pattern following different levels of changes in the Covid panic index levels. Specifically, we use the DCC-MIDAS madel to allow the long-term correlation to be a function of explanatory variables, we show that the cryptocurrencies correlation is driven by the the ravenpack coronavirus panic index (PI).

Finally, we enriched the cryptocurrency market literature to enhance the understanding of the digital cryptocurrencies'dynamics, especially during a pandemic crisis. Our study should be of great value to the policymakers, investors, and regulators alike.

The remainder of this paper is structured as follows: Section1 provides a brief review of the relevant literature. Section 2 describes the data and outlines the empirical methodology. Section 3 presents and discusses the main empirical results. Section 4 concludes.

2. LITERATURE REVIEW

Several recent empirical studies focus on the dynamics of the volatility of cryptocurrency returns. Many features, such as volatility spillovers among cryptocurrencies and presence of long memory dependence structures in the cryptocurrency's value asset class were, identified.

Chaim and Laurini (2019). show by mixing short memory processes with time varying conditional volatility the presence of level shifts in the structure of volatility that can reproduce the long memory behavior of cryptocurrencies. Their results are relevant in terms of volatility predictability, portfolio allocation, and risk management.

Long range dependence in cryptocurrency volatility was documented by Bariviera et al. (2017). In their study, they calculate the Hurst exponents for Bitcoin returns volatility and provide that there is evidence of self-similarity.

Lahmiri and Bekiros (2020) compare several GARCH specifications to Bitcoin and provide evidence of long-range dependence in seven Bitcoin markets using a fractionally integrated GARCH model.

Luo and Wang (2006) show that structural breaks affect the parameters of processes driving conditional volatility and returns. They incorporate a long-run volatility component, to give the best fit for cryptocurrencies. They also perform unconditional and conditional value at risk coverage tests.

Other aspects related to the presence of long memory in the cryptocurrency market were found. Charfeddine and Maouchi (2018) employ several tests to study the relationship between long memory and market inefficiency for cryptocurrencies; their results indicate that cryptocurrency volatility has a long memory rather than level shifts.

In the recent literature, several authors studied the "connectedness of cryptocurrency," which refers to the market inter-dependencies between cryptocurrencies. Ji et al. (2018) studied the connectedness between seven cryptocurrencies, using the VAR model. Their results show that the Bitcoin and Litecoin are the most influential cryptocurrencies and Ethereum and Stellar are the most impacted by volatility spillovers.

Stosica et al. (2018) find evidence of hierarchical cryptocurrency structure in the market by using the Random Matrix Theory and Minimum-Spanning Tree methodology.

Corbet et al. (2020) use the generalized variance decomposition methodology to study the interdependencies between three cryptocurrencies and six traditional assets. They find that cryptocurrencies are tightly connected.

Borgards et al. (2020) stated that in a highly uncertain situation, Bitcoin showed a high correlation with the equity markets, and dropped in value in tandem with the other financial markets, they explain this result by the lack of demand for risky assets during the pandemic.

Various academic studies reported the presence of long memory effects in digital currency financial data. Lahmiri et al. (2018), using a fractionally integrated GARCH model, provide evidence of long-range dependence in seven Bitcoin markets. Bariviera et al. (2017), by calculating Hurst exponents for currencies returns volatility, argue there is evidence of long memory rather than level shifts.

Charfeddine and Maouchi (2018) show that stationary models augmented with levels shifts are often the source of long memory features in financial asset data, they employed several spectral-based estimators and provide that volatility displays long memory characteristics.

Rognone et al. (2020) argued that cryptocurrencies' behavior is different from traditional assets; cryptocurrencies overreact against the negative news more profoundly when compared with the traditional equities' behavior. Investors' enthusiasm driven by the extreme positive and negative news causes an increase in the crypto-market returns.

Bouri et al. (2017) founded a relation between news about U.S growth uncertainty and bitcoin price dynamics. However, more efforts can be made following this direction.

To enrich the discussion on the relation between news and Bitcoin price. Gurdgiev and O'Loughlin (2020) provided the importance of introducing sentiment scores on a continuous scale to fully reflect the investor's intensity reactions to the news entirely.

To study the long-term correlation between cryptocurrencies, we use the DCC-MIDAS model of Colacito et al. (2011); this model allows high-frequency data and low-frequency variables to be incorporated directly for dynamic correlations and presents two components of stock market volatility, one short-term component and one long-term component. The DCC-MIDAS model has been widely used in many areas. Virk and Javed (2017) used the DCC-MIDAS model to study the integration patterns of seven leading European stock markets and to explore dynamic correlations.

Feng et al. (2018) apply it to study the U.S stock and bond market and to analyze the influence of economic policy uncertainty on the dynamic long-term correlation based on the DCC-MIDAS model.

The DCC-MIDAS model also tends to be extended in several ways. Conrad and Kleen (2018) use the GARCH-MIDAS model to extract the long- and short-term volatility components of cryptocurrencies, they find that S and P 500 realized volatility has a negative and highly significant effect on long-term Bitcoin volatility and that Bitcoin volatility is closely linked to global economic activity.

The current work aims to study the dynamic interdependence maps of the COVID panic index and cryptocurrency markets. In the wake of conflicting evidence on the cryptocurrencies' behavior, it is interesting to examine how these cryptocurrencies perform during the Covid 19 pandemic crisis which is a rare event with unprecedented characteristics.

3. DATA AND METHODOLOGY

3.1. Data

For the purpose of this paper, daily observations starting from December 1, 2019, and ending on May 31, 2021, have been collected. This period captures the initial bear market inequities associated with the COVID-19 pandemic. The current work aims at investigating how cryptocurrencies behave during this crisis period. In other words, it is checked whether, it is possible to identify regularities in cryptocurrency price dynamics. To this extent, we analyze interdependencies between the cryptocurrencies values and the coronavirus panic index (PI).

Our sample consists of nine major cryptocurrencies with the highest market capitalization, where the data is available throughout the entire analyzed period. We used daily prices of all cryptocurrencies, denominated in USD. The source of the data is the database of coinmarketcap.com, which is the most comprehensive cryptocurrency database available, sampling 9 cryptocurrencies: Bitcoin (BTCUSD), LiteCoin (LTC-USD), Ethereum (ETHUSD), Binance Coin (BNB-USD), Stellar (XLM-USD), Cardano (ADA-USD), Thether (USD-TUSD), Chainlink (Link-USD), Ripple (XRP-USD), The Coronavirus index Panic data (PI) is obtained from Ravenpack, it measures the level of news that refers to panic and coronavirus. The index value lies between 0 and 100, with 100 indicating the highest level of news talking about panic and coronavirus and 0 implying the lowest level.

The main idea is that COVID panic index might shape investors' decision, affecting price expectation.

3.2. Methodology

3.2.1. Non parametric power spectral density

The power spectrum reveals the existence of repetitive patterns and correlation structures in a signal process. The classic method for estimation of the power spectral density is the periodogram defined as:

$$\hat{P}_{xx}(f)=\frac{1}{N}\left|\sum_{i=1}^{N}x(m)e^{-j2\pi fm}\right|^{2} \quad (1)$$

The power-spectral density function, defined in Equation (1), is the basis of non-parametric methods of spectral estimation. Owing to the finite length and the random nature of most signals, the spectra vary randomly about an average spectrum.

In the Averaging Periodograms method, in order to reduce the variance of the periodogram. several periodograms, from different segments of a signal, are averaged in order to reduce the variance of the periodogram. The Bartlett periodogram is obtained as the average of K periodograms as:

$$\hat{P}_{xx}(f)=\frac{1}{N}\sum_{i=1}^{k}\hat{P}_{xx}{}^{i}(f) \quad (2)$$

Where $\hat{P}_{xx}(f)$ is the periodogram of the i^th^ segment of the signal. The expectation of the Bartlett periodogram $\hat{P}_{xx}(f)$ is given by:

$$E\left(\hat{P}_{xx}(f)\right)=E\left(\hat{P}_{xx}{}^{i}(f)\right)$$

$$\hat{P}_{xx}(f)=\frac{1}{N}\sum_{i=1}^{k}\hat{P}_{xx}{}^{i}(f) \quad (3)$$

Where $(sin\pi fN/sin\pi f)^2/N$ is the frequency response of the triangular window $1-|m|/N$. The Bartlett periodigramis asymptotically unbiased. The variance of is 1/K of the variance of the periodogram, given by:

$$V\left(\hat{P}_{xx}(f)\right)=\frac{1}{K}P_{xx}(f)\left[1+\frac{sin2\pi fN}{Nsin2\pi fN}\right]^{2} \quad (4)$$

3.2.2. The autoregressive kernel model

The autoregressive kernel model for a univariate time series is built in five steps, namely, the estimation of the density function, the determination of an optimal bandwidth for the kernel function, the determination of the exact number of lags to be included in the regression equation, and the estimation of the conditional mean and volatility.

The non-parametric regression produces a reasonable analysis of the unknown response function f, for N data points (x_t,y_t), the relationship can be modeled as:

$$y_t=m(x_t)+\varepsilon_t \qquad t=1,2\ldots N$$

The conditional expectation functn is modeled by using the semi-parametric approach, m (.) has some parameters to be estimated. Non-parametric models attempt to discover the approximate relation between x_t and y_t. Kernel regressions are weighted average estimators that use kernel functions as weights.

Recall that the *kernel K* is a continuous, bounded and real symmetric function, which integrates to 1. The weight is defined by:

$$w_i(x)=k(x-x_i)/f_{(x)} \quad (5)$$

$$\text{Where } f_{(x)}=N^{-1}\sum_{i=1}^{N}k(x-x_i), and\ k(u)=h^{-1}k(u/h) \quad (6)$$

The kernel's functional form the virtually always implies that the weights are much more extensive for the observations where x_i is close to x_0. We calculate using standard statistical formulas:

$$m(x)=\int yf_c(x|y)d_y \quad (7)$$

Where f_c is the distribution of y conditional on x. We can express this conditional distribution in several ways. In particular:

$$E(Y|X)=m(x)=\frac{\int_{-\infty}^{\infty}yf_c(x|y)d_y}{f_M(x)} \quad (8)$$

We use the density estimation results where M and J refer to the marginal and the joint distributions, respectively.

$$\hat{f}_M(x_0)=\hat{f}(x_0)=N^{-1}\sum_{i=1}^{N}K\frac{(x_i-x_0)}{h} \quad (9)$$

The shape of the kernel weights is determined by K and the size of the weights is parameterized by h.

Many K(.) are possible. Practical and theoretical considerations present several choices: namely Epanechnikov, Gaussian, Quartic, and Tricube. In this study, we consider *Epanechnikov* kernel estimation which is the optimal kernel density estimator corresponding to the optimal bandwidth that has been suggested by Epanechnikov (1969):

$$k_1(x)=\begin{cases}\frac{3}{4}(1-x)^2 & if\ |x|\le 1\\ 0 & else\end{cases} \quad (10)$$

Given a choice of kernel K, and a bandwidth, kernel regression is defined by:

The estimation of the conditional mean and volatility is modeled by a non-linear autoregressive heteroskedastic process:

$$Y_t=m(y_{t-1},y_{t-2},\ldots..y_{t-L})+\varepsilon_t \quad (11)$$

Where $\varepsilon_t=\sigma_t e_t$ and $m(y_{t-1},y_{t-2},\ldots y_{t-L})$ represents the conditional mean and the conditional volatility is:

$$\sigma^2=Var(\varepsilon_t/(Y_{t-1},Y_{t-2},\ldots..Y_{t-L})=x) \quad (12)$$

The kernel regression can also be rewritten in terms of the conditional mean and the conditional volatility as follows:

$$Y_t = m\left(Y_t / (Y_{t-1}, Y_{t-l}\right) = x) + \sigma_t e_t \quad (13)$$

This model assumes linear dependence on past stock prices. Using the least square cross-validation method with K(.) consias weight function, the Nadaraya-Watson estimator of the conditional volatility is then obtained when the degree of the polynomial being fit to the stock price conditional volatility is zero:

$$\sigma^2(X_{\sigma_t}, 0, h_{opt}) = \frac{\sum_{t=1}^{T} K_{h_{opt}}\left(X_{\sigma_t} - x_\sigma\right)\varepsilon_t^2}{\sum_{t=1}^{T} K_{h_{opt}}\left(X_{\sigma_t} - x_\sigma\right)} \quad (14)$$

3.2.3. Conditional correlation and DCC-MIDAS model

The DCC-MIDAS specification proposed by Colacito et al. (2011) decomposes the correlation between two returns into short-term high-frequency) and long-term (low-frequency) components. The long-term correlation is modeled as the weighted average of the lagged values of the realized correlation and the explanatory variables;

Instead of modeling the correlation matrices Rt directly, we follow Engle (2002) and first specify the so-called 'quasi-correlations' Qt = [qij,t]i,j=1,2 a as:

$$Q_t = \left(1 - a - b\right)\overline{R_t} a\eta_{t-1}\eta_{t-1}^{'} + BQ_{t-1} \quad (15)$$

$$q_t = \overline{\rho_t} + a\left(\eta_{t-1}\eta_{t-1}^{'} - \overline{\rho_t}\right) + b(q_{t-1} - \overline{\rho_t}) \quad (16)$$

Where $a+b<1$ and $\overline{R_t} = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}$., $\eta_t = \left(\eta_{t-1}\eta_{t-1}^{'}\right)$ is the standardized residual vector from the GARCH-MIDAS model.

Colacito et al. (2011) assume that $\overline{\rho_t}$ is a function of a weighted average of K prior realized correlations (RC).

$$\overline{\rho_t} = \sum_{k=1}^{K} \rho_K w_{12} RC_{t-K} \quad (17)$$

Where

$$RC_t = \frac{\sum_{k-t-N}^{K} \rho_{1,K}\rho_{2,K}}{\sqrt{\sum_{k-t-N}^{K} \rho_{1,K}^2 \sum_{k-t-N}^{K} \rho_{2,K}^2}} \quad (18)$$

The long-term component of the correlation $\overline{\rho_t}$ is given by:

$$\overline{Z_t} = m + \theta_c \sum_{k=1}^{K} (w_{c1}, w_{c1}) X_{t-k} \quad (19)$$

The quasi-correlation matrix Qt is transformed, the correlation matrix Rt:

$$R_t = (Q_t^*)^{-1/2} Q_t (Q_t^*)^{-1/2} \quad (20)$$

With $Q^*=diagQ_t$; In the bivariate model, the off-diagonal elements of Rt are less than one in absolute term with Fisher's transformation. DCC-MIDAS becomes extremely complex when the number of return series is larger than two, and positive semi-definition conditions cannot be satisfied.

To estimate this model, The log likelihood function can be expressed as:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}(2\ \log(2\pi) + 2\ \log(|\,\mathrm{D}\,|) + \ \varepsilon_t\ D^{t-2}\ \varepsilon_t\,)$$
$$-1/2\sum_{t=1}^{T}\log\left(R_t\right) + \ \eta_{t-1}R_t\eta_{t-1}^{'} - \eta_{t-1}\eta_{t-1}^{'} \quad (21)$$

Which can be maximized over the parameters of the model. Therefore, we estimate our model and use the two-step approach of Engle (2002) and Colacito et al. (2011)even when the covariance matrix is very large.

$\theta=(\mu,\alpha,\beta,\gamma,m,\theta_v,\omega_1,\omega_2)$ is the parameters in the GARCH-MIDAS model and $\theta=(m,a,b,\theta_c,\omega_{1c},\omega_{2c})$, the parameters in DCC-MIDAS model. The log-likelihood LLF can be written as the sum of a volatility part LLFv and a correlation part LLFc :

$$\mathrm{LLF}_V(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(2\log(2\pi) + 2\log(|\,\mathrm{D}\,|) + \varepsilon_t D^{t-2}\varepsilon_t) \quad (22)$$

$$\mathrm{LLF}_V\left(\theta,\phi\right) = -1/2\sum_{t=1}^{T}\log\left(R_t\right) + \ \eta_{t-1}R_t\eta_{t-1}^{'} - \eta_{t-1}\eta_{t-1}^{'}$$

$$\mathrm{LLF}_V\left(\theta,\phi\right) = -1/2\sum_{t=1}^{T}\log\left(R_t\right) + \eta_{t-1}R_t\eta_{t-1}^{'} - \eta_{t-1}\eta_{t-1}^{'}\ \eta_{t-1}\eta_{t-1}^{'} \quad (23)$$

the likelihood function LLF(Θ) is firstly maximized and then takes this value in the second stage: $max_\phi LLF_C\left(\theta,\phi\right)$ (24)

4. EMPIRICAL FINDINGS

4.1. Descriptive Statistics

We examine the characteristics of the cryptocurrencies, and COVID panic index over the period December 2019–May 2021, incorporating the ongoing COVID-19 related market turmoil. We choose the daily frequency for data analysis because the PI is available only on a daily basis.

The descriptive statistics displayed in Appendix A1 show that the cryptocurrencies'returns present a positive means over the considered sample,covering all the study periods.

Standard deviations are high relative to more traditional financial assets, as is characteristic of this particular asset class. Link, Stellar, XRP and Cardano are the most volatile cryptocurrency, and Tether is the less volatile cryptocurrency, with daily returns varying, on average, 0.03%. While the COVID Panic Index display a high Standard deviation.

Etherom and Link have a maximum loss of −58,96% and −63,7% respectively. The Bitcoin has a maximum loss of −49%. Except for Stellar and Tether, cryptocurrencies display right skewed returns, which means that most of the values are lower than the mean. Daily returns are leptokurtic, as is expected from financial assets, and some cryptocurrencies have very large outlier realizations.

Link has the highest mean, as well as the highest standard deviation, of realized variance. While the distributions of realized measures for all cryptocurrencies exhibit positive skewness, Stellar and Tether are negatively skewed.

The kurtosis of a univariate normal distribution, indicating high peaks and fat tails for all distributions of realized measures, the kurtoses are substantially higher than the critical value for all the cryptocurrencies. Therefore, based on these two statistical measures, we can conclude that none of the realized measures'distributions are normally distributed, confirming the Jarque-Bera statistics.

Daily coronavirus panic index (PI) is leptokurtic, and exhibits a negative average value during the period analyzed. Figure 1 plots daily log returns of the nine cryptocurrencies in our sample and the COVID Panic index, over the entire sample period December 2019 – May 2021, it is clear some of the cryptocurrencies, such as Bitecoin, Litecoin, and Ether, present huge outliers, possibly due to covid 19 crisis in those markets. The irrational could explain major peaks on investors'part due to the COVID panic index's increase. Investor reactions are strong following the bad news.

A steep decline in the values of all currencies is visible during March. Hence, it is very much possible that the small and the large changes in the COVID19 panic index intensity may affect the returns of the digital cryptocurrencies differently, at various times.

Appendix A2 shows a correlation between contemporaneous daily returns of digital currencies in our sample and the COVID Panic Index. Correlation is overall positive and higher between the cryptocurrencies during COVID 19 crisis and highest with Bitcoin. Primary Results show that, there is a possible evidence of herding. We can observe a negative correlation between the cryptocurrencies and the COVID Panic Index. We conclude that the value of cryptocurrencies decreases when the Covid panic index increase.

4.2. Evaluation of Long Memory Parameter

The weak form of informational efficiency excludes the possibility of finding, systematically, profitable trading strategies especially during a crisis. As a corollary, returns time series cannot exhibit predictable memory content. However, there are several studies that find long memory in financial time series, using different methods. Kristoufek (2015) showed that the possible presence of long memory has an important consequences for the predictability of the cryptocurrencies, in portfolio allocation procedures and risk management.

The possible long-memory effects may be an effect generated by the aggregation of several short- memory processes, as discussed by Lai and Xing (2006) or spurious statistical effects generated by the presence of structural breaks, changes in parameters and regimes. Several tests were employed by Charfeddine and Maouchi (2018) to argue that cryptocurrency volatility has true long memory rather than level shifts.

In this subsection, we study the presence of long memory in cryptocurrencies value by applying the semi-parametric G-P-H Procedure and the Hurst exponent estimation to characterizes the scaling behavior of the range of cumulative departures of a time series of cryptocurrencies from its mean.

4.2.1. Estimation method based on the G-P-H procedure

To test the presence of long memory effects in digital currency financial data during the COVID-19 crisis, we apply the semi-parametric estimation method, which allows us to determine the coefficient (d); the fractional integration parameter in the conditional variance equation. The advantage of this parameter characterizes the long-term behavior of the cryptocurrencies series. The short-term behavior itself is considered through the autoregressive moving average parameters of ARFIMA (p,d,q).

Figure 1: Plots daily cryptocurrencies values and COVID Panic Index

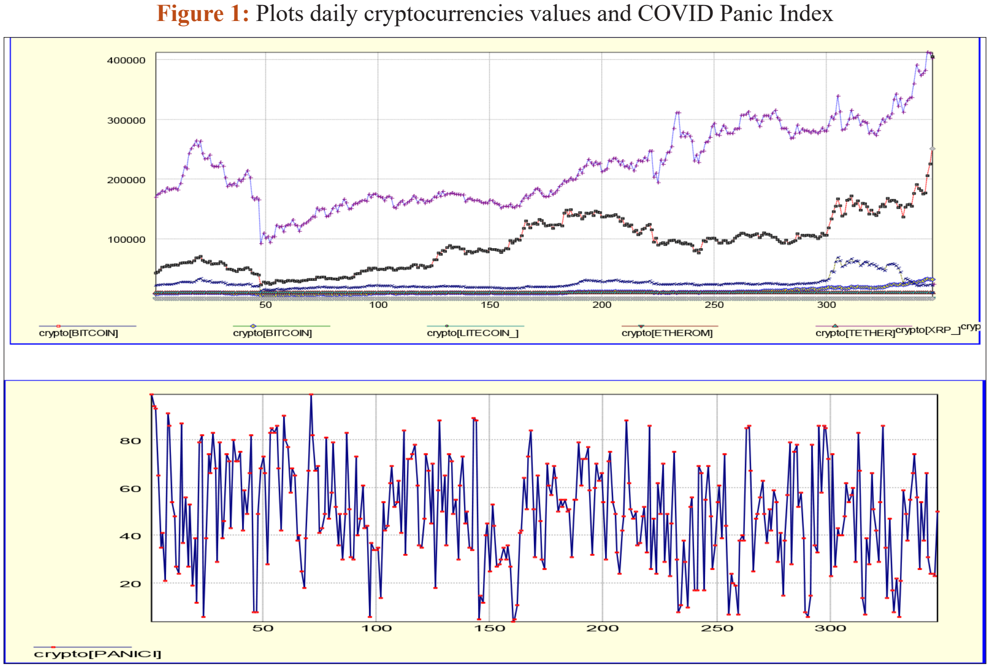


Table 1: Parameter (d) estimation by the GPH method

Cryptocurrencies	0.5	0.6	0.8
BTC	0.0789	0.0896	0.0547
	(0.6721)	(0.8243)	(0.8543)
ADA	0.0542	0.0588	0.0682
	(0.8433)	(0.6751)	(0.6543)
ETH	0.0724	0.0832	0.0520
	(0.6721)	(0.9243)	(0.8543)
LINK	0.0478	0.0421	0.0353
	(0.6871)	(0.6993)	(0.7966)
LTC	0.0682	0.0643	0.0442
	(0.7643)	(0.7092)	(0.6792)
XLM	0.0443	0.0509	0.0623
	(0.6441)	(0.4356)	(0.5079)
TUSD	0.0624	0.0632	0.0578
	(0.6643)	(0.7543)	(0.7321)
XRP	0.0743	0.0643	0.0588
	(0.8032)	(0.9054)	(0.5432)
BNB	0.0643	0.0773	0.0754
	(0.6685)	(0.7906)	(0.7345)

Table reports Geweke and Porter-Hudak (1983) long memory parameter d estimates, of the nine cryptocurrencies in our sample, t_d is the statistical value of Student

Table 2: Hurst exponent

Hurst exponent	R/S	Rescaled R/S	
	H	H	V
BTC	0.9763	0.8992	1.4321
ADA	0.8442	0.7012	1.2064
ETH	0.6904	0.6004	1.2318
LINK	0.6231	0.5962	1.3097
LTC	0.8940	0.7123	1.2128
XLM	0.6504	0.5730	1.4521
TUSD	0.7723	0.7432	1.2241
XRP	0.6798	0.6213	1.2113
BNB	0.7621	0.6623	1.1453
PI	0.4614	0.4233	1.0871

Values of H estimated by the traditional R/S and rescaled R/S of the nine cryptocurrencies in our sample and the covid panic index. V is the limit distribution of the rescaled R/S

The GPH estimator is based on the representation:

$$f_g(\omega) = \left|1-\exp(-i\omega)\right|^{-2(d-1)} f_u(\omega)$$
$$= (2\,\sin(\omega/2))^{-2(d-1)} f_u(\omega) \qquad (25)$$

Where f_g (ω) and f_u (ω) are the spectral densities of x_t and g_t, respectively, d is the long memory parameter. The estimator is obtained by taking the logaritm of $f_g(\omega)$, adding and subtracting the log-periodogram of $\{g_t\}$, $LnI_{(w)}$, and doing the same with $Lnf_{u,}$ (0).

$$\ln I(w_j) = \ln(f(u_{(0)})) - (d-1)\ln(4sin^2 \left(\frac{w_j}{2}\right) + \ln\left(f_u(w_j)/f(u_{(0)}\right) + \ln\left(I(w_j)/f_g(w_j)\right) \qquad (26)$$

The application of the G-P-H Procedure application revealed the presence of long memory in cryptocurrencies returns only when the fractional integration parameter is positive and significantly different from zero. Table 1 shows that the coefficient (d) is significantly positive at the 10 %, d ∈ [0;0,5]. The cryptocurrency returns series are not independent in time. The impact of the parameter d decreases hyperbolically when the lag increases, while the effects of moving and autoregressive average parameters decrease exponentially. The G-P-H method, applied to the cryptocurrency market, allows us to conclude that the series can be predicted in the long term, this kind of dynamics could produce the volatility clustering. However, the long-term behavior of returns could hide some complex underlying dynamics, which will be analyzed in the following subsections.

Table 3: Predicted mean square errors and volatilities

Cryptocurrencies	Mean square errors	Volatilities	AIC	BIC
BTC	0.04250	1.7245	−1.4670	−1.4338
ADA	0.03391	1.9765	−2.6946	−2.6614
ETH	0.03667	1.5169	−2.8916	−2.85852
LINK	0.02121	1.6876	−2.4259	−2.3928
LTC	0.04832	1.7865	−2.4211	−2.6321
XLM	0.04329	1.2643	−3.1978	−1.2309
TUSD	0.02107	1.3519	−1.828	−1.7958
XRP	0.06389	1.4583	−2.6518	−2.6186
BNB	0.05325	1.3421	−3.0158	−2.9827

Values of mean square errors and volatilities of nine cryptocurrencies estimated by kernel regression

4.2.2. Hurst exponent and the R/S analysis

We study the presence of long memory in cryptocurrencies value by estimating the Hurst exponent, (parameter H, also called auto-similarity parameter), which refers to two statistics: traditional R/S and modified R/S. Traditional R/S statistic checks if the estimator of the Hurst exponent has a persistence phenomenon. To remedy the problem of robustness of the R/S statistic in the presence of short memory and heteroscedasticity. Early studies of the R/S statistic. Lo (1991) developed the rescaled R/S range as an extension of the traditional R/S statistic.

The statistic is defined as:

$$R_{I_m} \qquad (27)$$

To linearize the equality $R/S_t = ct^H$, we simply apply the logarithm:

$$\log(R/S_t) = \log(c) + H\,log(t) \qquad (28)$$

The value of H can be estimated by linear regression. Since R_{I_m} is ≥0 and S_{I_m} . is >0, the value of H will have a lower limit close to zero, depending on the value of c.

Table 2 shows the values obtained from estimating R/S and rescaled R/S; the limit distribution denoted V of the rescaled R/S is compared to the critical value proposed. cryptocurrencies returns series has a long-term dependence structure if the V statistic's value is greater than the Lo's critical value (1991). It is clear from the results that the values of H estimated by the traditional R/S and rescaled R/S are both significantly higher than 0.5 for cryptocurrencies; the process of cryptocurrencies has a long memory with positive autocorrelations that decay slowly with the increase of the number of lags.

The hypothesis of the presence of long memory is then retained. We note that for the case of the rescaled R/S, the R/S value estimated through the Hurst exponent is greater than that estimated by the Lo method. Thiconfirms the presence of time-series long-term dependence for cryptocurrencies, especially that the rescaled R/S has a limit distribution robust in the presence of short memory. All criptocurrencues'returns series has a long-term dependence structure and are persistent during covid crisis and do not follow a random walk. The most persistent of cryptocurrency is Bitcoin, which is the oldest, the most commonly used and the most liquid.

The R/S value of the COVID Panic Idex is slightly smaller than that of the cryptocurrencies. The dynamic R/S analysis shows that the degree of persistence during the COVID 19 crisis varies over the time, and fluctuates around its average.

Overall, the time series of daily returns exhibit a persistent behavior, manifested in Hurst exponents >0.5. However, the R/S method is biased to finding long memory in all the time series. It is unable to discriminate different dynamic regimes, present in the daily returns of the cryptocurrency market.

4.3. The Nadaraya–Watson Kernel Regression

In various statistical problems, regression techniques are commonly used for modeling the relationship between response variables and covariates for time series data. The subsection's main purpose is to study an easily implemented smoothing method for exploring the association between cryptocurrencies'retun and covid panic index.

In the time series context, the non-parametric estimates of regression function have been investigated by many authors in the case where the observations exhibit some kind of dependence such as long-range memory processes, association random variables, etc. Shao and Yu (1996) proposed a nonparametric estimator of the CES and used the Nadaraya-Watson (NW) type double kernel estimator of the conditional density and the conditional quantile associated with the estimated conditional density, Bosq (1998) employed the Nadaraya–Watson method to estimate regression curves.

This paper uses the Nadaraya–Watson method to analyze the resulting estimator's asymptotic properties at both interior and boundary points, and to compare Nadaraya–Watson method with non linear MIDAS models. The spectral analysis (in Appendix A4.) provides complementary evidence of co-movements of the cryptocurrencies'returns and the covid panic index. It also reveals distinctive patterns of frequency evolution. The aggregate daily cryptocurrencies'returns exhibit fractal fluctuations. The estimation presents periodicities identified from periodogram spectral analysis. We conclude that the frequencies are remarkably variable. The existence of unstable characteristic frequencies provides valuable information about structural changes.

A kernel regression model was built. The optimal kernel density estimator corresponding to the optimal bandwidth has been suggested by Epanechnikov (1969), and is given by:

$$k_1(x) = \begin{cases} \frac{3}{4}(1-x)^2 & if\ |x| \leq 1 \\ 0 & else \end{cases} \quad (29)$$

The Nadaraya–Watson Kernel regression is used to estimate the variables'conditional expectation and to explore a non-linear relation between a cryptocurrencies'return and a covid Panic index. The smoothing para.eter h of the Nadaraya-Watson kernel estimator called the "bandwidth" controls the smoothing level of the estimation and has a prominent effect on the shape of the estimator of the kernel estimators. The independent variable is daily cryptocurrencie's return, The dependent variable is covid Panic Index. An optimal bandwidth selection is used for lag selection for the non-linear autoregressive kernel regression and the estimation of the conditional mean and volatility for each one of the cryptocurrencies. The dataset encompasses December 2019 to January 2021. In the Figure 2 the blue points are taken from the function including random noise; Kernel Regression arrives at the red line's approximated function.

Table 3 contains the predicted mean square error and volatility of forecasts generated from the kernel regression. Results reveal that Nadaraya-Watson kernel regression estimators with an optimal parameter search provide good estimates Nevertheless, it presents the lowest criteria information of Akaike and Schwartz compared to the non linear models developed in the next section.

Overall, it can be seen that the implementation of the Nadaraya–Watson estimate of regression function is much easier than the non-linear method. However, it is well-known that the Nadaraya–Watson method is inferior to the non-linear approach due to the limitations such as larger bias, non-adaptation and boundary effects.

4.4. Analysis of Impulse Response Functions (IRF)

It is well known that the impulse response's dynamic properties depend on the VAR model's lag order fit to the data. The choice of the appropriate lag-order affects the substantive interpretation of VAR impulse response estimates[1].

The most common strategy in empirical studies is to select the lag-order by some pre-specified criterion and to condition on this estimate in constructing the impulse response estimates. We use the likelihood ratio test (LR) to select the appropriate lag length. To verify the stability of the model, we check if all eigenvalues lie in the unit circle. The autocorrelation of model residuals is tested with VAR order. We provide from the results obtained from the Likelihood Ratio test and the information criteria (the schwarz information criterion (SIC), the hannan-quinn criterion (HQC), the akaike information criterion (AIC), that in most cases, VAR

1 unrestricted VAR models are used for forecasting. The consensus from the point of view of practitioners who use VAR models. is that univariate ARMA models, Bayesian VAR models implemented without the use of lag order selection criteria, and dynamic factor models are the methods of choice for generating out-of-sample forecasts. To study the mechanisms of cryptocurrencies' market in the form of impulse response functions, the method of choice is the unrestricted VAR models.

Figure 2: Nadaraya–Watson Kernel regression

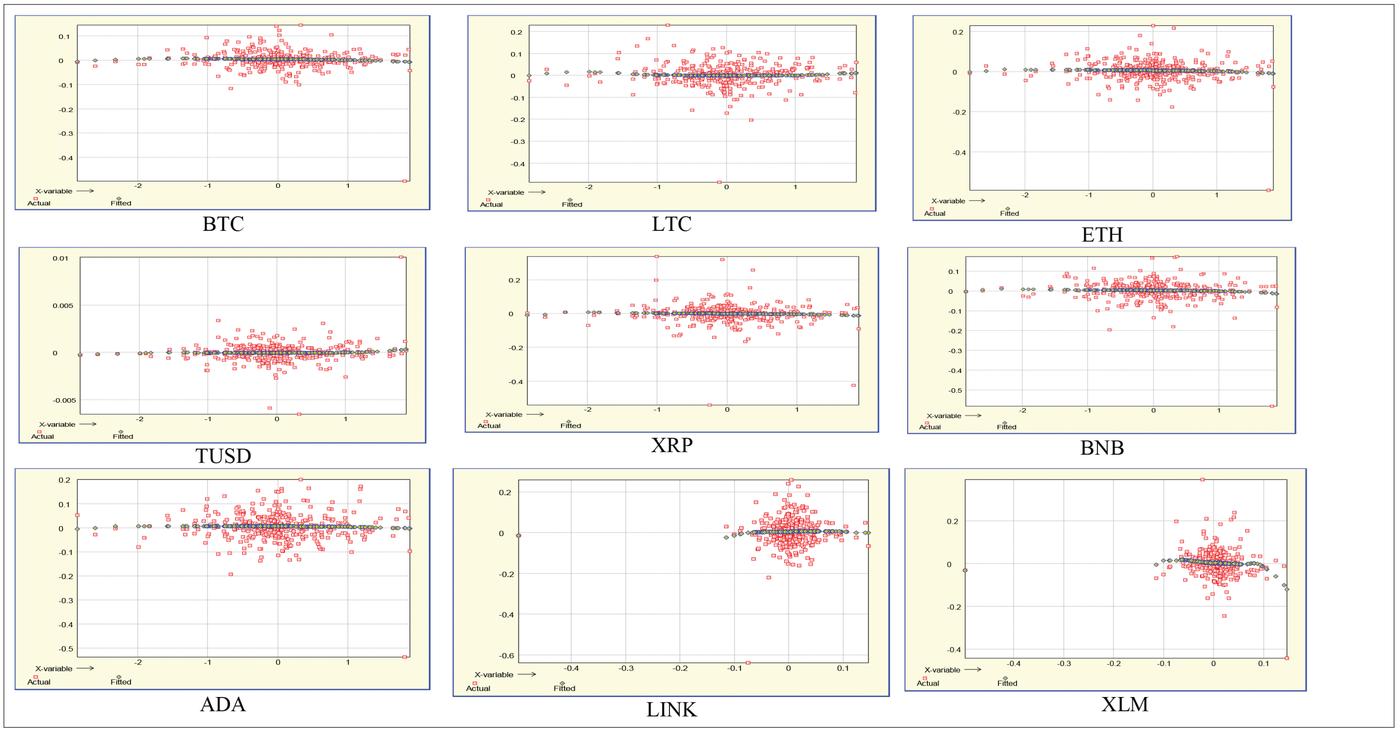
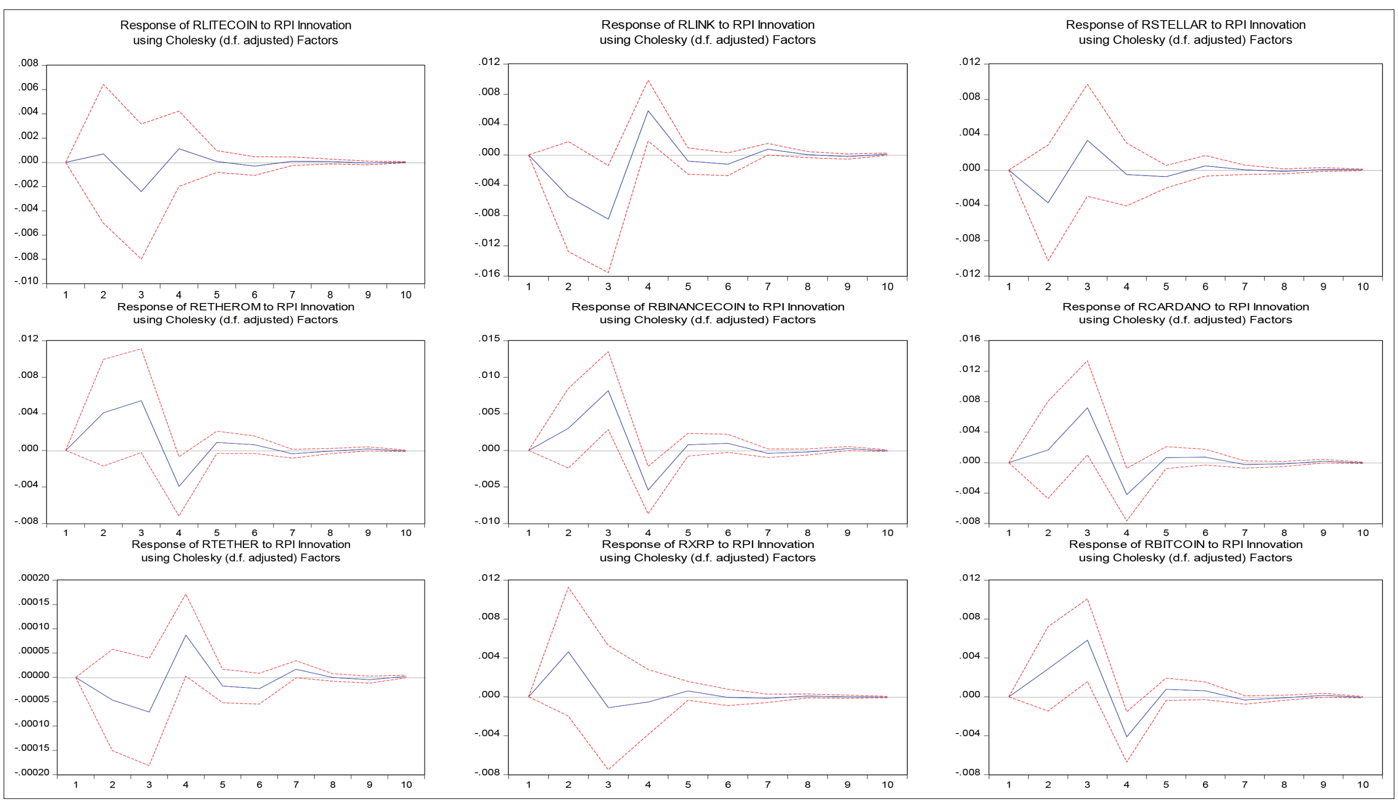


Figure 3: Impulse Response of cryptocurrencies to COVID panic index



(2) is the appropriate lag length order. Therefore, we focus on results obtained from VAR (2) analysis.

We analyze the impulse response functions, the results are summarized in graphical response surfaces of COVID panic index to cryptocurrencies's return for the structural impulse responses based on VAR models. Figure 3 illustrates the relationship between the Covid Panic Index and cryptocurrencies from volatility impulse response functions. We find that Covid Panic Index cause substantial increases in the volatility of the cryptocurrencies' returns. The results obtained from the IRF analysis show that in most cases the results of the IRF analysis are consistent with the results obtained from the Granger causality test. Both granger test and IRF analysis indicate that the statistically significant relationships from Granger test are also statistically significant in the case of Impulse Response Functions. The relationships between COVID panic index and cryptocurrencies's return are statistically significant in the case of the entire sample period.

The main differences between IRFs on different cryptocurrencis are the longevity of responses to the COVID panic index before converging to zero, the number of oscillations estimated in our study corresponds to a one-time unit increase.

However, the relationships for the impulse response functions of cryptocurrencies's return to the COVID panic index are not statistically significant in the case of the entire sample period. IRF analysis indicates that the relationship between variables is unidirectional.

4.5. Causality Test

To examine COVID panic index's role in the cryptocurrency market, we analyze cryptocurrency price's responses to changes in COVID panic index and whether changes in COVID panic index have any effect on future prices of cryptocurrencies.

Therefore, we verify the following hypotheses:
H_1: cryptocurrencies's return is affected by covid panic index;

H_2: Covid panic index is affected by cryptocurrencies's returnThe results of Table 4 present an empirical evidence of causal relationships. The results show that Covid Panic Index cause in Granger sense cryptocurrencies's return: namely Bitcoin, Litecoin,Cardano, XRP and Ether. We note that there is a statistically significant casual relationships, in Granger sense, for these cryptocurrencies with Covid Panic Index, in the entire sample period. We reject the null hypothesis of no causality at 5% significant level.

The results confirm that covid panic index is related to the cryptocurrencies's value highlighting a convergence of cryptocurrencies value expectation. A level of the panic index can be an important informative signal for the convergence of price expectations. We conclude that there is an important link between covid panic index and price formation since a high level of panic index leads to falling prices and convergence of expectations.

Moreover, the most significant causality between the PI and the cryptocurrencies is observed for the Bitcoin; we associate this result with the investor's sentiment and the panic market movement. The highly aligned comovements during the crisis period indicate that the panic selling or panic buying limit the diversification strategies. Moreover, the market is severely influenced by herd behavior. The diversification strategies, which could be valuable under normal market conditions, fail during this crisis period. The relationship between Covid panic index and convergence of price dynamics offers important insights for investors, since it remarks how the evaluation of cryptocurrencies is volatile and anchored to investors' panic sentiment.

We can provide that more signals deriving from the Covid Panic Index (PI) are associated with reducing returns dispersion and convergence of beliefs. Such effect is amplified weighting for days when Panic Index is high.

The causal relationships from cryptocurrencies's return to PI are not significant. The results reveal a unidirectional causality between the covid panic index and cryptocurrencies's return.

We show strong evidence of the existence of linear causal relationships from the Panic index to cryptocurrencies'returns and no evidence from the opposite direction.

We analyze the Wald test and provide inter-relationships between the cryptocurrencies and covid panic index. The wald test for granger causality shows not only significance of direct Granger causality between acryptocurrencies's return and covid panic index but also the significance of each variable's causalitys. The results contain p-values for variable's causality and the statistically significant causal relationships between variables at 5% significance level.

Covid panic index granger cause bitcoin, litecoin, cardano, XRP and Ether during the analyzed period, which supports the hypothesis H_1. However, in the entire sample period Litecoin, Stellar and Tether does not granger cause covid panic index. The causal relationships from cryptocurrencies's return to the Covid Panic index are not significant.

4.6. Volatility Models

In this paper, we analyze the determinants of cryptocurrency volatility. As potential drivers of cryptocurrencies volatility. The

Table 4: Granger causality test on cryptocurrencies value

Cryptocurrencies	Cryptocurrency → COVID panic index	Probability	Causality	COVID Panic Index→ Cryptocurrency	Probability	causality
BTC	2.17945	0.1147	No	6.01560	0.0027	Yes
ADA	2.64733	0.0723	No	3.28498	0.0386	Yes
ETH	1.27280	0.2814	No	3.64761	0.0271	Yes
LINK	0.67828	0.5082	No	5.04273	0.0069	Yes
LTC	0.74735	0.4744	No	0.37734	0.6860	No
XLM	0.38659	0.6797	No	1.01401	0.3639	No
TUSD	2.30149	0.1017	No	2.24578	0.1074	No
XRP	0.71667	0.4891	No	0.98307	0.3752	Yes
BNB	2.32656	0.0992	No	6.59051	0.0016	Yes

The symbol "Cryptocurrency → COVID panic index" indicates the null hypothesis of cryptocurrency returns does not Granger cause COVID panic index and the symbol "COVID panic index→ cryptocurrency" indicates the null hypothesis of COVID Panic Index does not granger cause cryptocurrency returns. The significance denotes the rejection of the null hypothesis. The p-values are presented in the table

GARCH-MIDAS allows us to combine lagged realized correlation, with the covid panic index explanatory variables, and to check whether the covid panic index has explanatory power for the long-term correlation when controlling for lagged realized correlation.

As a Benchmark model, we estimate a simple GARCH (1,1) for the cryptocurrency returns. The parameter estimates are presented in the Table 5. The sum of the estimates of α and β is slightly above one and the two GARCH parameters are highly significant.

For describing the persistence in the volatility of a time series, we estimate a fractionally integrated generalized autoregressive conditional heteroscedastic model (FIGARCH), mainly it is generally assumed that large shocks tend to follow large shocks and similarly, the small shocks tend to follow small shocks, a phenomenon known as volatility clustering. The primary purpose of the FIGARCH model is to present a conditional variance of time series'cryptocurrencies that are capable of detecting the observed temporal dependencies in cryptocurrencies'market volatility and can accommodate the time dependence of the variance and a leptokurtic unconditional distribution for the returns with a long memory behavior.

FIGARCH(p, d, q) model may be obtained as:

$$\left[(1-\beta(L)\right]h_t = \alpha_0 + \left[1-\beta(L)-\phi(L)(1-L)^d\right] \qquad (30)$$

The conditional variance h_t of y_t is given by:

$$h_t = \alpha_0\left[1-\beta(1)\right]^{-1} + \left\{\left[1-\beta(L)\right]^{-1}\phi(L)(1-L)^d\right\}$$
$$\epsilon_t^2 = \alpha_0\left[1-\beta(1)\right]^{-1} + \lambda(L)\epsilon_t^2 \qquad (31)$$

The FIGARCH model is obtained by replacing the first difference operator in the ARCH model with the fractional differencing operator d, where d is a fraction 0 < d < 1. It allows a slow hyperbolic rate of decay for the lagged innovations in the conditional variance function.

Figure 4 represents the dynamics of daily-realized volatility of cryptocurrencies's return; it clearly indicates that duringhe Covid 19 crisis, the peaks of volatility result are related to the irrational responses of the investors (e.g. panic and herd behavior). Investor reactions are strong following the increase of COVID panic index.

Appendix A3 presents the godness of fit estimation relevant to the FIGARCH model to assess the performance of a model . The high Akaike and Schwarz's Bayesian Information Criterion indicates a poor fit compared to non linear models. The estimates of the fractional difference parameter d are between 0.18 and 0.45 which indicate that returns volatility of cryptocurrencies display long range dependence characteristics essentially due to structural breaks that affect parameters driving returns and volatility dynamics.

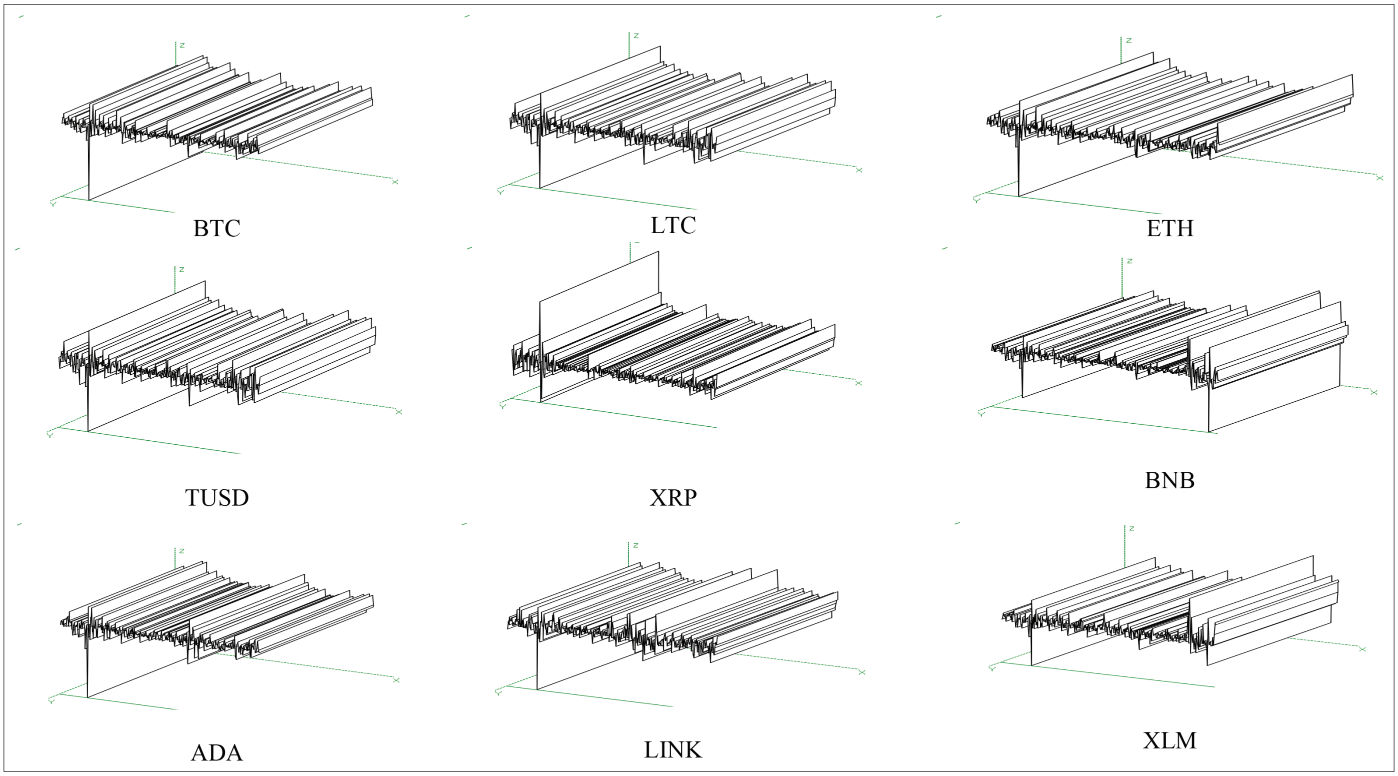
By considering the covid panic index, the cryptocurrency's prices are much more volatile and particularly sensitive to market events.

Table 5: DCC-RC and DCC-RC-PI model estimation

Cryptocurrencies	α	β	λ	θ_{RC}	θ_{PI}	AIC	BIC	LLF
BNB GARCH	0.1684*	0.1478*	0.8567*	0.31982*	-	5.6751	5.6789	−4613.58
DCC-RC	0.1602*	0.1342*	0.6443*	0.2224*	-	5.7838	5.7856	−4699.35
DCC-RC-PI	0.1641*	0.1321*	0.6426*	0.4023*	−0.003*	5.9765	5.9774	−4714.32
BTC GARCH	0.1049*	0.1228*	0.7861*	0.2419*	-	5.9876	5.9885	−4337.92
DCC-RC	0.1127*	0.1167*	0.5848*	0.2897*	-	5.9865	5.9868	−4345.33
DCC-RC-PI	0.1198*	0.1182*	0.5765*	0.3929*	−0.0012*	5.9906	5.9923	−4241.65
ADA GARCH	0.1439*	0.1145*	0.4215*	0.1997*	-	5.0876	5.0889	−4241.09
DCC-RC	0.1522*	0.1076*	0.3678*	0.2224*	-	5.0765	5.0772	−4434.64
DCC-RC-PI	0.1589*	0.1043*	0.3652*	0.1049*	−0.006*	5.0098	5.1121	−4529.39
ETH GARCH	0.1321*	0.1365*	0.5876*	0.3002*	-	6.2250	6.2259	−4318.98
DCC-RC	0.1362*	0.1267*	0.4432*	0.2188*	-	6.7561	6.7572	−4489.63
DCC-RC-PI	0.1394*	0.1234*	0.4376*	0.1876*	−0.0007*	6.8806	6.8811	−4517.35
LINK GARCH	0.1084*	0.1228*	0.6568*	0.3082*	-	5.6688	6.6690	−4213.21
DCC-RC	0.1099*	0.1186*	0.5809*	0.3024*	-	5.7965	6.7969	−4230.09
DCC-RC-PI	0.1141*	0.1168*	0.5428*	0.1193*	−0.0014*	5.4325	6.9333	−4318.58
LTC GARCH	0.1421*	0.1164*	0.4426*	0.2218*	-	6.4076	6.4088	−4684.90
DCC-RC	0.1448*	0.1033*	0.3976*	0.3087*	-	6.3209	6.3217	−4789.07
DCC-RC-PI	0.1498*	0.1014*	0.3499*	0.2453*	−0.0028*	6.9765	6.9768	−4794.90
XLM GARCH	0.1143*	0.1276*	0.6985*	0.31982*	-	5.0757	5.0766	−4887.24
DCC-RC	0.1187*	0.1209*	0.5994*	0.1987*	-	5.0868	5.0899	−4862.20
DCC-RC-PI	0.1198*	0.1198*	0.5321*	0.2160*	−0.0035*	5.1453	5.8472	−4919.79
TUSD GARCH	0.1498*	0.1324*	0.4987*	0.3155*	-	5.2254	5.2261	−3687.22
DCC-RC	0.1502*	0.1287*	0.3321*	0.1987*	-	5.2081	5.2089	−3868.94
DCC-RC-PI	0.1541*	0.1265*	0.3171*	0.1654*	−0.0005*	5.2966	5.8972	−3913.98
XRP GARCH	0.1334*	0.1109*	0.5506*	0.2143*	-	5.8643	5.8651	−4315.18
DCC-RC	0.1447*	0.1032*	0.4320*	0.1284*	-	5.7476	5.7482	−4397.39
DCC-RC-PI	0.1478*	0.1018*	0.4224*	0.1029$	−0.0034*	5.8788	5.8792	−4465.44

The table reports cryptocurrencies-wise estimation results for the DCC-RC, and DCC-RC-PI (covid panic index) model estimation. The CR_i are the correlation ratios. AIC is the Akaike information criterion and BIC the Bayesian information criterion. LLF is the log-likelihood function. ***, **, and * indicate significance at the 1% level, 5% level, and 10% level, respectively

Figure 4: Cryptocurrencies' volatility structure (FIGARCH estimation)



We conclude that this model is suitable for describing the volatility returns during the sample period and that the cryptocurrency returns are not independent. Therefore, the estimated GARCH model does not satisfy the condition for covariance stationarity.

4.7. DCC-MIDAS Model of Realized Correlation and DCC-RC-PI Model

We first present the results for the DCC mixed data sampling (MIDAS) model of realized correlation (RC) to describe the long-term correlation of cryptocurrency returns, then we estimate the DCC-MIDAS-PI model for cryptocurrencies returns when we incorporate the Covid panic Index in the MIDAS equation.

The DCC-MIDAS parameter estimates of realized correlation (RC) are shown in Table 5; the MIDAS filter in the DCC-MIDAS model can extract the slowly moving secular component around which daily volatility moves, which helps us to capture the long-term cryptocurrencies' volatility more effectively.

We can find that θ_{RC} indicates that volatility's response to realized correlation is significant and that almost all parameters are significant at the 5% level. The stationary condition is satisfied as the sums of α and β take values noticeably less than but close to 1 for all cryptocurrencies which implies high persistence of cryptocurrencies' volatility. For this model, the estimates of α and β satisfy the condition for covariance stationary.

The θ_{RC} estimates are statistically significant and positive. The results of the DCC-MIDAS dynamic correlation estimation, θ_{RC} reflects that the current long-term cryptocurrencies correlation is positively related to the COVID panic index. The λ estimates imply that the optimal weights on the lagged RC vanish after about 1 year.

We extend the specification by estimating the DCC-MIDAS model for cryptocurrencies returns by incorporating the investor' COVID panic index in the MIDAS equation as additional predictors of the long-term correlation. We use the DCC-MIDAS-PI model to allow long-term volatility and correlation to be affected by the COVID panic index. The model combines daily cryptocurrencies returns with the monthly COVID panic index and decomposes the total dynamic correlation into long- and short-term components.

The results in Table 5 show that the θ_{RC} estimates in the DCC-RC-PI models are positive and highly significant for all cryptocurrencies. In all specifications the short-run volatility component is mean-reverting to the long-run trend. We, therefore, conclude that the long-run volatility is mostly related to the realized correlation (RC).

The coefficient θ_{PI} is negative and significant at the 5% level for all the cryptocurrencies, which consistently indicates that panic index has a significantly negative influence on volatility and that long-run volatilities of cryptocurrencies increase when the COVID Panic Index slows down During the Covid 19 crisis.

Our finding confirms the negative relationship between panic index and cryptocurrency volatility. The estimated coefficient θ_{PI} of the stock market is significantly negative, which means clearly that the effect of sentiment on the long-term stock volatility is important during the Covid 19 crisis.

We compare the models' performance in terms of Akaike (AIC) and Bayesian (BIC) information criteria. According to the AIC and

BIC criteria, the DCC-RC-PI is clearly preferred to the DCC-RC. The specifications which additionally include the COVID Panic Index lead to further improvements in the model fit.

5. CONCLUSION

This study attempts to explore the impact of COVID-19 on the market returns of nine cryptocurrencies to check how the Covid Panic Index intensity affects the returns of the cryptocurrencies.

Results reveal that the cryptocurrency market's overall trend is the same for all cryptocurrencies; the volatility decreases in response to the higher covid panic index. Furthermore, the cryptocurrencies present persistence during the market crisis. Such a behavior shows the cryptocurrencies' ability to absorb small external shocks during the Covid panic index increase.

In combating the negative impacts of the COVID-19 panic index on financial markets, and serving as an alternative investment tool in the times of panic and uncertainty,cryptocurrencies could be considered as a safe-haven during the crisis. This finding shows the hedging role of cryptocurrencies against the uncertainty raised by COVID-19 and is in line with previous studies that provide evidence on the hedging role of Bitcoin against uncertainty (Fang et al., 2018; Goodell and Goutte., 2020). Most of the other cryptocurrencies in our sample posted positive gains in response to an increase in the Covid-panic index.

Therefore, a selective and cautious approach needs to be adopted to diversify with cryptocurrencies against systematic risks. Since our results suggest that cryptocurrency volatility forecasts based on the DCC-MIDAS model are superior to forecasts based on simple GARCH models, it would be worthy of discussing the causal linkage among investor's sentiment deeply and to construct improved time-varying portfolio weights during financial market-crisis.

These results offer interesting insights for future research and have important implications for investors, especially in understanding the cryptocurrencies' behavior in times of huge stress such as a pandemic. Blockchain technology are theoretically capable of mitigating some of the issues that come with the new realities that the pandemic has brought. Investors should consider including cryptocurrencies in their portfolios depending on the COVID-19 phases; regulators and governments may formulate policies for stabilizing the market and reducing its high volatility.

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APPENDIX

Appendix A1: Descriptive statistics of daily returns cryptocurrencies

Cryptocurrencies	BNB	BTC	ADA	ETHU	LINK	LTC	XLM	TUSD	XRP	PI
Mean	0.002476	0.003882	0.004960	0.005486	0.004734	0.002493	0.002977	3.16E-06	3.57E-05	−0.001726
Median	0.004258	0.004492	0.005814	0.005358	0.004415	0.002969	0.003843	0.000000	0.002549	0.000000
Maximum	0.17463	0.145941	0.200831	0.230189	0.260037	0.229910	0.392428	0.10102	0.339714	1.884541
Minimum	−0.581308	−0.497278	−0.536050	−0.589639	−0.637153	−0.486778	−0.440312	−0.06525	−0.541017	−2.867899
Std. Dev.	0.053671	0.042759	0.062571	0.056990	0.071523	0.055546	0.062838	0.01079	0.064038	0.692697
Skewness	−3.813228	−4.390063	−1.649306	−3.025778	−1.775787	−1.891426	0.044984	1.383343	−1.627825	−0.223643
Kurtosis	43.35750	56.87796	18.79413	37.44651	21.80524	20.97238	15.41734	30.31789	26.57504	4.702170
Jarque-Bera	24389.62	43084.76	3764.014	17685.19	5295.375	4877.032	2229.452	10900.45	8188.939	44.78394

This table presents descriptive statistics of daily log returns of the nine cryptocurrencies in our sample and COVID-panic index. First column displays the mean. Third and fourth columns show smallest and largest observations, respectively. Fifth column shows standard deviations. Seventh and eighth column reports skewness and kurtosis coefficients, and the eighth column presents the Jarque-Bera statistics

Appendix A2: Correlation between daily returns of digital currencies and COVID19 panic index

Cryptocurrencies	BNB	BTC	ADA	ETHU	LINK	LTC	XLM	TUSD	XRP	PI
BNB	1.000000	0.842747	0.751187	0.898792	0.766388	0.713387	0.675676	−0.394808	0.586023	−0.200628
BTC	0.842747	1.000000	0.806020	0.951401	0.646437	0.863731	0.799897	−0.399018	0.601419	−0.163063
ADA	0.751187	0.806020	1.000000	0.883778	0.790708	0.610520	0.847911	−0.442604	0.594149	−0.167305
ETH	0.898792	0.951401	0.883778	1.000000	0.807613	0.789704	0.825758	−0.370876	0.654048	−0.187117
LINK	0.766388	0.646437	0.790708	0.807613	1.000000	0.456184	0.683605	−0.290485	0.578871	−0.157393
LTC	0.713387	0.863731	0.610520	0.789704	0.456184	1.000000	0.692595	−0.243779	0.565230	−0.092581
XLM	0.675676	0.799897	0.847911	0.825758	0.683605	0.692595	1.000000	−0.390448	0.838170	−0.148063
TUSD	−0.394808	−0.399018	−0.442604	−0.370876	−0.290485	−0.243779	−0.390448	1.000000	−0.272519	0.170043
XRP	0.586023	0.601419	0.594149	0.654048	0.578871	0.565230	0.838170	−0.272519	1.000000	−0.124876
PI	−0.200628	−0.163063	−0.167305	−0.187117	−0.157393	−0.092581	−0.148063	0.170043	−0.124876	1.000000

The table presents the correlation between daily returns of different digital currencies and the correlation between daily returns of digital currencies and COVID-panic index

Appendix A3: Godness of fit estimation relevant to the FIGARCH model

	AIC	BIC	LLF
BNB	4.22716	4.22894	-1945.751
BTC	4.83231	4.82045	-2143.806
ADA	4.83486	4.82079	-2154.981
ETH	4.60141	4.60566	-1878.283
LINK	4.62382	4.62424	-1954.791
LTC	4.80566	4.83486	-2070.610
XLM	4.22895	4.20413	-2053.847
TUSD	4.82716	4.82588	-2254.442
XRP	4.83231	4.82486	-2345.987

The table presents FIGARCH estimation of daily log returns of the nine cryptocurrencies in our sample