Has the Pandemic Impacted the Volatility and Returns Structure of Bitcoin?

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Abstract: The current pandemic caused by COVID-19 is bringing unprecedented economic downturn worldwide. As this pandemic is rapidly wreaking havoc on an almost daily basis on every aspect of global economic activities, economists, planners, policy makers and especially the public are wondering how its impact can be assessed and quantified to craft viable responses. In the exotic field of cryptocurrencies, prior to the Pandemic, everyone is excited about Bitcoin and its multitude of potentials as an alternative currency, store of value, medium of exchange, hedge against inflation and a viable investment opportunity. However, when the pandemic was officially announced by World Health Organization (WHO), the rate of return to Bitcoin precipitously dropped by an unheard-of figure of **-46.5%** and people started to rethink the prospects of Bitcoin in the light of the pandemic, particularly its dynamic risk-return profile. This study aims to analyze the daily rate of return to Bitcoin using one year of uninterrupted daily data for each of the subperiods labeled Pre-pandemic and Pandemic eras using cutting-edge econometric modeling, stylized facts analysis and relevant statistical testing. The general conclusion of the study – Pandemic or not, Bitcoin is strong, and may even be stronger during than before the pandemic.

Key Words: COVID-19 Pandemic; Bitcoin; risk-return trade-off; Autoregressive Mean Equation; GARCH Variants

1. INTRODUCTION

The current pandemic caused by COVID-19 is bringing unprecedented economic downturn worldwide. As this pandemic is rapidly wreaking havoc on an almost daily basis on every aspect of global economic activities, economists, planners, policy makers and especially the public are wondering how its impact can be assessed and quantified to craft viable responses. In the exotic field of cryptocurrencies, prior to the Pandemic, everyone is excited about Bitcoin and its multitude of potentials as an alternative currency, store of value, medium of exchange, hedge against inflation and a viable investment opportunity. However, when the pandemic was officially announced by World Health Organization (WHO), the rate of return to Bitcoin precipitously dropped by an unheard-of figure of -46.5% and people started to rethink the prospects of Bitcoin in the light of the pandemic, particularly its dynamic risk-return profile.

This study aims to analyze the daily rate of return to Bitcoin using one year of uninterrupted daily data for each of the subperiods labeled Pre-pandemic and Pandemic eras using cutting-edge econometric modeling, stylized facts analysis and relevant statistical testing.

2. METHODOLOGY

2.1 Data

The data used in the study is sourced from the website www.CoinMarketCap.com and is composed of the daily closing price of Bitcoin (in US$ per coin) and its continuously compounded returns (in %). A total of 724 daily observations from March 16, 2019 to March 10, 2021 are extracted. This full sample period is subdivided into two subperiods (Pre-pandemic and Pandemic) using March 11, 2020 – the day when the World Health Organization (WHO) formally declared the onset of the Covid-19 Pandemic (https://pubmed.ncbi.nlm.nih.gov/32191675) as the breakpoint of the two subperiods.

2.2 Stylized Facts Analysis and Testing for the ARCH Effect

Daily closing prices (P) and Returns (rr) of Bitcoin within the sample horizon are subjected to a battery of graphical and descriptive analyses of their first four representative moments (Mean, Standard Deviation, Skewness and Kurtosis) over the two sub-periods. In quantifying the returns series, the continuously confounded rate of return formula is used in this study:

$$rr_t = 100 * \ln(P_t / P_{t-1}) \qquad (1)$$

To ascertain the presence of the so-called ARCH Effect or volatility clustering, the Lagrange Multiplier (LM) test is implemented on the return series. Normality testing of the series is undertaken by the Jarque-Bera (JB) test.

2.2 The ARCH/GARCH Models

The ARCH Effect (Engle 1982) is an almost unique phenomenon associated with modeling returns to financial assets. ARCH stands for AutoRegressive Conditional Heteroscedasticity. In classical regression analysis, the presence of ARCH is a complete anathema to all the classical model stands for. Hence, instead of just modeling the mean return equation (or the population regression function (PRF) of the average return), the conditional variance equation is likewise specified owing to the presence of the time varying second moment. The basic ARCH(q) model is specified as follows:

Mean Equation:

$$E_{t-1}(rr_t) = \phi' rr_{t-1} + u_t \qquad (2)$$

Conditional Variance Equation:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \qquad (3)$$

Bollerslev (1986) saw the need to generalize the ARCH effect to augment the current conditional variance with its past values, up to lag p The conditional variance equation for the classic GARCH(q,p) is now:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (4)$$

2.3 The GARCH Variants

To check for the presence of certain special volatility effects (e.g. leverage effect, asymmetric effects, etc.), two different families of GARCH models are introduced in the literature: the APARCH (Asymmetric Power ARCH) and the EGARCH (Exponential GARCH) models.

The APARCH Family (Ding, et. al., 1993)

This family of GARCH models can accommodate various asymmetric effects and power transformations of the conditional variance. The general specification of the conditional volatility equation of the APARCH family is as follows:

$$\sigma_t^\delta = \omega' z_t + \sum_{i=1}^{q} \alpha_i (|u_{t-i}| - \gamma_i u_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \qquad (5)$$

where $\sigma_t = \sqrt{h_t}$

The power transformation parameter δ which ranges between 1 and 2 performs a Box-Cox transformation, while γ captures the asymmetric effects. Specific values for δ's and γ's give rise to different variants of the APARCH models:

ARCH (Engle 1982) - β's, γ's = 0, δ=2
GARCH (Bollerslev 1986) γ's = 0, δ=2
GARCH (Taylor 1986 and Schwert 1990)
γ's = 0, δ=1
GJR (Glosten, et.al. 1993) δ=2
TARCH (Zakoian 1994) δ=1
NARCH (Higgins and Bera 1992) β's, γ's = 0

The EGARCH Variant (Nelson 1991)

The Exponential GARCH, with the variance equation expressed in terms of log volatility captures the asymmetric effect as a function of standardized innovations. Thus, the conditional variance equation is specified as:

$$\ln h_t = \omega' z_t + \sum_{i=1}^{q}\left[\alpha_i(|\varepsilon_{t-1}| + \gamma_i \varepsilon_{t-i}) + \sum_{j=1}^{p}\beta_j \ln h_{t-j}\right] \quad (6)$$

with the error $\varepsilon_t = u_t / \sqrt{h_t} \sim N(0,1)$ or suitable distribution.

The Conditional Error Distribution

All of the above GARCH models are estimated using Maximum Likelihood (or Pseudo ML) Procedure, bringing to fore the choice of the most appropriate distribution of ε_t. In this study, five alternative error distributions are considered depending on the shape of the empirical distribution of the residuals. These are the following:

1. Standard Normal
2. Student's t
3. Generalized Error Distribution (GED)
4. Skewed Student's t
5. Skewed GED

Thus, in analyzing an empirical model for Bitcoin daily return, three specifications should be formulated:

1. The Mean equation
2. The Conditional Variance equation, and
3. The Error distribution

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Initial assessment of the time graph of the price and return series of Bitcoin over a sample horizon of 726 days reveals a great deal of special stylized facts. Shown in **Figure 1** below, daily closing price appear to be on a sustained uptrend that has become steeper during the more recent part of the Pandemic period. Daily returns on the other hand for the entire sample period somewhat cluster around a constant value and to some extent exhibit autoregressive behavior. Taking a hint on this observed stationary behavior, the mean equation of the return series may be specified as first order auto regressive linear equation plus a time varying noise element. The time graph of the return series also reveals a phenomenon of volatility clustering, as evidenced by episodes of wild swings and tranquil periods. As seen here, wild swings exceed calm episodes. It may be noted that the Pre-pandemic and Pandemic eras are separated conveniently by an extreme negative return which occurred a day after the Pandemic announcement by WHO (March 12, 2020). That day also appears to start a steady bull run in Bitcoin price which culminated in all-time highs towards the later pandemic period.

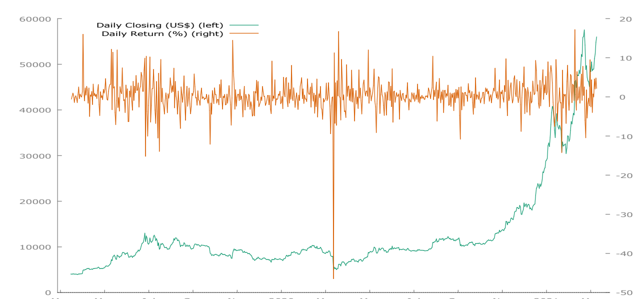

Figure 1. Daily Closing Price and Return to Bitcoin During the Pre-Pandemic (March 16, 2019 to March 11, 2020) and Pandemic (March 12, 2020 to March 10, 2021) Periods

Table 1. RAMSEY Reset of the Mean Equation (Null: Mean equation is adequately specified)

Pre-pandemic:	p-value = P(F(2,356) > 2.30) = 0.102
Pandemic:	p-value = P(F (2,36) > 1.499) = 0.225

The results of the Ramsey's Regression Error Specification Tests (RESET) reported in **Table 1** legitimize the empirical validity of the use of the first order autoregressive scheme specification for the mean equations of the return series for the two subperiods. The null hypothesis of adequate specification for the mean equation of each era is not rejected in all conventional level of significance.

3.2 Modeling Conditional Variance through Variants of GARCH Model

Using the stylized facts uncovered in the descriptive analysis, together with the results of the different statistical tests, modeling of the conditional variance in tandem with the mean equation model has become imperative. The seven (7) different GARCH variants discussed in section 2.3 as the alternative conditional variance formulations for the autoregressive mean equation are implemented for the Pre-pandemic and Pandemic periods. In addition, the three (3) different specifications on the error distribution give rise to a total of twenty-one (21) alternative models for the daily returns of the Bitcoin in each subperiod. To remain parsimonious, these models consider only p = 1 and q = 1 for good reasons. For one, GARCH (1,1) has been considered as the "gold standard" in the literature since adding more ARCH and GARCH terms (i.e., p, q > 1) rarely add more information and more significant coefficients to infer on the data generating process (DGP) of the series. Furthermore, this parsimonious representation has been known to be robust in modeling countless applied phenomena (Engle 2001). Tables 3, and 4 show the results of implementing the different GARCH variants using the GED which is found to be the most appropriate error distribution for both eras (model selection results are not shown here for lack of space). The skewed versions of the Student's t and GED are not considered because of the observed symmetry of the returns.

Examining the results presented in the two tables, it has become clear that volatility clustering is valid for Bitcoin returns by virtue of the significant estimates of the α and β parameters in all variants regardless of whether there is pandemic or not. Volatility persistence in all models captured by the estimate of $\alpha+\beta$ is not significantly greater than 1 in all models across eras. This is an indication of the well-behaved nature of future volatility, since according to the formula of unconditional future volatility:

$$h^2 = \frac{\omega}{1-\alpha-\beta} \qquad (7)$$

(Engle 2001), the unconditional variance may have negative value. Hence, when $\alpha+\beta>1$, the steady state standard deviation h may become unbounded, in other words, it may reach explosive levels. All gamma parameters of the asymmetric models (GJR, TARCH, APARCH and EGARCH) in Tables 3 and 4 reveal the absence of asymmetry and leverage effects. This implies that any negative shock (bad news) concerning Bitcoin does not increase volatility asymmetrically more than any positive shock (good news) of equal intensity, irrespective of era.

Incidentally, as one examines the last row of **Table 3** and **Table 4**, the best GARCH variant for the variance equation of the return series on the basis of it having the least AIC among GARCH models tested proved to be the TARCH model of Zakoian (1994), hence most of conclusions of the study are based on the properties of this estimated model.

4. CONCLUSIONS

The unfortunate appearance of the Covid-19 Pandemic has been leaving in its wake countless broken lives, devastated institutions, compromised processes – widespread suffering among various stakeholders of the global economy. Prior to the pandemic, Bitcoin has been hailed as the future of money with its numerous desirable attributes. Many are wondering about the future of Bitcoin in the light of the pandemic, which for a year now has been devastating the world. This study, through stylized facts analysis, statistical testing, and cutting-edge econometric modeling, hopes to contribute in understanding this most dominant cryptocurrency.

The general conclusion of the study – *Pandemic or not, Bitcoin is strong, and may even be* *stronger during, than before the pandemic.* Among the auxiliary findings of the study are the following:

1. Bitcoin generally performed better during the pandemic than during the pre-pandemic period. One day after the pandemic announcement Bitcoin started a sustained bull run.
2. All unit root tests confirm stationarity of the return series across all time periods.
3. All-time highest daily price of US$57,540 and all-time single day highest return of 17.182% happened during the pandemic era.
4. First order autoregressive mean return equation is statistically adequate.
5. Average Bitcoin price during the pandemic period is significantly higher statistically during the pandemic than during the pre-pandemic era, but the difference in average returns between eras is not significant.
6. There exists no "leverage effect" in the pre-pandemic era, but there is one during the pandemic period.
7. There is lesser likelihood of the occurrence of "bubbles" during the pandemic era.
8. TARCH (1,1) model is the best GARCH model for both eras.

Table 2. Stylized Facts and Relevant Statistical Tests

Time Period	Mean	SDev	Min	Max	Z-Stat	JB-Stat	ARCH-LM(p-value)
Pre-pandemic (T = 362 days)							
Daily Price (US$)	8,440	1942.7	3,963	13,016	12.93***	12.322**	xxxxx
Daily Return (%)	0.1856	3.6042	-15.182	16.004	1.18^{ns}	230.546***	0.00154**
Pandemic (T = 364 days)							
Daily Price (US$)	17,355	13009	4,971	57,540	xxxx	160.13***	xxxxx
Daily Return (%)	0.53769	4.4186	-46.473	17.182	xxxx	19477.3***	0.00153**

Figures reflected in the last two columns are p-values of the Difference Between two Means Z-test, JB Normality test and the ARCH-LM test of ARCH effects respectively

**p<0.01 ***p<0.001 ns-not significant (p>0.10)

Table 3. Estimates of the Alternative GARCH Models for the Daily Returns for Bitcoin using

Coefficients/ Models	GARCH (Bollerslev)	GARCH (Taylor/ Schwert)	NARCH (Higgins and Bera)	GJR (Glosten, et. al.)	TARCH (Zakoian)	EGARCH (Nelson)
Constant	0.351115 0.0000***	0.363013 0.0000***	0.349865 2.1e-111***	0.379756 0.0000***	0.380762 0.0000***	0.427884 0.0000***
AR(1)	-0.150103 0.0000***	-0.156199 0.0000***	-0.150296 7.6e-163***	-0.158562 0.0000***	-0.158838 0.0000***	-0.171906 0.0000***
Omega (ω)	0.308904 0.1264^{ns}	0.280543 0.1488^{ns}	0.220196 0.2719^{ns}	0.157380 0.1075^{ns}	0.234027 0.0387**	-0.0242276 0.4588^{ns}
Alpha (α)	0.0642298 0.0084***	0.0799866 0.0000***	0.0508695 0.0828*	0.0399045 0.0041***	0.0514704 0.0090***	0.0841116 0.0280**
Beta (β)	0.912631 1.0e-276***	0.927785 0.0000***	0.944831 6.5e-259***	0.933998 0.0000***	0.945871 0.0000***	0.0883157 0.0000***
Gamma (γ)				-0.557586 0.0011***	-0.972858 0.0241**	0.0883157 0.0005***
Delta (δ)			0.186538 0.4948			
AIC	1898.57917	1891.56671	1888.82515	1890.02206	*1884.12347*	1885.46088

Generalized Error Distribution (GED) During the Pre-*Pandemic Period (3/16/19 -3/11/20)*

**p<0.01 ***p<0.001 ns-not significant (p>0.10)

Coefficients/ Models	GARCH (Bollerslev)	GARCH (Taylor/ Schwert)	NARCH (Higgins and Bera)	GJR (Glosten, et. al.)	TARCH (Zakoian)	EGARCH (Nelson)
Constant	0.0389398 0.0000***	-0.0128350 0.0000 ***	Did not converge	0.0389094 0.0000***	0.0138484 0.0000***	0.0164810 0.0000***
AR(1)	-0.0336570 0.0000***	-0.0217900 0.0000 ***	Did not converge	-0.0336501 0.0000***	-0.0279059 0.0000***	-0.0285093 0.0000***
Omega (ω)	2.73256 0.0360**	2.48638 0.0485**	Did not converge	2.80239 0.0471**	2.43505 0.0645*	0.269154 0.2755^{ns}
Alpha (α)	0.230421 0.0436 **	0.261937 0.0059***	Did not converge	0.222579 0.0471***	0.222443 0.0227**	0.362190 0.0257**
Beta (β)	0.589061 5.02e-05 ***	0.642180 1.06e-06***	Did not converge	0.578440 0.0003***	0.651164 1.08e-05 ***	0.789084 8.29e-011***
Gamma (γ)				0.0549994 0.7843^{ns}	-0.0660781 0.7963^{ns}	-0.00995234 0.9172^{ns}
Delta (δ)			Did not converge			
AIC	1849.79242	1891.56671		1851.70359	*1848.38563*	1851.15041

Table 4. Estimates of the Alternative GARCH Models for the Daily Returns for Bitcoin using Generalized Error Distribution (GED) During the *Pandemic Period (3/12/20 -3/10/21)*

**p<0.01 ***p<0.001 ns-not significant (p>0.10)

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