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COVID-19 Pandemic & Financial Market Volatility; Evidence from GARCH Models

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Abstract: Across the globe, COVID-19 has disrupted the financial markets, making them more volatile. Thus, this paper examines the market volatility and asymmetric behavior of Bitcoin, EUR, S&P 500 index, Gold, Crude Oil, and Sugar during the COVID-19 pandemic. We applied the GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1) econometric models on the daily time series returns data ranging from 27 November 2018 to 15 June 2021. The empirical findings show a high level of volatility persistence in all the financial markets during the COVID-19 pandemic. Moreover, the Crude Oil and S&P 500 index shows significant positive asymmetric behavior during the pandemic. Apart from this, the results also reveal that EGARCH is the most appropriate model to capture the volatilities of the financial markets before the COVID-19 pandemic, whereas during the COVID-19 period and for the whole period, each GARCH family evenly models the volatile behavior of the six financial markets. This study provides financial investors and policymakers with useful insight into adopting effective strategies for constructing portfolios during crises in the future.

Keywords: COVID-19; financial markets; GARCH; GJR-GARCH; EGARCH; volatility

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1. Introduction

The COVID-19 pandemic has a significant influence on the global economy (Maital and Barzani 2020; McKibbin and Fernando 2020; Ozili and Arun 2020). Numerous countries have implemented strict policies on international travel, such as the adoption of quarantine, and several cultural festivals and sports events have been canceled, which limited economic activities across the globe. The evidence shows that the long-term impact of COVID-19 on economies will be high in terms of business failure and unemployment (Amankwah-Amoah et al. 2021; Holder et al. 2021; Montenovo et al. 2020) since the volatility and connectedness of financial markets have increased due to the COVID-19 pandemic (Aslam et al. 2020b; Chaudhary et al. 2020; Corbet et al. 2021; Khan and Khan 2021; Sadiq et al. 2021). The speculative bets in the financial markets by international investors generates an influx of financial transactions in the financial markets, creating an extreme level of volatile behavior in the prices of financial assets. A speculative bubble can be observed in the financial market in the last few years. The multiple crashes and high level of fluctuation in financial returns during the pandemic has a negative impact on international investment. These unexpected crashes and fluctuations have become a major problem for financial investors across the world. Furthermore, Zhang and Hamori (2021) concluded that COVID-19 has an adverse effect on the performance of the financial markets, with investor behavior also affected due to the fear and risk associated with COVID-19 (Budiarso et al. 2020; Ortmann et al. 2020). We explore the financial volatility of all six major financial markets by using one financial asset from each of the markets (cryptocurrency, exchange rate, stock index, metal market, oil, and agriculture) during the COVID-19 pandemic. The sample of financial assets used in the study are prominent in terms of market capitalization and have top trading representation in their respective financial markets.

In financial markets, there exists asymmetry in the return and volatility relationship. Under the black swan events hitting the financial markets, such as the COVID-19 pandemic, it is vital to analyze the dynamics of the volatility across the financial markets for the sake of investors and policymakers. Moreover, financial markets reflect a complex and dynamic asymmetric dependence (Baruník et al. 2016), with tail dependence across the equity sectors (Aslam et al. 2022). Furthermore, during the bearish trend in the financial markets, the correlation across the returns is stronger than the bullish trend. As a result of a stronger reaction to negative shocks, price volatility becomes asymmetric, reducing the benefits of diversification (Amonlirdviman and Carvalho 2010).

Considering the COVID-19 pandemic, studies have investigated the impact of this contagious disease on the financial markets. Empirical evidence suggests that when compared to other crises, COVID-19 has had devastating effects on the financial markets (Baker et al. 2020; Umar et al. 2021; Zhang et al. 2020). In particular, this pandemic caused severe losses to the stock markets (Khan et al. 2021; Pavlyshenko 2020; Topcu and Gulal 2020; Umar et al. 2021). Furthermore, Al-Awadhi et al. (2020) found that all companies' stocks in China reacted negatively to both the infected cases and deaths per day due to COVID-19. Similarly, Alfaro et al. (2020) showed that COVID-19 had a significant negative impact on the returns of US stock. Using GARCH family models, Osagie Adenomon et al. (2020) reported that COVID-19 negatively affected the Nigerian stock market returns.

Additionally, Zhang et al. (2020), found that COVID-19 had significant negative effects on the equity markets of Singapore, Japan, and Korea, along with the 10 other stock markets, having the highest number of infected cases in March 2020. Besides, Liu et al. (2020) and He et al. (2020) investigated the effects of COVID-19 on stock markets globally and reported that returns of these stock markets gave negative returns during the COVID-19 pandemic. Thus, the drastic effects of COVID-19 on financial markets have caused economic policymakers across the world to enact prohibitions to minimize market losses and reduce uncertainty (Kodres 2020).

The measurement of volatility has significant importance in economic and financial models. The estimation of financial risk is extremely critical in the financial markets. For example, financial stocks in the returns are highly dependent on the behavior of stock market volatility. Therefore, if we are able to estimate the market volatility, then we can also identify the asymmetric behavior in the financial retunes. In addition, the volatility in financial markets is highly connected to investment risk. Most of the portfolio allocations are based on the concept of volatility, such as the Markowitz mean-variance framework. Prior evidence also suggests that economic factors have a strong contribution to financial market volatility. For example, it is observed that the increase in the interest rate by the central bank has a strong impact on the financial market volatility behavior (Adrian et al. 2022). It is also reported that emerging markets across the globe are facing a high level of risks, such as high volatility in the commodity markets and a high level of inflation. Therefore, in this research paper, we examine the different aspects of volatility in the financial markets. The finding of the study reveals that a high level of volatility behavior can be observed at the beginning COVID-19 pandemic.

Financial time series data have a few characteristics that separate them from normal time series data. Researchers have previously recommended that the volatility of the time series returns is highly related to market uncertainty (Bali and Zhou 2016; Connolly et al. 2005). Hence, volatility is among the key parameters in most investment decisions. Volatility is defined as the best risk indicator for the unfailing forecasting of returns in the financial markets (Green and Figlewski 1999). Also, volatility refers to the magnitude of the uncertainty related to the changes in an asset's price. Higher volatility shows that an asset's price can potentially be spread out over an extensive range of values. In other words, the asset price can vary dramatically over the short term in either direction. IN contrast, lower volatility reflects that the asset's price does not vary dramatically and tends to be more stable. Higher volatility indicates a greater probability of a bearish trend in the market, whereas lower volatility is linked with increased chances of a bullish trend in the market (Ang and Liu 2007). Thus, the analysis of financial asset returns is different from the returns of other classes of assets, i.e., volatility clusters, the "fat-tail" phenomena, and the leverage effect. Thus, during periods of a financial crisis, the volatility of the returns cannot be modeled by methods based on the assumption of normal distributions. As a result, dynamic volatility models are required (Rastogi 2014). When modeling time-varying volatility, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model. Later, in order to incorporate the limitations of the ARCH model, Bollerslev (1986) came up with a generalized autoregressive conditional heteroskedasticity (GARCH) model.

The GARCH models have regularly been used in the financial literature, with the reason being their ability to give the most accurate results; therefore, the GARCH family of models has importantly become the standard methodology for modeling volatility in financial time series data (Brooks and Rew 2002). Thus, keeping in view the GARCH families, this study applied three different GARCH family models, namely GARCH (1, 1), GJR-GARCH (1, 1), and E-GARCH (1, 1), to identify the best-fitted model that captures the volatilities of the six representative assets of the financial markets and the effect of the COVID-19 outbreak on them. However, until now, there are very limited studies that investigate market volatility based on different GARCH family models, particularly during the COVID-19 pandemic. These alternative models used in this research paper have their own contribution to the existing literature. The GJR-GARCH model is based on the indicator function, which allows the model to react more toward negative shocks. Furthermore, the most significant advantage of the EGARCH model is its logarithmic specification, which enables the positive constraints among the parameters to be relaxed. Moreover, the EGARCH model also has a significant advantage since it is considered to be the most appropriate model for capturing volatility persistence shocks in a financial series. Moreover, this research paper used AIC to evaluate the most superior model for capturing the volatility in all six financial markets. The findings of this paper are compared over three different periods, i.e., the pre-COVID period, the COVID period, and the whole period. The results of our study indicate that the performance of the GARCH models is dependent upon the time period. Generally, the overall analysis showed that the asymmetric GARCH models are the best-fitted model for capturing market volatility in the financial time series. The results show that the EGARCH model is the best performing GARCH model for Bitcoin and EUR, while the GJR-GARCH model shows better performance in the volatility measurement of the S&P 500 index and Crude Oil.

This study is a unique contribution to the existing literature in distinct ways. Firstly, this paper investigated the performance of the volatility in the financial returns of all six major financial markets (Bitcoin, EUR, S&P 500, Gold, Crude Oil, and Sugar) during the period of the COVID-19 pandemic by applying the three most effective GARCH family models, known as GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1). Secondly, our findings show evidence of volatility clustering, leptokurtic phenomena, and leverage effects in financial returns of all financial markets during the COVID-19 pandemic. International investors have been using different instruments and strategies to invest in the financial markets since the COVID-19 pandemic. Therefore, the findings of the study provide detailed information for international investors to address their strategic requirements in terms of investing in the financial markets.

2. Materials and Methods

2.1. Data

We used six financial assets, i.e., one from each financial market based on their market capitalization (cryptocurrency, exchange rate, stock index, metal, oil, and agriculture). The financial commodities for metal, crude oil, and agriculture (Gold, Crude Oil, and Sugar) were collected based on real-time commodity future prices. The dataset of daily closing prices for this study was downloaded from investing.com over the period of 27 November 2018 to 15 June 2021, with a daily frequency for total observations of 650. The reason for choosing this data sample period was that on 11 March 2020, the World Health Organization (WHO) declared COVID-19 as a 'global pandemic'. Therefore, we divided our data set into three periods: The whole period, before COVID-19 period, and during COVID-19 period. Before the COVID-19 period starts from 27 November 2018 to 10 March 2021. In contrast, the during COVID-19 period starts from 11 March 2020 to 15 June 23 2021, with equal observations (325) in each period. Furthermore, the study used daily data due to the fact that they are superior for short-term econometric modeling. Additionally, daily data are quicker at reacting to level shifts and changes in trends, as the data are modeled daily vs. week/month to observe the new data. The daily returns are calculated via Equation (1).

$$R_t = ln(P_t/P_{t-1}) \tag{1}$$

where financial returns of the markets are denoted by R_t at time t. P_t and P_{t-1} represent the current price and previous day price, respectively.

Primarily, there are three measures of volatility, namely the standard deviation, skewness, and kurtosis. Among them, the standard deviation is the most used; however, it is based on the unrealistic assumption that returns follow the pattern of a normal distribution. Meanwhile, skewness focuses on the extremes in the data rather than incorporating the mean returns (Chang et al. 2013). Another volatility measure is known as 'Kurtosis', which also deals with the extremes in the dataset (Mei et al. 2017). However, an econometric test called Jarque-Bera is used to detect the normality in the data, i.e., if its value is different from zero, then this refers to the absence of the normal distribution in the dataset (Thadewald and Büning 2007). Summary statistics of financial returns are represented in Table 1, which includes the measures of central tendency. Moreover, we adopted the Jarque-Bera test to examine the goodness of fit for the distribution of the returns. It can be seen that the standard deviation of financial returns increased during the COVID-19 pandemic. Moreover, Crude Oil exhibits the highest market risk with an SD value of 0.058, followed by Bitcoin with a value of 0.049, during the COVID-19 period. However, Bitcoin is regarded as the riskiest among the set of financial assets, with an SD value of 0.042, followed by Crude Oil (0.028). The kurtosis coefficient of all the financial assets returns is greater than 3, except for Sugar for the whole period and during the COVID-19 period, which indicates fat-tail phenomena in the financial markets. Furthermore, the statistics extracted from the Jarque-Bera test prove that the returns of all six financial assets follow the asymmetric distribution in all three selected periods.

Table 2 illustrates the Augmented Dickey–Fuller (ADF) test results; it can be seen that the ADF values for each of the assets under observation are significant at a 1% critical level. Thus, the stationary characteristics in the returns series of the selected assets confirmed and rejected the null hypothesis statement of the presence of unit root.

Table 1. Summary Statistics for the selected financial assets.

Particulars	Bitcoin	EUR	S&P 500	Gold	Crude Oil	Sugar
			Whole Period			
Mean	0.003875	0.000103	0.000712	0.000561	0.000503	0.000512181
Standard Deviation	0.046004	0.003986	0.015302	0.01076	0.046245	0.017879922
Kurtosis	5.782102	4.008026	16.1689	5.736385	47.81848	1.605894798
Skewness	−0.379280	−0.385170	−1.03143	−0.15575	−2.74082	0.10688875
Range	0.518336	0.042611	0.217335	0.10748	0.891307	0.155743422
Minimum	−0.315290	−0.028140	−0.12765	−0.05121	−0.57167	−0.078285363
Maximum	0.203046	0.014467	0.089683	0.056266	0.319634	0.077458059
Jarque-Bera Test	904.27	442.44	7078.9	877.35	61768	69.216
Count	650	650	650	650	650	650
			Before COVID-19			
Mean	0.002273	0.000016	0.000231	0.000793	−0.00125	0.00002700
Standard Deviation	0.042580	0.003403	0.011625	0.008599	0.028384	0.01546058
Kurtosis	3.685524	1.655074	9.873348	9.734605	31.4296	2.55831721
Skewness	0.297774	0.294543	−0.966510	0.145929	−2.80747	0.48522149
Range	0.362072	0.026953	0.127414	0.103186	0.41915	0.13021202
Minimum	−0.159030	−0.01261	−0.079010	−0.04877	−0.28221	−0.05275396
Maximum	0.203046	0.014345	0.048403	0.054414	0.136944	0.07745805
Jarque-Bera Test	181.3	39.815	1325.2	1240.6	13378	97.32
Count	325	325	325	325	325	325
			During COVID-19			
Mean	0.005478	0.00019	0.001192	0.00033	0.002259	0.00099736
Standard Deviation	0.049205	0.004498	0.01826	0.012564	0.058924	0.02002169
Kurtosis	6.920719	4.253854	14.05538	3.665246	34.35576	0.95215866
Skewness	−0.84048	−0.69099	−1.01749	−0.21382	−2.41754	−0.09999114
Range	0.506817	0.042611	0.217335	0.10748	0.891307	0.14083676
Minimum	−0.31529	−0.02814	−0.12765	−0.05121	−0.57167	−0.07828536
Maximum	0.191527	0.014467	0.089683	0.056266	0.319634	0.06255140
Jarque-Bera Test	663.4	261.13	2642.5	177.05	15794	11.978
Count	325	325	325	325	325	325

Table 2. Augmented Dickey–Fuller test results for the selected financial assets.

Particulars	BTC	EUR	S&P 500	Gold	Crude Oil	Sugar
ADF Value	−17.8 ***	−16.68 ***	−17.765 ***	−18.078 ***	−19.99 ***	−17.373 ***
Probability Value	0.01	0.01	0.01	0.01	0.01	0.01

Note: *** shows the 1% significance level.

Figures 1 and 2 show the price trends and return fluctuations of the financial markets. An extensive decline has been observed in the price of the S&P 500 index, Crude Oil, and Sugar in March 2020. Additionally, the price of Bitcoin experienced a massive shock in May 2021. The returns graphs also show a high level of fluctuations at the beginning of the COVID-19 pandemic. Bitcoin and Crude Oil show a high level of volatility during COVID-19, ranging from −0.31 to 0.19 and −0.57 to 0.31, respectively. Moreover, the presence of volatility clustering can be seen in the returns graphs of all the financial markets.

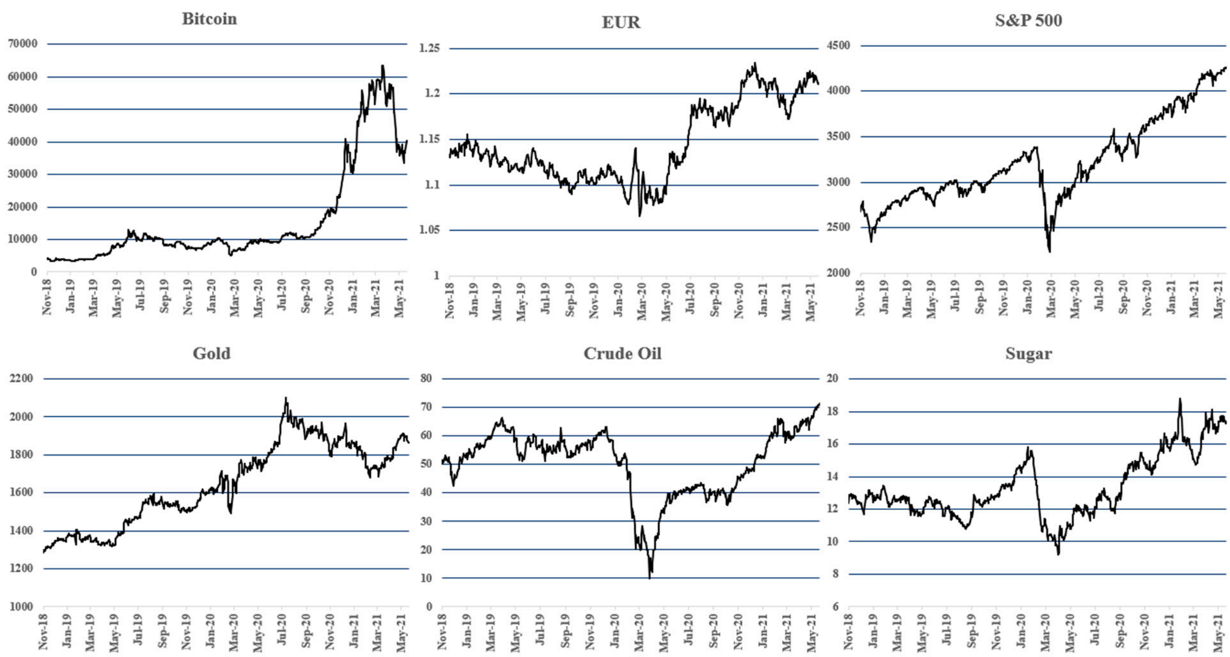

Figure 1. Price trends in the financial markets over the period of 27 November 2018 to 15 June 2021.

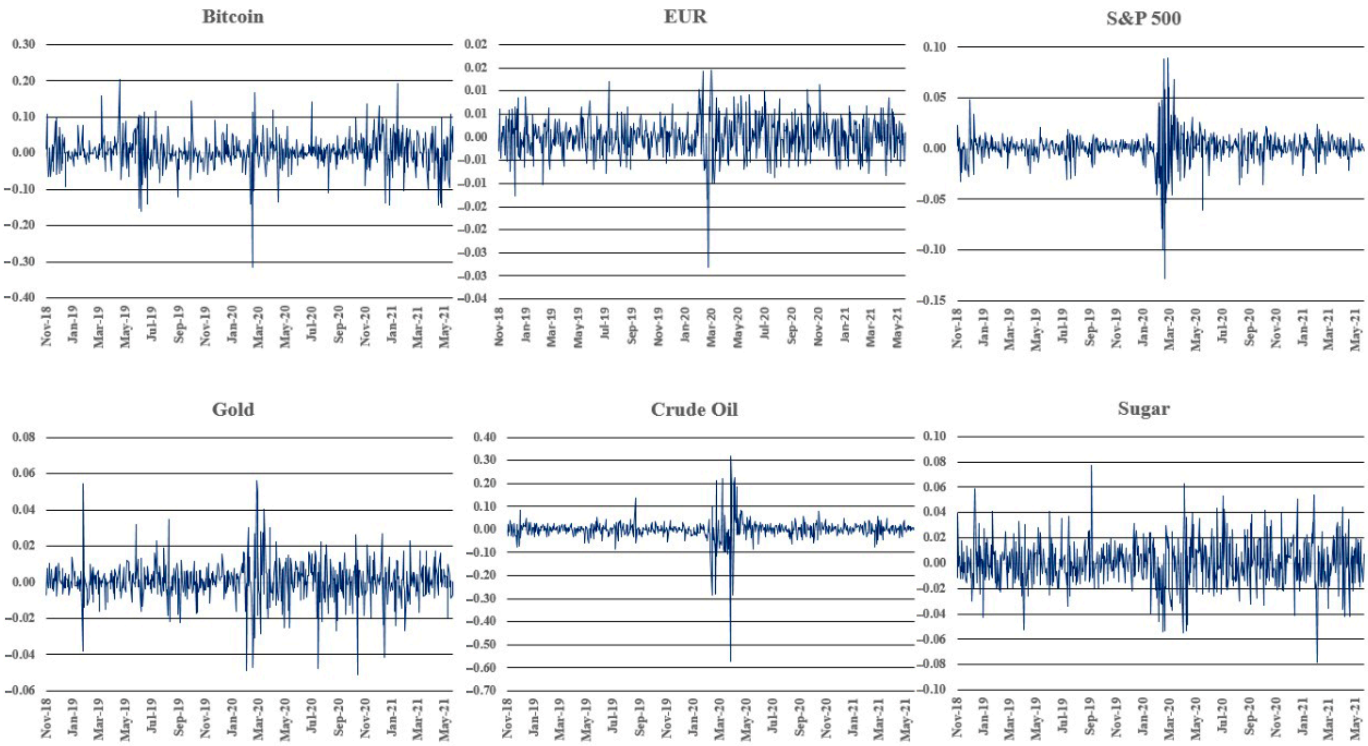

Figure 2. Returns fluctuations in the financial markets over the period of 27 November 2018 to 15 June 2021.

2.2. GARCH Model

The financial time series shows a period of low-level volatility, which is followed by a period of high-level volatility, which is called volatility clustering. ARCH and GARCH are the most common models adopted to model the volatility of both economic and financial time series. The GARCH model was proposed by Bollerslev (1986) and is an extension of the ARCH to model for conditional variance. The GARCH (p, q) model is represented as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \mu_t^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where the parameters of the model are denoted by ω, α_i, and β_j.

The GARCH family has the ability to account for dynamic volatility phenomena and volatility clustering in the modeling of financial returns volatility. Therefore, one of the models chosen is known as the GARCH (1, 1) model. Karmakar (2005) recommends GARCH (1, 1) to model the conditional volatility of market returns. Thus, the mathematical illustration of GARCH (1, 1) is given in Equation (3):

$$\sigma_t^2 = \omega + \alpha \mu_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

2.3. GJR-GARCH Model

The GJR-GARCH model is applied to financial returns to examine the asymmetric behavior of financial market returns. The model assumes that investor reaction toward negative returns has more concern when compared to positive financial returns, which results in the leverage effect. The GJR-GARCH (1, 1) model equation is computed as follows:

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta_i \sigma_{t-1}^2 + \gamma_i I_{t-1}\, u_{t-1}^2 \tag{4}$$

The symbol I_{t-1} in the equation above is the dummy variable:

$$I_{t-1} = \begin{Bmatrix} 1\ when\ \mu_{t-1} < 0\ shows\ postive\ shocks \\ 0\ when\ \mu_{t-1} \geq 0\ shows\ negative\ shocks \end{Bmatrix}$$

where the symbol σ_t^2 refers to the conditional variance, ω is the constant term, u_{t-1}^2 and σ_{t-1}^2 represent the return square at time $t-1$, and conditional variance at time $t-1$. γ refers to the leverage effect coefficient.

2.4. EGARCH Model

The exponential GARCH (EGARCH) model is proposed by Nelson (1991) to accommodate the asymmetry in the basic GARCH model. The EGARCH model has the ability to account for more lags in conditional variance. The mathematical equation of the EGARCH (1, 1) model is computed as follows:

$$\log h_t = (\omega - 1) + \alpha|\eta_{t-1}| + \gamma\eta_{t-1} + \beta \log h_{t-1} \tag{5}$$

where $\log h_t = E\left(\varepsilon_t^2 \middle| I_{t-1}\right)$, α, β, and γ are the parameters for the estimation of the model. There is no restriction with respect to the model parameters because the EGARCH model is based on log variance. Furthermore, investors are more reactive toward bad news than good news. Hence, it will have a strong impact on the returns volatility, and the expected value for the γ would be negative.

3. Results

The empirical results with respect to the different GARCH models for the three selected periods (before and during the COVID-19 pandemic and the whole period) are illustrated in Tables 3–5, respectively. As per Table 3, the Akaike information criteria (AIC) values for each of the six financial assets suggest that E-GARCH (1, 1), in comparison with the other GARCH family models, is the best-fitted model in terms of modeling the returns volatilities of BTC, EUR, S&P 500, Gold, Crude Oil, and Sugar before the COVID-19 pandemic. The volatility among all of the six financial market retunes is extremely high during the COVID-19 pandemic, as shown in Appendix A.

Table 3. Empirical results based on the GARCH models before the COVID-19 Pandemic (27 November 2018 to 10 March 2020).

Asset Class	Model	μ	ω	α (ARCH)	β (GARCH)	α+β	γ (Gamma)	Log Likelihood	AIC
BTC	GARCH (1, 1)	0.001575	0.000062	0.124018 *	0.874982 ***	0.999	-	619.8894	−3.7778
	GJR-GARCH (1, 1)	0.001534	0.000054	0.143439 *	0.887696 ***	1.031135	−0.061479	620.1043	−3.7729
	EGARCH (1, 1)	0.001244	−0.174239 *	0.036888	0.972107 ***	1.008995	0.258452 ***	624.1617	−3.7979
EUR/USD	GARCH (1, 1)	−0.000093	0.000001	0.076241	0.845516 ***	0.921757	-	1398.076	−8.5666
	GJR-GARCH (1, 1)	0.00003	0.000001	0.118079 **	0.894921 ***	1.013	−0.114815	1398.97	−8.566
	EGARCH (1, 1)	0.000001	−1.058863 ***	0.098288 **	0.906961 ***	1.005249	0.116547 ***	1399.502	−8.5692
S&P 500	GARCH (1, 1)	0.001054	0.000004	0.247109 ***	0.72983 ***	0.976939	-	1104.323	−6.7589
	GJR-GARCH (1, 1)	0.000627	0.000004 ***	0	0.76639 ***	0.76639	0.37726 ***	1115.677	−6.8226
	EGARCH (1, 1)	0.000445	−0.575678 ***	−0.310019 ***	0.940752 ***	0.630733	0.095304 ***	1120.224	−6.8506
Gold	GARCH (1, 1)	0.000738	0	0.002481	0.99647 ***	0.998951	-	1143.298	−6.9988
	GJR-GARCH (1, 1)	0.000776	0	0.009621	0.999803 ***	1.009424	−0.021082 ***	1143.438	−6.9935
	EGARCH (1, 1)	0.000563	−3.918943 ***	−0.057158	0.592084 ***	0.534926	0.412796 ***	1146.25	−7.0108
Crude Oil	GARCH (1, 1)	−0.000072	0.000043	0.122254*	0.827323 ***	0.949577	-	790.1403	−4.8255
	GJR-GARCH (1, 1)	−0.000989	0.000015 ***	0	0.919419 ***	0.919419	0.130378 ***	795.7955	−4.8541
	EGARCH (1, 1)	−0.001059	−0.178794 ***	−0.14327***	0.975897 ***	0.832627	0.030163 **	797.5716	−4.8651
Sugar	GARCH (1, 1)	−0.00005	0	0	0.999 ***	0.999	-	906.4832	−5.5414
	GJR-GARCH (1, 1)	−0.000144	0.000052	0	0.678175 ***	0.678175	0.234051 *	911.2845	−5.5648
	EGARCH (1, 1)	−0.00019	−1.69632 *	−0.12458 *	0.79802 ***	0.67344	0.22667 *	911.3619	−5.5653

Note: *** refers to 1% significance level, ** refers to 5% significance level, and * refers to 10% significance level.

Table 4. Empirical results based on the GARCH models during the COVID-19 Pandemic (11 March 2020 to 15 June 2021).

Asset Class	Model	μ	ω	α (ARCH)	β (GARCH)	α+β	γ (Gamma)	Log Likelihood	AIC
BTC	GARCH (1, 1)	0.005133	0.000046	0.086228 ***	0.912772 ***	0.999	-	575.4589	−3.5044
	GJR-GARCH (1, 1)	0.005136	0.000036	0.096668 **	0.919377 ***	1.016045	−0.033637	575.6774	−3.4996
	EGARCH (1, 1)	0.00523	−0.067	0.035923	0.98845 ***	1.024373	0.191335 ***	577.3427	−3.5098
EUR/USD	GARCH (1, 1)	0.000215	0	0.009999	0.986357 ***	0.996356	-	1309.744	−8.023
	GJR-GARCH (1, 1)	0.000178	0	0.002145	0.987274 ***	0.989419	0.012225	1310.42	−8.021
	EGARCH (1, 1)	0.000248	−0.727561 ***	−0.023663	0.933762 ***	0.910099	0.136151 ***	1311.029	−8.0248
S&P 500	GARCH (1, 1)	0.001318	0.000007	0.21278 ***	0.754481 ***	0.967261	-	993.6005	−6.0775
	GJR-GARCH (1, 1)	0.001023	0.000008	0.102173 *	0.765049 ***	0.867222	0.19395 **	995.3024	−6.0819
	EGARCH (1, 1)	0.000802	−0.423212 **	−0.104427 **	0.952725 ***	0.848298	0.367853 ***	993.2619	−6.0693
Gold	GARCH (1, 1)	0.000468	0	0.021306	0.973694 ***	0.995	-	998.6812	−6.1088
	GJR-GARCH (1, 1)	0.000459	0	0.012131	0.977937 ***	0.990068	0.011201	998.8752	−6.1038
	EGARCH (1, 1)	0.000395	−0.300879 ***	−0.017036	0.966609 ***	0.949573	0.138397	998.9916	−6.1046
Crude Oil	GARCH (1, 1)	0.002534	0.000037 *	0.21892 ***	0.762427 ***	0.981347	-	705.1272	−4.3023
	GJR-GARCH (1, 1)	0.001641	0.000033 ***	0.000142	0.815486 ***	0.815628	0.296711 ***	711.4222	−4.3349
	EGARCH (1, 1)	0.001699	−0.220348 ***	−0.177449 ***	0.970494 ***	0.793045	0.250228 ***	710.1545	−4.3271
Sugar	GARCH (1, 1)	0.001186	0.000108	0.117035	0.603234 *	0.720269	-	818.7832	−5.0017
	GJR-GARCH (1, 1)	0.001087	0.000008 ***	0.000002	0.969072 ***	0.969074	0.018919	815.9888	−4.9784
	EGARCH (1, 1)	0.001229	−1.745254	0.040641	0.778879 *	0.81952	0.207247 *	818.2776	−4.9925

Note: *** refers to 1% significance level, ** refers to 5% significance level, and * refers the 10% significance level.

Furthermore, the parameters of the E-GARCH (1, 1) model show that each of the financial market's representatives exhibit a long-term memory effect and an asymmetric effect at different significance levels. With respect to the EGARCH model, the finding confirms that the financial markets show significant asymmetric behavior (except for the gold market) during the COVID-19 pandemic. However, the leverage effect was observed in the gold commodity before the COVID-19 pandemic, with a leverage coefficient of 0.41. Moreover, BTC shows the highest volatility persistence ($\beta = 0.98$), followed by crude oil ($\beta = 0.97$) during the pandemic. The gold commodity also shows higher volatility persistence ($\beta = 0.96$) during COVID-19 when compared to before the pandemic

($\beta = 0.59$), which indicates that the COVID-19 pandemic had a strong impact on the gold price.

Table 5. Empirical results based on the GARCH models for the whole period (27 November 2018 to 15 June 2021).

Asset Class	Model	μ	ω	α (ARCH)	β (GARCH)	$\alpha+\beta$	γ (Gamma)	Log Likelihood	AIC
BTC	GARCH (1, 1)	0.0033	0.000046	0.098295 ***	0.900705 ***	0.999	-	1193.305	−3.6532
	GJR-GARCH (1, 1)	0.003312	0.00004	0.108002 ***	0.907544 ***	1.015546	−0.031982	1193.576	−3.651
	EGARCH (1, 1)	0.002644	−0.107781 *	0.029598	0.98199 ***	1.011588	0.237742 ***	1198.772	−3.667
EUR/USD	GARCH (1, 1)	0.000057	0.000001	0.070414 **	0.886033 **	0.956447	-	2706.761	−8.31
	GJR-GARCH (1, 1)	0.000099	0	0.082489	0.919543 ***	1.002032	−0.056764	2707.987	−8.3107
	EGARCH (1, 1)	0.000101	−0.430652 ***	0.043688	0.961453 ***	1.005141	0.134607 ***	2708.079	−8.311
S&P 500	GARCH (1, 1)	0.001122	0.000004	0.224243 ***	0.755825 ***	0.980068	-	2100.47	−6.4445
	GJR-GARCH (1, 1)	0.000776	0.000005	0.056481	0.774716 ***	0.831197	0.284695 ***	2109.279	−6.4685
	EGARCH (1, 1)	0.000617	−0.365606 ***	−0.168038 ***	0.960603 ***	0.792565	0.266212 ***	2108.935	−6.4675
Gold	GARCH (1, 1)	0.000799	0.000003	0.076819	0.92117 ***	0.997989	-	2139.454	−6.5645
	GJR-GARCH (1, 1)	0.000793	0.000003	0.071891	0.921787 ***	0.993678	0.00818	2139.469	−6.5614
	EGARCH (1, 1)	0.000705	−0.16336 **	0.009072	0.98167 ***	0.990742	0.172849	2139.152	−6.5605
Crude Oil	GARCH (1, 1)	0.001229	0.000041 ***	0.163904 ***	0.796179 ***	0.960083	-	1492.581	−4.5741
	GJR-GARCH (1, 1)	0.000472	0.000034 ***	0.002758	0.839875 ***	0.842633	0.220441 ***	1502.661	−4.602
	EGARCH (1, 1)	0.000539	−0.234677 ***	−0.145662 ***	0.968419 ***	0.822757	0.200642 ***	1500.59	−4.5957
Sugar	GARCH (1, 1)	0.00072	0.000043 *	0.121029 ***	0.745903 ***	0.866932	-	1721.499	−5.2785
	GJR-GARCH (1, 1)	0.00059	0.000007 ***	0	0.955467 ***	0.955467	0.050876 ***	1720.485	−5.2723
	EGARCH (1, 1)	0.000592	−0.772434	−0.0231	0.904781 ***	0.881681	0.224624 ***	1722.728	−5.2792

Note: *** refers to the 1% significance level, ** refers to the 5% significance level, and * refers to the 10% significance level.

Moreover, Table 4 refers to the empirical results of the different GARCH family models during the COVID-19 pandemic. Our basic emphasis is on the selection of the best fitted GARCH model that determines the volatilities of the representatives of the six financial markets under observation. Based on the numerical results provided by the AIC, GARCH (1, 1) is regarded as the best model for describing the volatilities of Gold and Sugar; meanwhile, GJR-GARCH (1, 1) is the most suitable model in terms of modeling the volatilities of Crude Oil, and S&P 500; the volatilities of BTC and EUR are best modeled by E-GARCH (1, 1). Concerning the E-GARCH (1, 1) results, both the BTC and EUR returns series show high persistence behavior due to the fact that the sum of the ARCH and GARCH parameters are either greater than 1 or close to it (1.024373, 0.910099). This high persistence probably is the result of the COVID-19 pandemic. Alongside, both of them also show significant asymmetric effects (gamma) at the 1%, 5%, and 10% significance levels because of the drastic economic impacts. In contrast, the returns volatilities of S&P 500 and Crude Oil based on the GJR-GARCH (1, 1) model also show persistent behavior but are lower than that of BTC and EUR; moreover, S&P 500 shows a significant asymmetric effect at the 5% and 10% significance levels and Crude Oil exhibits a significant asymmetric effect at the 1%, 5%, and 10% significance levels. Contrarily, the Gold and Sugar returns series exhibit persistent behavior along with the symmetric effect; however, Gold shows more persistent behavior ($\alpha + \beta = 0.955$) when compared to Sugar ($\alpha + \beta = 0.720269$); the reason might be that COVID-19 had a negligible effect on Gold and Sugar. On the other hand, Metal has been considered a safe haven financial instrument during various forms of financial crises (Bouri et al. 2020; Jareño et al. 2020; Selmi et al. 2018). Studies confirm that the price of gold increased during the global financial crisis, whereas, the prices of other financial assets decline drastically (Beckmann et al. 2015). Furthermore, Conlon and McGee (2020) found that Bitcoin did not act as a safe-haven instrument during the COVID-19 outbreak. Klein et al. (2018) also reported that Bitcoin returns have an asymmetric response to market shocks.

Table 5 illustrates the application of GARCH (1, 1), GJR-GARCH (1, 1), and E-GARCH (1, 1) on the representatives of the six financial markets for the whole period. According to the AIC values, with regard to the returns series of the Gold commodity, GARCH (1, 1) is the best-suited model for capturing the volatility. The results suggest that the Gold returns series possess symmetric phenomena and high persistent behavior ($\alpha + \beta = 0.997989$). Whereas, for most of the asset returns, including BTC, EUR, and Sugar, the E-GARCH (1, 1) model is the most suitable model in terms of determining their volatilities. Moreover, among them, BTC and EUR exhibit the strongest persistence, whereas all three show a significant asymmetric effect at the 1%, 5%, and 10% significance levels. Alongside, GJR-GARCH (1, 1) was selected as the best model to capture the volatilities of the Crude Oil and S&P 500 index returns. Additionally, a significant asymmetric effect was present in the returns series of the Crude Oil and S&P 500 index returns at a significance level of 1%, 5%, and 10%. Meanwhile, high persistent behavior was shown by the S&P 500 returns and the Crude Oil returns.

Overall, after analyzing the results for the three different periods, it can be concluded that a single model is not enough to model the volatilities of the selected financial assets. Each model provides different estimations for the different periods, i.e., E-GARCH (1, 1) provides a better fit for the assets under observation before the COVID-19 pandemic. Whereas the model fitness changes during the COVID-19 pandemic, that is volatilities of Gold, and Sugar are modeled by GARCH (1, 1) showing persistent behavior, S&P 500, and Crude Oil are modeled by GJR-GARCH (1, 1) exhibiting significant leverage effect and persistence phenomena. Moreover, E-GARCH (1, 1) captures the leverage effect and persistent behavior of BTC and EUR. In contrast, different results are shown for the whole period, where only the returns series of the Gold commodity was modeled by GARCH (1, 1), showing high persistence with no leverage effects, whereas the BTC, EUR, and Sugar volatilities are described by E-GARCH (1, 1), exhibiting significant leverage effects and persistence effects; furthermore, S&P 500 and Crude Oil returns volatilities are captured by GJR-GARCH (1, 1), addressing persistence behavior and leverage phenomena.

4. Discussion and Conclusions

The COVID-19 pandemic had a catastrophic influence on the financial markets (Ali et al. 2020; Aslam et al. 2020a; Haroon and Rizvi 2020; Sansa 2020), and the volatility behavior of the financial returns were shaken by this crisis. In this study, we investigated the market volatility of six financial markets during the COVID-19 pandemic by adopting three GARCH family models [GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1)]. The findings of the study indicate that the exponential GARCH model is appropriate for BTC and EUR, while GJR-GARCH (1, 1) is appropriate for S&P 500 and Crude Oil. These findings are supported by Iqbal et al. (2021), who reported that, for modeling volatilities, the EGARCH model outperforms the traditional GARCH model. The volatility persistence of all financial markets was high during the COVID-19 pandemic. The findings of this study also confirm the insignificant asymmetric effect in the volatility of the Gold returns during the pandemic. However, Crude Oil had a significant positive asymmetric effect during this pandemic. Moreover, Shehzad et al. (2021) in their study also reported that crises like COVID-19 have abruptly affected both the stock and oil markets. Furthermore, the increase in the volatility of the financial markets generated a fear of losing money among investors due to the COVID-19 pandemic (Chen et al. 2020).

This study makes a significant contribution to the existing literature; this has been the first attempt to highlight the volatility behavior of all the major financial assets from the six major financial markets during the COVID-19 pandemic. A very significant question arises: were all of the financial markets affected by the tragic pandemic? Despite the new phase of COVID-19 cases and the extensive fluctuation in the financial markets across the world, the markets indicate a recovery pattern. Given the uncertainty, it is very challenging to predict the long-term financial impact of COVID-19. The crypto market experienced a massive crash during the COVID-19 pandemic. The finding also revealed potential evidence of a volatility trend over the period and a high level of volatility persistence for Bitcoin. During the COVID-19 pandemic, a significant increase has been reported in the volatility of Bitcoin.

This can be explained by the irrational behavior of investors, which leads to speculation in the financial market. In a speculative bubble situation, the news of prices can affect irrational investors' decisions, which leads to catastrophic results in the market like a virus.

4.1. Implications

The empirical results of this study provide useful implications for policymakers, international investors, and financial risk managers across the countries where the current pandemic has drastically affected the financial markets. First, because of the COVID-19 outbreak in almost all countries, this study illustrates the volatilities of the major financial markets, including the stock market, currency market, crypto market, metal market, oil market, and agriculture market. Second, this study describes the usefulness of the application of GARCH (1, 1), GJR-GARCH (1, 1), and E-GARCH (1, 1) in advanced-level time-series analysis. Third, this study provides useful input for policymakers globally to formulate their countries' economic policies. This can be carried out by analyzing the volatilities across the financial markets. Last, this research recommends implementing health policies during the outbreak to minimize the spread of this deadly virus and also the execution of macroeconomic policies to stabilize the economies. Furthermore, the finding of our study is interesting to portfolio managers that are dealing with active investments in the financial markets. Thus, an optimal portfolio is very effective for portfolio managers to avoid shocks in the market due to COVID-19 lockdowns. Additionally, policymakers can address such financial anomalies generated by the COVID-19 pandemic to monitor the stability of an economy.

4.2. Limitations

We incorporated three potential GARCH models from the GARCH family to investigate the impact of COVID-19 on the financial markets since these models are considered to be effective for estimating volatility behavior regarding financial returns. However, it is very challenging to incorporate every aspect of market volatility regarding COVID-19; therefore, it was essential to limit our research study to a certain level. This research can be further extended to model volatility in high-frequency data. We also suggest further studies can be conducted based on an alternative model, such as the threshold ARCH model.

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Appendix A

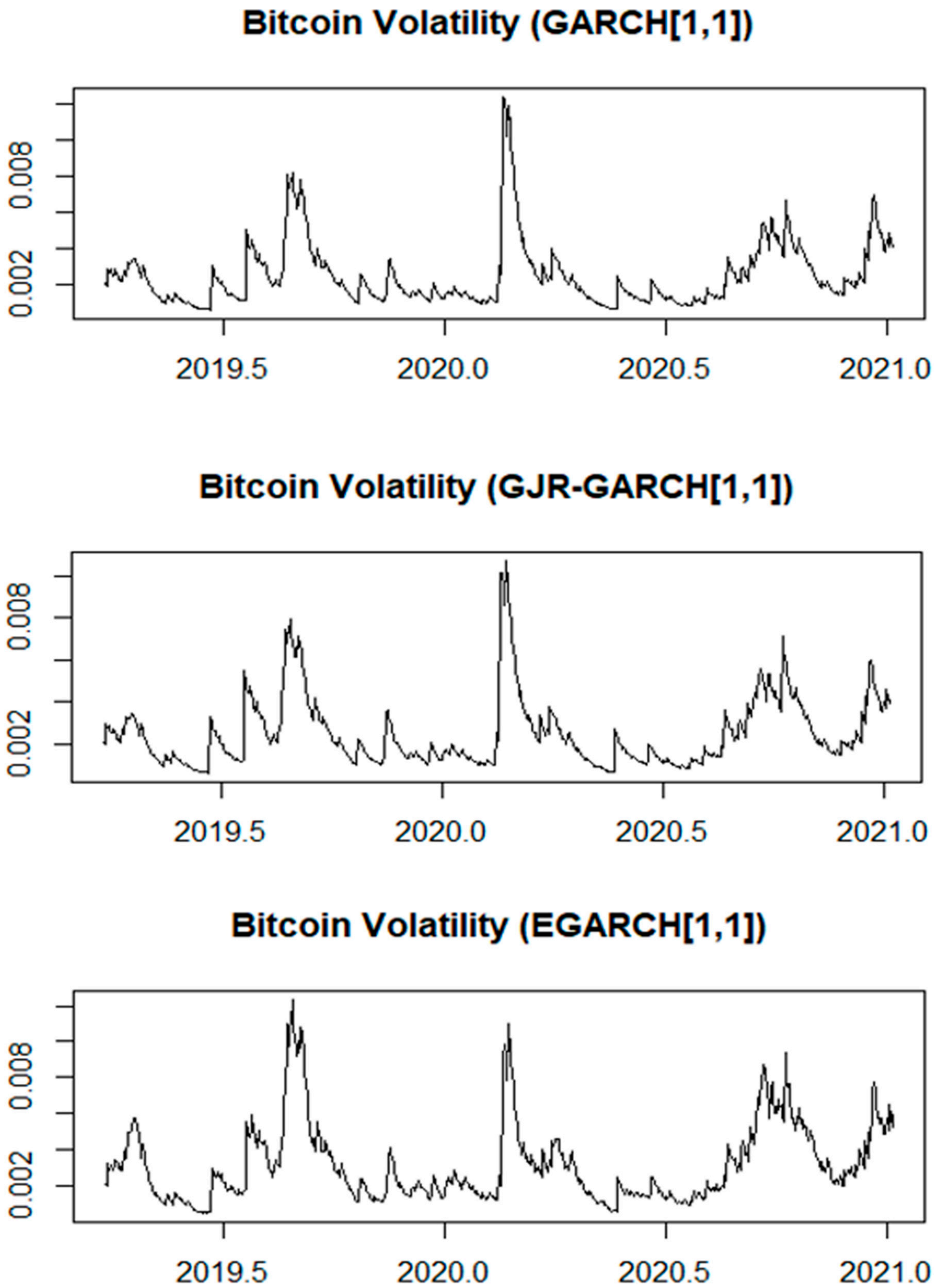

Figure A1. Volatility in Bitcoin Time Series.

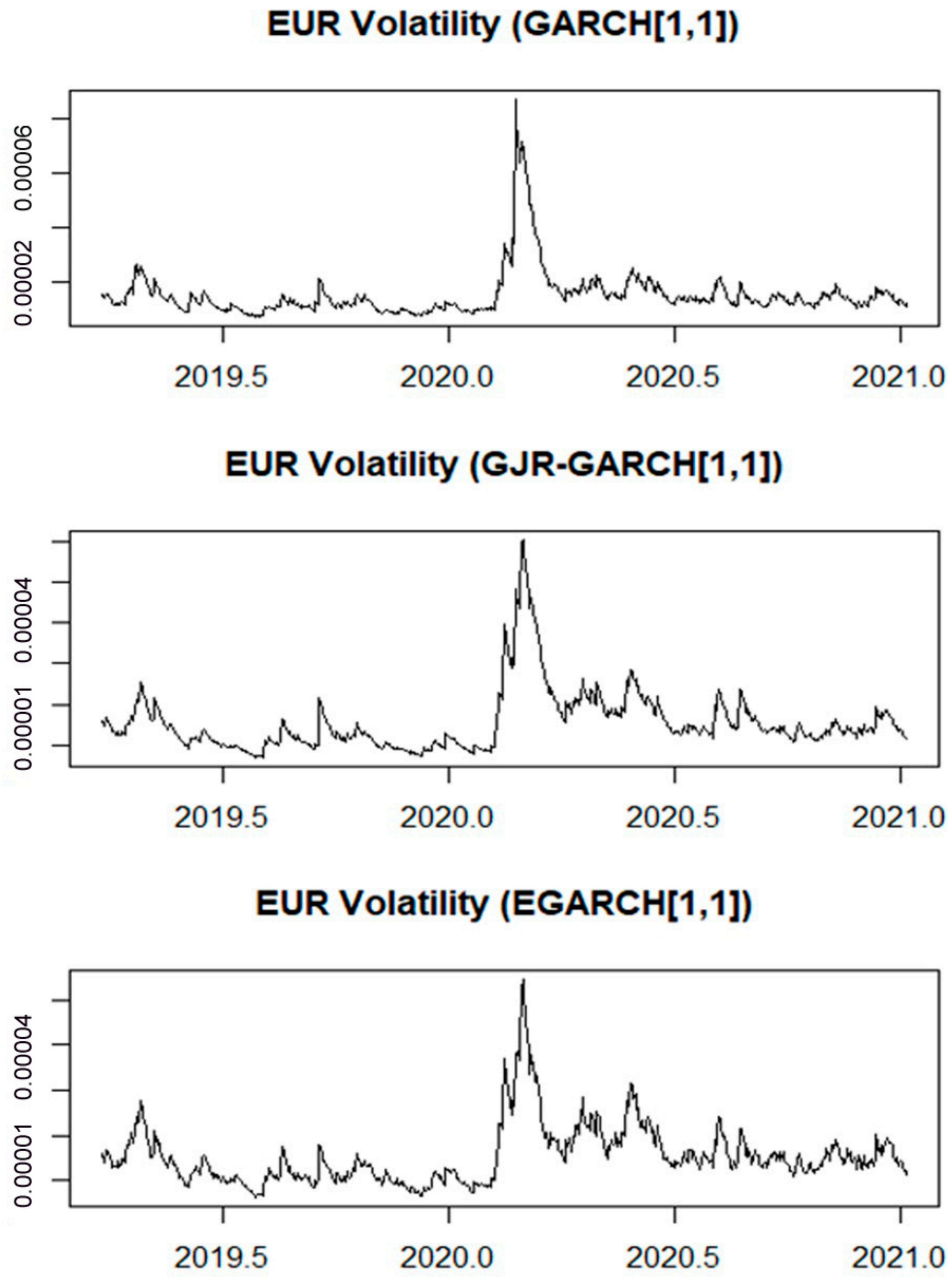

Figure A2. Volatility in EUR time series.

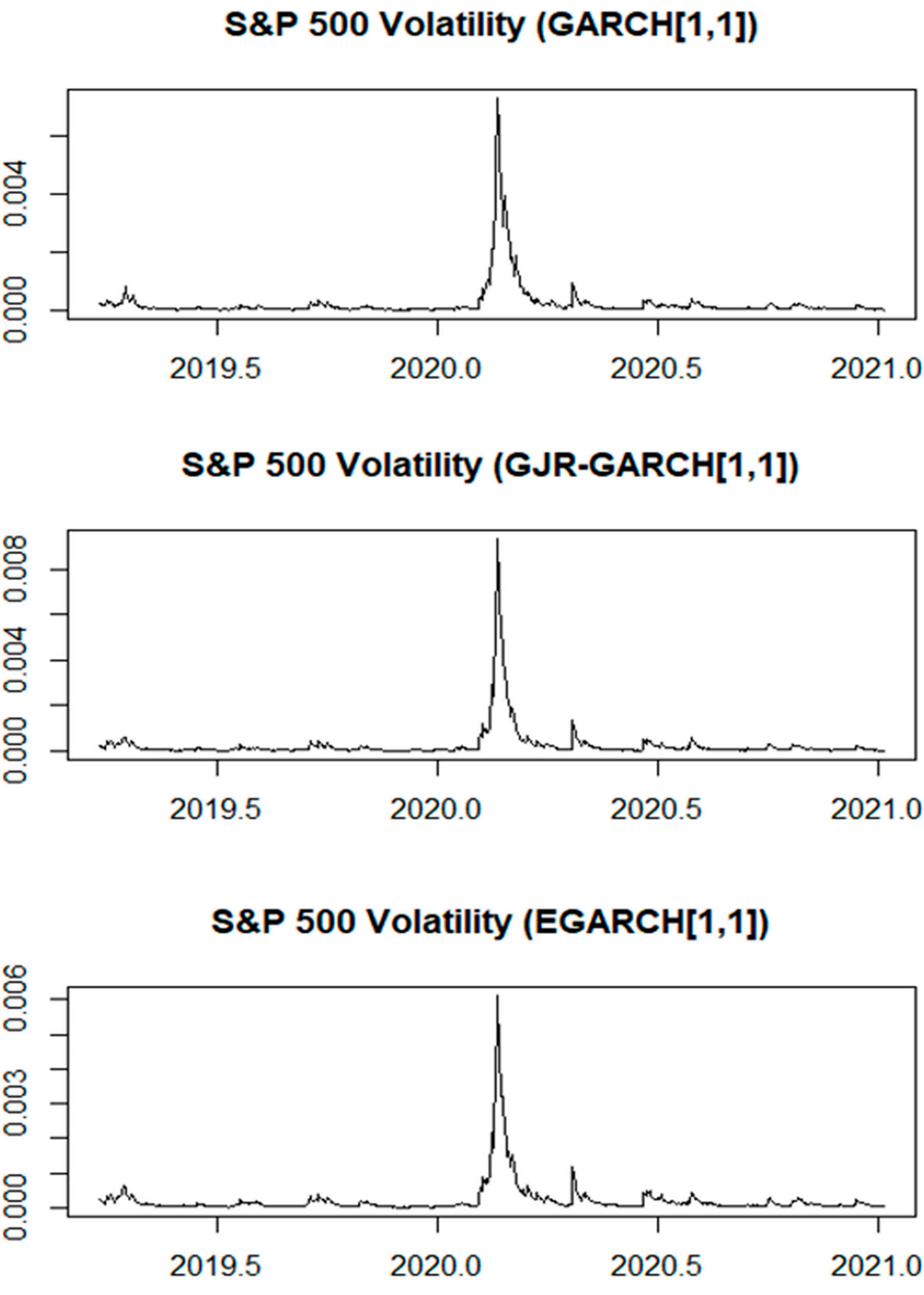

Figure A3. Volatility in S&P 500 time series.

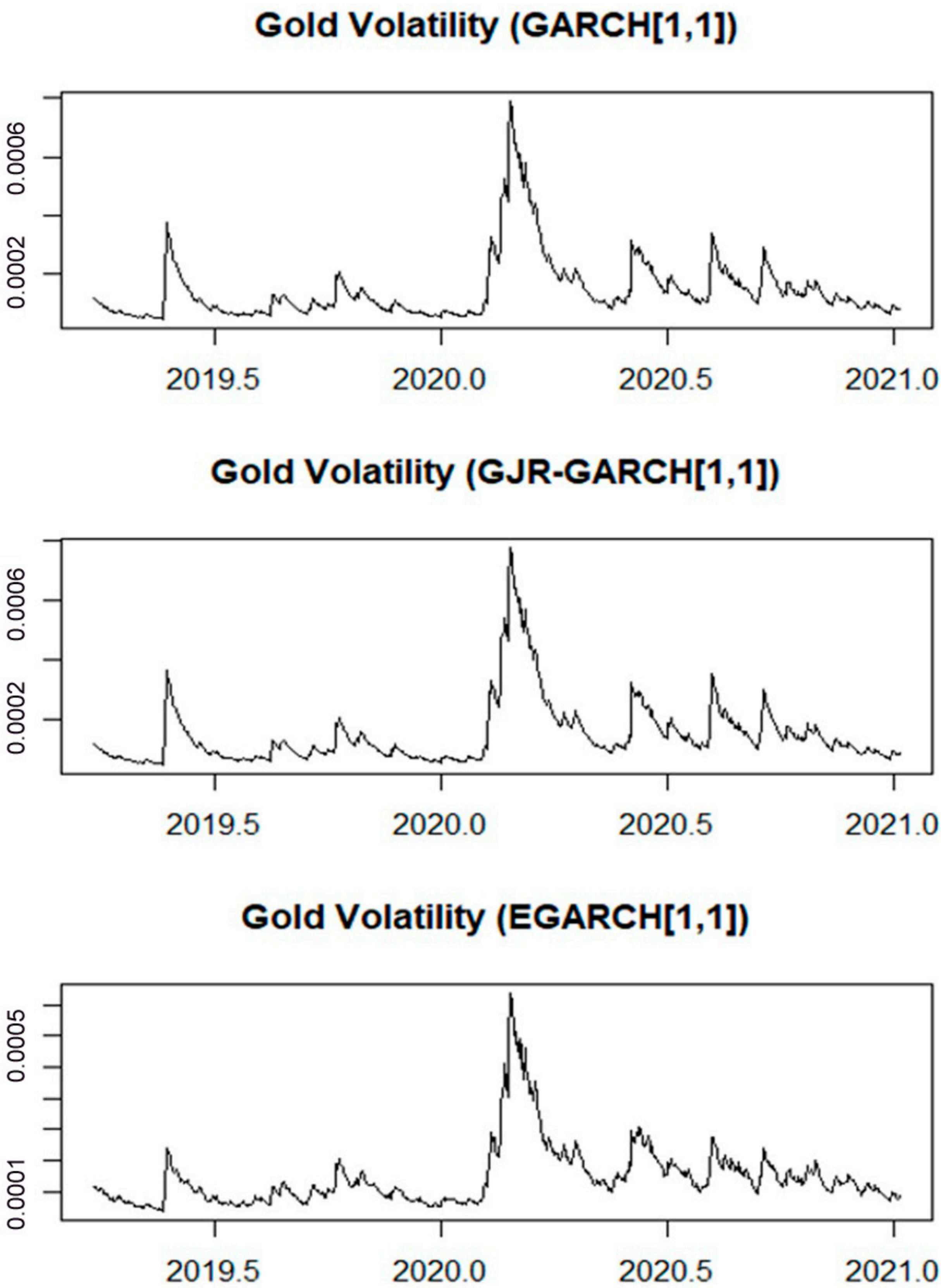

Figure A4. Volatility in Gold time series.

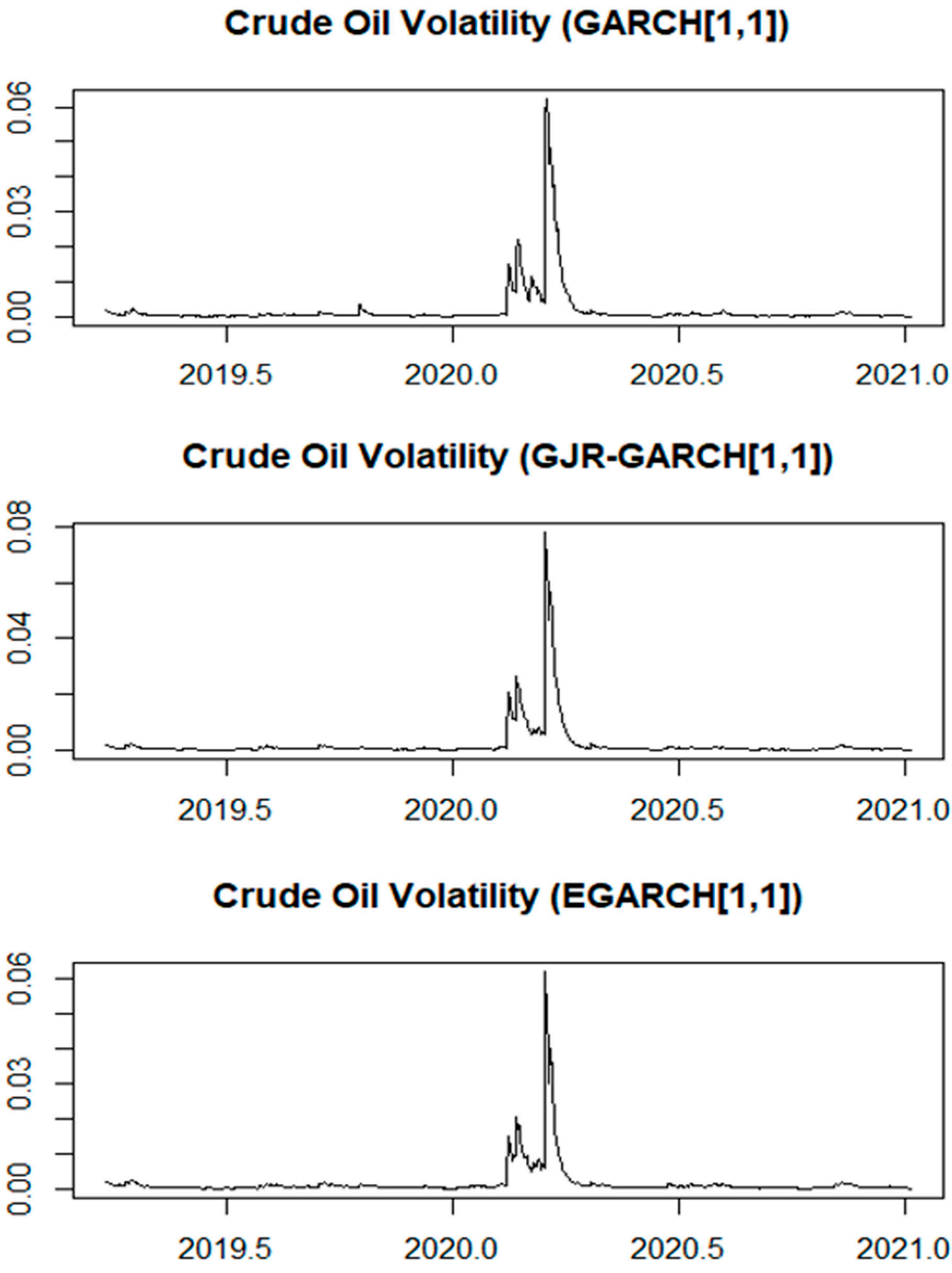

Figure A5. Volatility in Crude Oil time series.

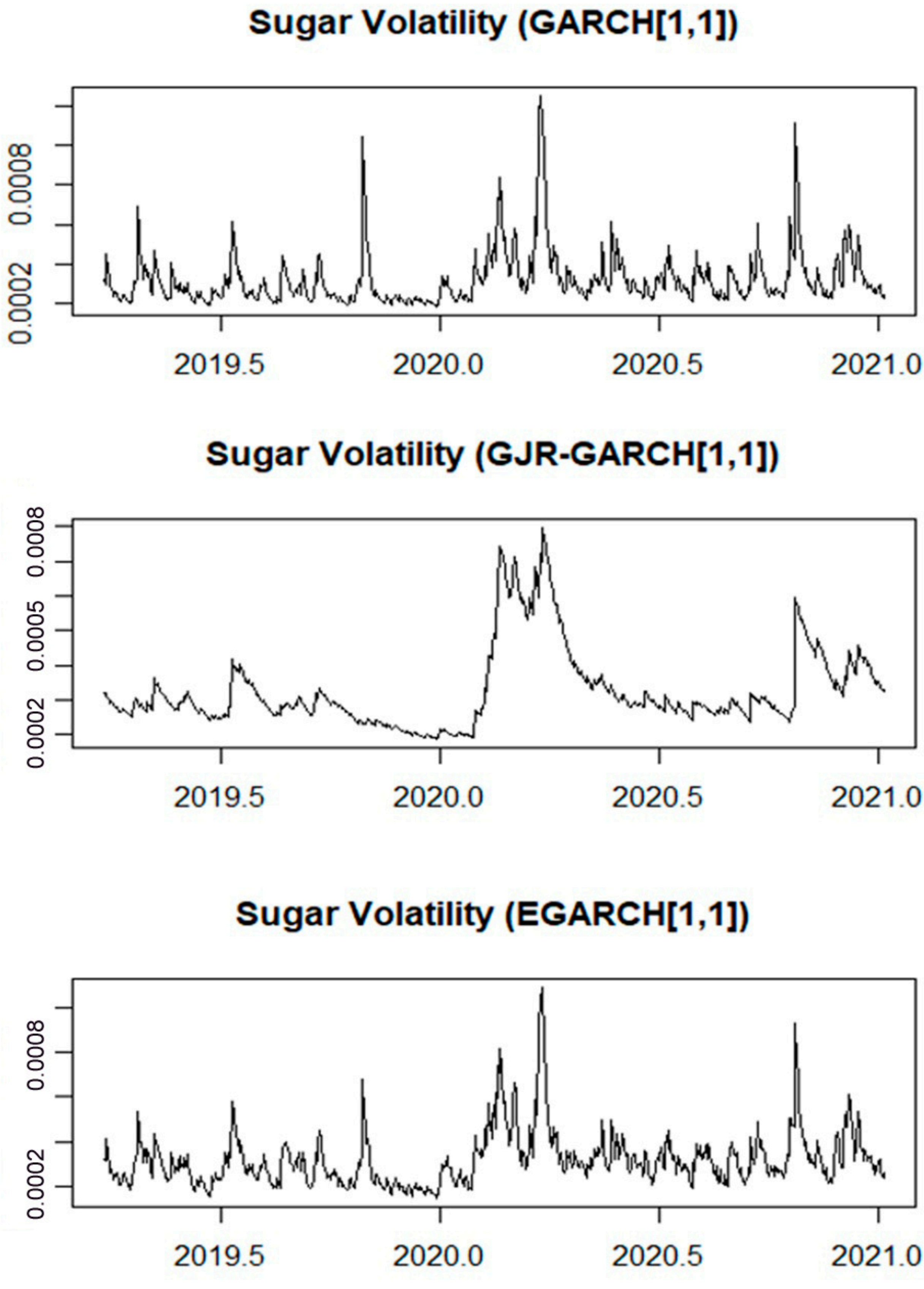

Figure A6. Volatility in Sugar time series.

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