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Impact of COVID-19 Crisis on Volatility Spillovers across Global Financial Markets: Evidence from Asymmetric GARCH Models

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Abstract This study investigates the market volatility and asymmetric behavior in the commodity market, foreign exchange market, cryptocurrency, and stock markets by employing asymmetric GARCH models on the daily time series returns. The data covers the period from March 8, 2017, to March 17, 2023, and is divided in to three sub-periods: the entire sample period (March 8, 2017, to March 17, 2023), the pre-COVID-19 period (March 8, 2017, to March 10, 2020), and the during the COVID-19 period (March 11, 2020, to March 17, 2023). The empirical results show a high level of volatility persistence in all the financial markets during the COVID-19 pandemic. Additionally, the results indicate significant positive asymmetric behavior in the crude oil and stock markets during the pandemic. The findings further document that gold exhibits a strong resilience during the pandemic period, indicating its hedging ability during crisis periods. Moreover, the results suggest that the EGARCH model is the most appropriate model to capture the volatilities of the financial markets both before and during the pandemic. The findings of this study provide useful insights for investors and policymakers, enabling them to adopt effective strategies for investing in portfolios during crisis periods in the future.

Keywords: bitcoin, commodity, exchange, stocks, COVID-19 pandemic, volatility spillover

JEL Classifications: G01, G15, G32, E44, F15

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I. Introduction

The recent COVID-19 pandemic had a devastating impact on global financial markets, leading to heightened volatility worldwide (Al-Awadhi et al. 2020 and Baker et al. 2020)[1). This study investigates the impact of the pandemic on various financial markets, including stock markets, commodity markets, foreign exchange markets and cryptocurrencies. Specifically, it assesses the impact of the pandemic on developed, emerging and the U.S. stock markets as well as variations in crude oil, gold, sugar and cocoa prices in the commodity market. The Euro/Dollar exchange rate is used to analyze interactions with other financial assets, and Bitcoin's daily closing prices represents the cryptocurrency market. The findings will provide insights into

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the dynamic relationships among these key financial markets during the crisis period.

The pandemic's restrictions, such as international border closures, lockdowns, event cancellations, and business facility closures, resulted in economic slowdowns globally. This led to a sharp decline in commodity demand as related industries faced disruptions. Economic activities were negatively affected by reduced work hours, social distancing, and other workplace restrictions. The long-term impacts of the pandemic are yet to unfold, potentially resulting in business failures and unemployment. World industrial production index data showed negative changes of -4.21 % and -10.08 % on March 11 and 12, 2020, respectively, with average growth rates remained lower in 2020 compared to 2019[2)].

The world economy's integration through financial deregulation, technological advancements, regional blocks, and financial innovations has led to highly integrated financial and commodity markets. Consequently, shocks and volatility due to significant events like the Global Financial Crisis (GFC) or the COVID-19 pandemic can transmit risks to other markets, spreading the impact across the globe.

Stock markets worldwide, including the U.S. market, experienced high level of volatility during the pandemic. The U.S. market observed three of its worst trading days in March 2020 due to lockdowns, with the circuit-breaker mechanism activated four times within 10 days compared to just once in 1997 (Ali et al., 2022). Over the period of three months (December 31, 2019 - March 20, 2020), Dow Jones Industrial Average (DJIA) dropped by 33 percent while the Standard and Poor's Index (S&P 500) plunged by 29 percent. Additionally, the stock market crash was not limited to the U.S. market, there were shocks to other major markets across the globe. On March 20, 2020, stock market in United Kingdome showed a decline of 10 percent, while the Tokyo Stock Exchange in Japan dropped by more than 20 percent from its highest level recorded in December, 2019. The uncertainty caused by the pandemic led to economic turmoil, investor fear, market variations and sectoral performance changes.

This study expands upon previous research by analyzing not only the intensity but also the direction of risk transmissions among markets, focusing on volatility spillovers between commodity, cryptocurrency, exchange rate, and stock markets. Using a daily dataset from March 8, 2017, to March 17, 2023, the study investigates pre- and during-COVID-19 periods employing EGARCH and TGARCH models for volatility transmissions. Additionally, the study examines cross-markets variance spillovers to identify risk recipients and transmitters across these markets during this time.

The paper's implications are significant for investors, policymakers, academics, and market participants. First, it measures asymmetric volatility spillovers in commodity, exchange rate, cryptocurrency, and stock markets of developed and emerging markets. Second, it examines

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1) According to the WHO, the COVID virus has killed 6.95 million people worldwide with a total of 7686 million confirmed cases at the time of writing (WHO, 2023).

2) The average growth was calculated on a yearly basis from MSCI World Industrial Production Index.

volatility connections in both pre- and during-COVID-19 pandemic periods using asymmetric GARCH models. Third, it employs various techniques, including EGARCH and TGARCH models, for analysis. Finally, while numerous studies in the literature have examined the symmetric volatility transmissions across international markets during the recent pandemics, no previous studies have assessed the asymmetric volatility spillover across stocks, commodity, Bitcoin, and exchange markets before and during the COVID-19 crisis. This paper tries to fill this gap in the literature.

The rest of the paper is organized as follows: Section 2 presents a review of relevant literature, Section 3 describes the methodology used for analysis, Section 4 reports the empirical results, and section 5 concludes the paper.

II. Literature Review

In the recent times, there has been a growing interest in investing in commodity markets, as evidenced by investors diversifying their investments through various commodities futures. Numerous studies have focused on this area, employing various methodological approaches to analyze linkages, co-movements, contagion effects, returns and volatility spillovers, and volatility connectedness.

One group of studies in the literature has focused on the interconnections and volatility spillovers among stock markets during the COVID-19 pandemic. For instance, Cheng et al. (2022) found that overall volatility connectedness strengthened and remained high throughout 2020 due to the pandemic, with China showing disconnection from global markets until late November 2020. Wang et al. (2022) investigated volatility spillovers among major financial markets during the pandemic and found that total spillovers increased, reaching a historical high in March 2020, and then declining, possibly due to the monetary and fiscal measures introduced by various countries. Choi (2022) also found increased interdependence among Northeast Asian markets and the U.S. market during the pandemic and the GFC. These results imply limited diversification benefits during the pandemic due to high risk connections among the markets.

Another group of studies has focused on modelling and forecasting volatility in commodity markets, given its importance in assets allocation, asset pricing, and financial risk management. GARCH family models have been commonly employed to analyze conditional volatility. For example, Aziz et al. (2020) examined volatility spillovers between commodity markets and stock markets and found no volatility connections between the two, suggesting that combining gold and equity can minimize risk due to their limited connections in terms of return and volatility[3].

An alternate strand of research examined the ever-changing association between stock markets and commodity markets. Comprehending the volatility linkages that exist among global stock markets, commodities, cryptocurrencies, and exchange rates is imperative for adapting policies in response to dynamic market conditions. Prior investigations have predominantly centered on the correlation between equities and the oil market. For instance, Boldanov et al. (2016) probed the connection between oil prices and stock markets in both oil-importing and oil-exporting nations, uncovering diverse correlation patterns influenced by economic and geopolitical events. More recently, Ali et al. (2022) explored the repercussions of the COVID-19 pandemic on the spillovers between oil prices and stock markets in key importing and exporting countries, exposing a linkage where bearish stock market trends coincided with a downward trajectory in oil prices[4)].

Commodity markets play a pivotal role in shaping the global economic landscape, exerting both direct and indirect influences on equity prices. As an illustration, Choi and Hammoudeh (2010) contended that portfolio investors meticulously monitor fluctuations in commodity and stock prices to make well-informed portfolio decisions. Consequently, there exists a mechanism for portfolio rebalancing and potential substitution between commodity and financial assets. Additionally, the work of Sadorsky (1999) and Arouri and Nguyen (2010) postulated that surges in commodity prices, like oil, can trigger a decline in production, consequently contributing to inflation. In such inflationary scenarios, the anticipated earnings from the stock market for investors may diminish, resulting in lower stock prices. Hence, in countries that heavily rely on oil imports, rising oil prices can lead to a decrease in stock prices. Conversely, in oil-exporting nations, an increase in oil prices has been observed to positively influence stock markets due to enhanced national income (Tiwari et al., 2022).

While exploring the interconnections between equity, energy, and gold markets, Elgammal et al. (2021) uncovered bidirectional spillovers in returns and volatility among these markets. They posited that during the COVID-19 pandemic, these spillovers intensified, affirming the previously established notion of robust linkages during crisis periods. More recently, Tiwari et al. (2022) detected time-varying dependencies in the returns of oil, natural gas, cocoa, and nine sectoral indices within the Australian market. Their findings suggested that crude oil served as an effective hedge for the financial sector, natural gas exhibited hedging potential for all sectors except real estate, and cocoa's returns were closely associated with those of the technology, industrial, and real estate sectors. Additionally, Chkili (2016) contended that investing in oil

3) The study applied GARCH (1, 1) model on monthly data for the period of February 2005 to December 2016. They investigated the equity market (S&P 500) and commodity markets (gold, oil, gas, and rice).

4) This study utilized the daily closing spot prices of WTI crude oil futures and stock indices from five significant oil-dependent nations: the S&P 500 index for the United States, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela. Additionally, they incorporated Europe Brent crude oil futures for comparative analysis. The dataset covered observations from January 1, 2019, to March 31, 2021.

and gold markets offered opportunities for hedging against exposure to developed stock markets.

Numerous studies have investigated the spillovers of returns and volatility between commodity and stock markets (Elgammal et al. 2021; Pinho and Maldonado, 2022) as well as foreign exchange markets and equity markets (Devpura, 2021; Khan et al, 2023). However, a limited number of such investigations have explored the dynamics between global stock markets and global commodity markets, particularly in the context of the COVID-19 pandemic. One of the primary objectives of this study is to scrutinize the volatility spillovers among global developed and emerging stock markets, the commodity market, the cryptocurrency market, and exchange rates on a global scale. The insights gained from this research are anticipated to offer valuable guidance to investors and policymakers as they consider diversification strategies across equity, commodity, cryptocurrency, and exchange markets.

III. Data and Methodology

In this study, daily data spanning from March 8, 2017, to March 17, 2023, is employed to examine the transmission effects among worldwide stock, commodity, cryptocurrency, and exchange markets, both prior to and during the COVID-19 era. The primary variables under scrutiny encompass closing prices for the S&P 500 index, Bitcoins, the Euro/Dollar exchange rate, the emerging market index, the developed markets index (excluding the U.S.), WTI crude oil, gold, as well as futures for sugar and cocoa[5]. The dataset is segmented into three distinct sub-periods: the complete duration of the study, spanning from March 8, 2017, to March 17, 2023; the period prior to the onset of the COVID-19 pandemic, encompassing March 8, 2017, to March 10, 2020; and the period during the COVID-19 pandemic, covering March 11, 2020, to March 17, 2023. The demarcation point for these segments aligns with March 11, 2020, which corresponds to the declaration of COVID-19 as a global pandemic by the World Health Organization (WHO)[6]. This demarcation point is consistent with earlier research conducted by Ali et al. (2022) and Corbet et al. (2020). The daily closing price data were sourced from investing.com. The selection of variables for this examination was influenced by prior research, which had utilized these specific variables either individually or in combinations to investigate return and volatility spillovers across various timeframes. Furthermore, Khan et al. (2023) noted that these financial assets possess the most substantial market capitalization and representation within their respective markets. Daily returns were computed using the following equation:

5) The selection of the variables was based on their high market capitalization, data availability and wide use by previous studies.

6) https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-mediabriefing-on-covid-19---11-march-2020

$$R_t = \mathrm{Ln}\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the financial returns of the market at the end of day t, P_t is the current price level of the financial asset at the end of day t, P_{t-1} represents the price level of the assets for the previous day, and Ln represents the natural logarithm.

To investigate volatility spillovers among these markets, numerous researchers have turned to models within the GARCH family. However, a limitation of the standard GARCH model lies in its treatment of "good" and "bad" news in a symmetric manner. It focuses on the absolute values of innovations and disregards their signs, leading to positive and negative shocks having equal impacts on the volatility series. Nonetheless, existing literature demonstrates that "bad" news tends to have a more pronounced effect on volatility compared to "good" news. For instance, Basuony et al. (2021) discovered that bad news had a more significant impact on market volatility than the positive news of recovery, emphasizing the asymmetric influence of such crises on financial markets. In light of this, the present study adopts the EGARCH model, originally proposed by Nelson (1991), to address the asymmetry issue inherent in the basic GARCH model. Furthermore, the EGARCH model possesses the capability to incorporate more lags in conditional variance. The mathematical equation for EGARCH (1,1) model is given below;

$$\log h_t = c + \alpha \left|\mu_{t-1}\right| + \gamma\mu_{t-1} + \beta\log h_{t-1} \tag{2}$$

The EGARCH (p, q) model is expressed as follows to capture the asymmetric nature of volatility effects:

$$Log(h_t) = c + \sum_{j=1}^{q} \alpha_j \left|\frac{\mu_{t-j}}{\sqrt{h_{t-j}}}\right| + \sum_{j=1}^{q} \gamma_j \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \beta_i \log(h_{t-i}) \tag{3}$$

Where c is the constant term, α represent the ARCH effect, β represent the GARCH effect and γ represent the asymmetric effect. If value of $\gamma 1 = \gamma 2 = \ldots\ldots = 0$, it implies a symmetric model. If $\gamma < 0$, it indicates that bad news generates larger volatility than good news, capturing the asymmetric volatility spillovers among financial assets. As investors are more reactive to bad news than good news, this model will capture the asymmetrical volatility spillovers among the financial assets sectors.

To measure the magnitude of the asymmetric effect of "good" and "bad" news on the volatility spillovers, the paper employs Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) model proposed by Glosten et al. (1993) and Zakoian (1994). The conditional variance equation for a TGARCH (1, 1) model is given as:

$$h_t = c + \alpha_1 \mu_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 \mu_{t-1}^2 \lambda_{t-1} \tag{4}$$

The higher order TGARCH (p, q) model is expressed as follows to capture the asymmetric nature of volatility effects:

$$h_t = c + \sum_{k=1}^{p} \beta_k h_{t-k} + \sum_{i=1}^{q} (\alpha_i + \gamma_i \lambda_{t-i}) \mu_{t-i}^2 \tag{5}$$

Where λ_t takes the values of 1 for $\mu_t < 0$ (bad news) and 0 when $\mu_t > 0$ (good news). This model recognizes that 'good' and 'bad' news might have different impacts. Good news has an impact of α_1 and bad news has an impact of $(\alpha_1 + \gamma_1)$. γ_1 is the asymmetry or leverage term, and any value greater than 0 for this coefficient indicates asymmetry in how returns respond to news, while a value equal to 0 would suggests symmetry. As the paper focuses on estimating the impact of COVID 19 on global financial markets volatility spillovers, the TGARCH model is employed for the analysis[7].

IV. Empirical Results

Table 1 provides a summary of the statistical characteristics of the financial returns. Panel 1 presents the results for the entire sample period, while Panels 2 and 3 display the descriptive statistics for the periods before and during COVID-19, respectively. The table furnishes measures of central tendency. Additionally, the goodness of fit for the distribution of returns is assessed using the Jarque-Bera test. It's worth noting that during the COVID-19 pandemic period, the primary risk measure, i.e., the standard deviation, is notably higher compared to the period before COVID-19. Specifically, crude oil and bitcoins exhibit the highest market risk, with standard deviation values of 0.0679 and 0.0427, respectively, during the COVID-19 period. Across the entire sample period, bitcoin is consistently considered the riskiest among the set of financial assets, with a standard deviation value of 0.0422, followed by crude oil at 0.0314. Furthermore, it's important to highlight that the kurtosis coefficient of returns for all financial assets exceeds 3 in all three sample periods. This signifies a fat-tail phenomenon in financial markets. Lastly, the Jarque-Bera statistics indicate that the returns of all series confirm to asymmetric distributions

7) The study utilized EGARCH (1, 1) and TGARCH (1, 1) models to examine asymmetric volatility spillovers. The determination of lag order selection relied on the Akaike Information Criterion (AIC). This choice was made because the AIC consistently indicated a lag order of (1) for the unrestricted VAR for the entire period, the period before and during the COVID-19 pandemics, as it yielded the lowest AIC values among the criteria considered.

in all sub-periods.

Table 1. *Descriptive Statistics for the Selected Financial Assets over the Three Sub-Periods*

	BC	Cocoa	DM	EM	Gold	EUR	Oil	S&P500	Sugar
Mean	0.0009	0.0002	0.0001	-0.0001	0.0003	0.0000	0.0007	0.0003	0.0000
Std. Dev.	0.0422	0.0175	0.0118	0.0139	0.0093	0.0045	0.0314	0.0128	0.0175
Skewness	0.1281	-0.0822	-1.2415	-0.9136	-0.2012	0.0493	0.0409	-0.8297	0.1222
Kurtosis	9.4829	15.379	19.205	13.989	7.9714	4.3886	29.665	17.776	5.0309
Jarque-Bera	2660.6	9687.5	16988.9	7843.8	1572.4	122.5	44944.7	13975.6	264.48
Obs.	1517	1517	1517	1517	1517	1517	1517	1517	1517
Before COVID 19 Period									
Mean	0.0006	0.0003	4.42×10^{-5}	-9.81×10^{-5}	0.0004	6.19×10^{-5}	-0.0018	0.0003	-0.0005
Std. Dev.	0.0416	0.0195	0.0077	0.0148	0.0083	0.0040	0.0589	0.0096	0.0177
Skewness	-0.4134	-0.1072	-0.9421	-1.6212	0.3035	0.0479	-23.390	-1.0899	0.3382
Kurtosis	9.9015	18.965	6.7041	18.766	11.943	3.8796	60.965	13.822	5.6997
Jarque-Bera	1521.9	8030.7	544.0	8160.7	2531.1	24.659	116617	3839.1	243.99
Obs.	756	756	756	756	756	756	756	756	756
During COVID 19 Period									
Mean	0.0013	7.87×10^{-5}	0.0002	4.80×10^{-5}	0.0002	-5.31×10^{-5}	0.0003	0.0004	0.0007
Std. Dev.	0.0427	0.0154	0.0147	0.0129	0.0101	0.0049	0.0679	0.0154	0.0173
Skewness	0.6233	-0.0440	-1.1369	0.1619	-0.4691	0.0608	-8.1850	-0.7049	-0.1011
Kurtosis	9.0637	3.2208	15.114	5.1042	5.7199	4.3382	21.091	15.011	4.3789
Jarque-Bera	1215.1	1.7916	4817.0	143.71	262.47	57.254	1379.0	4637.3	61.595
Obs.	761	761	761	761	761	761	761	761	761

Table 1 summarizes descriptive statistics for the financial markets included in the study over the three sub-periods, Entire sample period, (March 8, 2017 - March 17, 2023); Before COVID-19 period, (March 8, 2017 - March 10, 2020) and During COVID-19 period (March 11, 2020- March 17, 2023). In particular, the table shows the mean (Mean), the standard deviation (Std. Dev), the Kendall-Stuart measures of skewness (Skewness) and kurtosis (Kurtosis) and the Jarque-Bera test (Jarque-Bera) for normality.

Table 2 presents the correlation outcomes for the return series of financial assets across the entire sample period, along with the two sub-periods before and during COVID-19. A visual examination of Table 2 reveals varying correlations among the assets during these three periods. Throughout the entire sample period and during the COVID-19 pandemic, the S&P 500 exhibits the strongest correlation with emerging markets, featuring coefficient values of 0.179 and 0.330, respectively. It's noteworthy that the correlation values during the COVID-19 period are notably higher than those before the pandemic. Significantly, during the COVID-19 period, there is a negative correlation between gold and oil, underscoring gold's safe-haven characteristics during crisis times. Similarly, the negative association between gold and bitcoin suggests that these two assets could serve as substitutes during crisis periods. In general, the connections among the commodity market, exchange market, and stock markets increase during pandemics, affirming that these markets are more interconnected with each other during crises. Furthermore, the negative correlations between gold, oil, and stock markets imply that gold and oil futures can be considered as options for investors seeking to hedge against stock market exposures during turbulent times. These findings align with the observations of Roll (1989), who argued that global markets tend to become more closely linked during crises. Akter and Nobi (2018) also noted an augmented degree of association during and after crises compared to the periods preceding crises. More recently, Khan et al. (2022) found that market integration increased following the GFC. These heightened linkages among markets hold significant implications for both domestic and international investors contemplating these assets for portfolio investments.

Table 2. *Correlation*

	BC	COCOA	DM	EM	EUR	GOLD	OIL	S&P500	SUGAR
BC	1.000								
COCOA	0.017	1.000							
DM	0.005	-0.003	1.000						
EM	-0.003	0.028	0.029	1.000					
EUR	-0.004	0.001	-0.017	0.012	1.000				
GOLD	-0.017	0.049	-0.009	0.007	-0.065	1.000			
OIL	0.029	-0.048	-0.034	0.026	-0.007	-0.008	1.000		
S&P500	0.007	0.111	-0.002	0.179	0.008	0.023	-0.009	1.000	
SUGAR	0.001	0.052	0.019	0.006	-0.034	-0.085	-0.020	0.006	1.000
Before COVID-19									
BC	1.000								
COCOA	-0.004	1.000							
DM	-0.013	-0.024	1.000						
EM	-0.050	-0.002	0.117	1.000					
EUR	-0.052	0.025	-0.023	-0.034	1.000				
GOLD	-0.012	0.079	-0.039	-0.026	-0.017	1.000			
OIL	0.007	-0.029	-0.075	-0.051	0.028	-0.137	1.000		
S&P500	-0.048	0.021	-0.001	-0.017	0.007	-0.012	-0.185	1.000	
SUGAR	0.015	0.044	-0.005	-0.057	0.006	-0.055	0.050	0.003	1.000
During COVID-19									
BC	1.000								
COCOA	0.044	1.000							
DM	0.014	0.010	1.000						
EM	0.049	0.071	-0.021	1.000					
GOLD	-0.021	0.019	0.002	0.039	1.000				
EUR	0.034	-0.024	-0.014	0.055	-0.096	1.000			
OIL	0.000	-0.121	-0.056	-0.019	0.004	-0.008	1.000		
S&P500	0.040	0.194	-0.002	0.330	0.042	0.009	-0.090	1.000	
SUGAR	-0.014	0.065	0.034	0.079	-0.110	-0.067	-0.052	0.009	1.000

This paper employs the Augmented Dicky-Fuller (ADF) and Phillip and Perron (P-P) tests to assess the presence of a unit root, while the ARCH-LM test is applied to examine heteroscedasticity in the residuals. Table 3 presents the outcomes of these tests.

The results from Table 3 reveal that all variables exhibit non-stationarity at their base level but become stationary when transformed into their first-differenced form. The test statistics' values are notably significant at the 1 percent level. Consequently, the null hypothesis suggesting the existence of a unit root in the returns series is decisively rejected, affirming the stationarity of the returns series for the chosen assets. Furthermore, the ARCH-LM test statistics provide evidence of an ARCH effect within the return series, thereby substantiating the use of GARCH family models.

Table 3. *Unit Root Test and ARCH-LM Test*

Variables	ADF Test		P-P Test		Arch LM Test_
	Level	1^{st} Diff:	Level	1^{st} Diff:	
BC	-1.40	-40.23*	-1.38	-41.29*	19.81*
COCOA	-3.65	-41.45*	-3.55	-41.73*	266.09*
DM	-2.29	-20.48*	-2.29	-41.23*	68.67*
EM	-1.85	-44.29*	-1.97	-43.10*	59.96*
GOLD	-0.98	-39.45*	-0.81	-40.07*	41.44*
EUR	-1.74	-38.19*	-1.67	-38.41*	19.34*
OIL	-1.77	-25.07*	-1.90	-53.05*	133.14*
S&P 500	-1.42	-11.88*	-1.34	-43.61*	195.55*
SUGAR	-1.30	-37.97*	-1.26	-38.13*	13.83*

The table shows unit root test results using the Augmented Dicky-Fuller (ADF) and the Phillips-Perron (P-P) and ARCH-LM tests. The critical values are based on MacKinnon (1996). An * indicates significance at 1% level.

Figures 1 and 2 visually represent the price trends and return fluctuations of the financial assets. A noticeable price decline is evident across all financial assets, except for gold, during the peak of the 2020 pandemic. Particularly, a substantial shock affected bitcoins, as well as developed and emerging markets, oil, and sugar prices in mid-2020. The S&P 500 exhibited a decline in prices, particularly in March 2020. Conversely, gold prices displayed an increase, showcasing a contrasting performance during the pandemic period. This suggests that investors might enhance diversification by incorporating gold into their stock portfolios. The return plots also reveal heightened volatility levels during the pandemic period, with all assets experiencing significant fluctuations. Moreover, all these graphs demonstrate volatility clustering, implying that current-period volatility influences future periods of volatility. Furthermore, it's worth noting that all returns appear to revert to their mean values, indicating stationarity in all financial assets.

Figure 1. Price trends in the financial markets over the period of March 8, 2017 to March 17, 2023

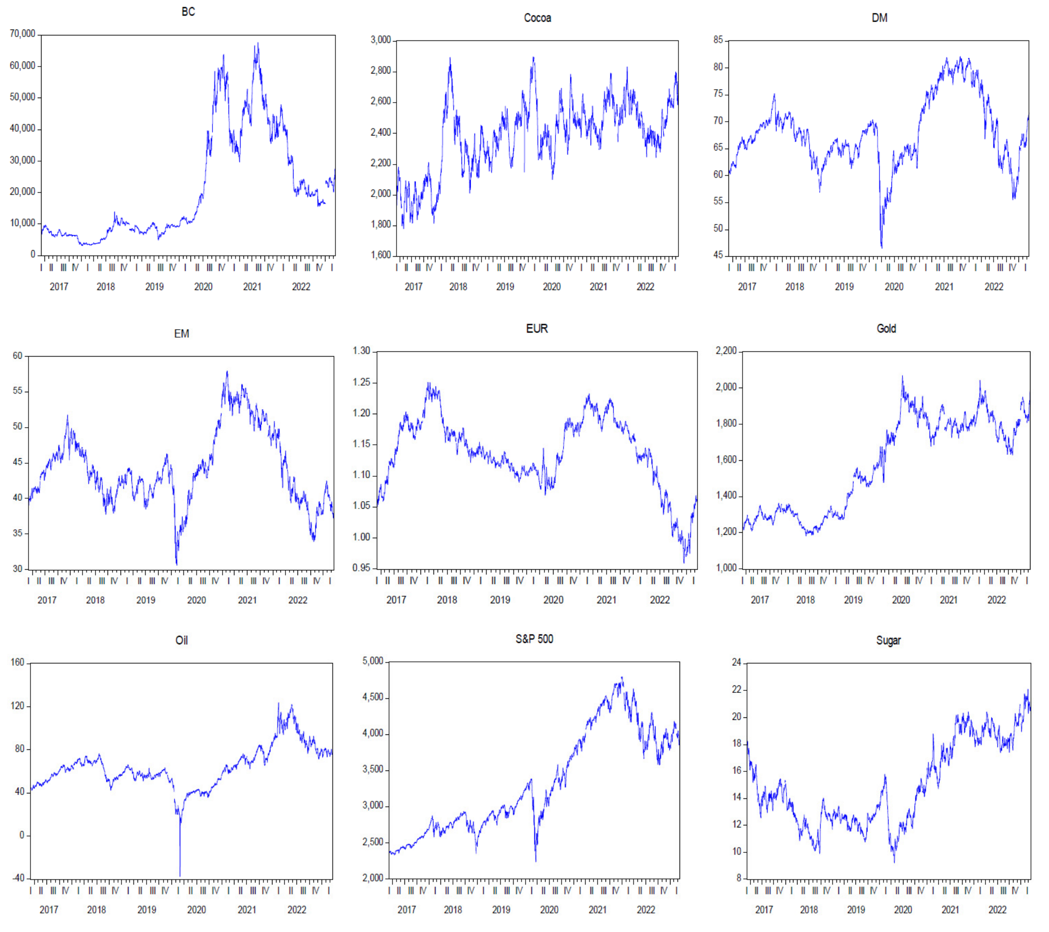


Figure 2. Returns fluctuations in the financial markets over the period of March 8, 2017 to March 17, 2023

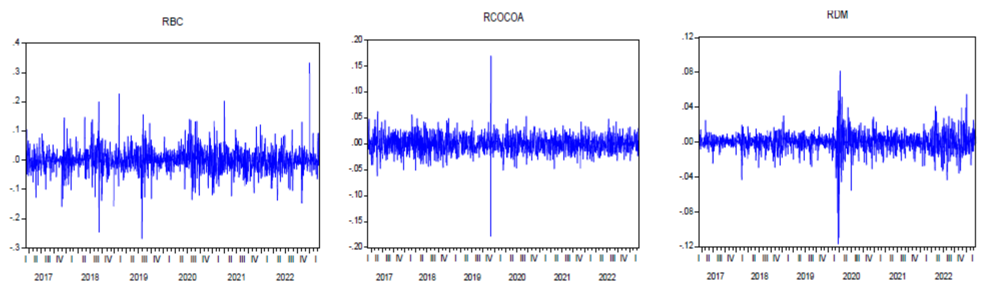
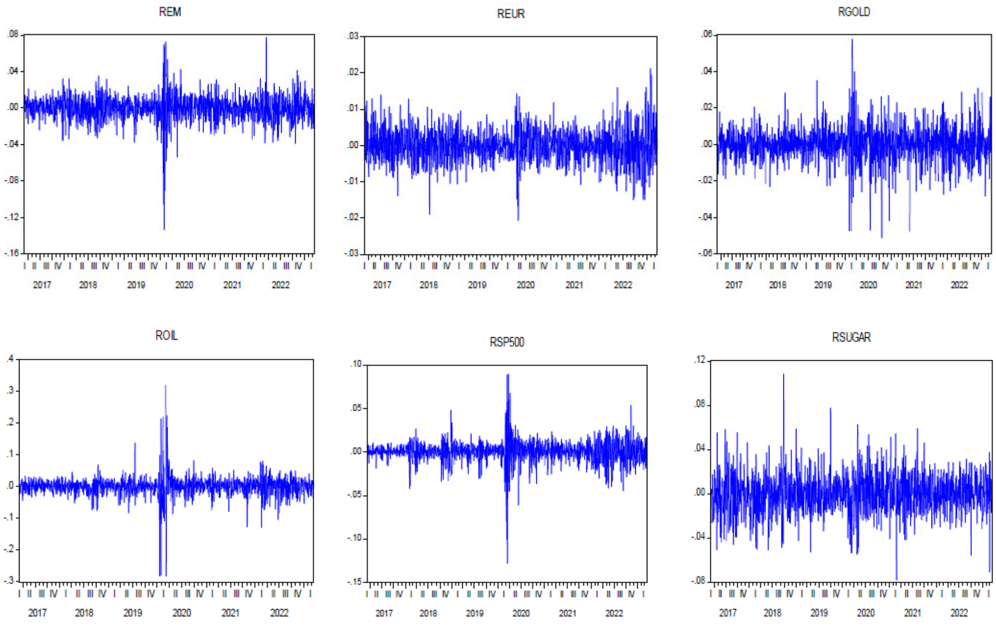


Figure 2. Continued



A. Results for the entire sample period

Table 4 provides the outcomes of the EGARCH model for the entire sample period. Examining the coefficient values, it's evident that the ARCH (α) term is statistically significant for all variables at a 1% significance level. This signifies that past shocks have a substantial impact on the conditional variance. In contrast, the GARCH terms (β) exhibit notably higher coefficients for all variables, ranging from 0.465 for BC to 0.999 for gold. These high coefficients indicate a considerable degree of volatility persistence. The sum of the ARCH and GARCH coefficients (α + β) is close to 1, varying from 0.808 for Cocoa to 1.272 for S&P 500, implying covariance stationarity with a high level of persistence and long memory in the conditional variances.

The asymmetric term (γ) is significant for nearly all assets, with the exceptions being BC, EUR, and Sugar. This suggests the presence of asymmetric effects, where negative shocks have a more substantial impact on the conditional variance compared to positive news.

Regarding cross-volatility transmissions, there is no evidence of volatility spillovers from BC to other financial assets. The oil market, on the other hand, transmits volatility shocks to both developed and emerging markets stocks, as well as to the gold market. Volatility spreads from the S&P 500 to world developed and emerging markets, as well as to commodity markets such as oil, gold, and cocoa. Gold exhibits spillovers to BC. The Sugar market serves as a volatility transmitter to other assets, including cryptocurrencies, Cocoa, Oil, and Gold.

Table 4. *Empirical Results Based on EGARCH Model for the Whole Period (March 8, 2017- March 17, 2023)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	-9.479*	-2.939*	-0.295*	-0.449*	-0.069*	-0.373*	-0.005	-0.664*	-1.164*
α	0.199*	0.153*	0.157*	0.164*	0.057*	0.214*	0.004	0.317*	0.172*
γ	0.013	-0.115*	-0.094*	-0.083*	-0.010	-0.095*	0.029*	-0.138*	-0.002
β	-0.465*	0.655*	0.981*	0.963*	0.998*	0.972*	0.999*	0.955*	0.873*
BC		-0.262	-0.079	0.505	-0.059	0.351	0.085	-0.432	-0.338
Cocoa	-2.680**		-2.939*	-0.415	-0.064	1.692*	-0.743	-2.285**	-0.864
DM	-15.27*	4.521***		0.556	-1.701**	1.168	-0.521	-0.058	2.676
EM	3.091*	-0.848	0.039		-1.797**	0.219	-3.031*	-1.939	2.961**
EUR	5.072	9.565	4.186	-1.381		2.749	2.294	-0.213	4.057
OIL	-1.943	-1.630	-0.642**	-1.046*	0.983*		-0.761*	-0.664	0.439
Gold	-1.853*	2.926	1.828	-0.512	1.236	0.319		-2.186	2.517
S&P 500	3.538	-7.051*	-5.715*	-1.371	0.432	-2.969**	1.916**		-2.155
Sugar	3.039*	-3.936*	0.627	1.658***	-0.889	-1.614**	0.537	-0.475	
AIC	-3.521	-5.314	-6.549	-6.011	-8.046	-4.713	-6.678	-6.522	-5.279
SIC	-3.472	-5.265	-6.499	-5.962	-8.001	-4.667	-6.633	-6.476	-5.233

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

Table 5 presents the outcomes of the TGARCH model for the entire sample period. The coefficients (α) and (β), representing the ARCH and GARCH terms in the model, are statistically significant, indicating the presence of ARCH and GARCH effects. The ARCH coefficient reveals that past shocks had a substantial impact on the asset's conditional variance. Notably, the GARCH coefficient (β) suggests a high degree of volatility persistence in all assets except Bitcoin. The gold market exhibits the highest volatility persistence, with a coefficient value of 1. The asymmetric term, denoted by (γ), is positive and significant for all assets except the exchange rate, indicating an asymmetric effect for news in these assets. Regarding cross-assets volatility spillovers, the results indicate that during the entire period, crude oil, developed markets, and cocoa played a role in explaining conditional volatility in the cryptocurrency market. Exchange market shocks were statistically significant in explaining volatility in cocoa and emerging markets stocks. However, in general, the commodity market showed fewer spillovers to other markets. The U.S. stock market's volatility was transmitted to cocoa, developed markets, and the gold market.

Comparing the results from Tables 4 and 5, the Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) values for each financial asset suggest that the EGARCH model, except for EUR, S&P 500, and sugar, provides a better fit for modeling volatility compared to the TGARCH model.

Table 5. *Empirical Results Based on TGARCH Model for the Whole Period (March 8, 2017- March 17, 2023)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	0.001*	8.7×10^{-5}*	1.4×10^{-6}*	5.7×10^{-6}*	5.9×10^{-8}	2.2×10^{-5}*	-1.3×10^{-7}	2.8×10^{-6}*	5.4×10^{-5}*
α	0.077*	-0.028	0.035*	0.020	0.025*	0.057*	0.009*	0.131*	0.089*
γ	-0.095*	0.109*	0.069*	0.115*	0.006	0.119*	-0.014*	0.182*	0.021
β	0.125	0.685*	0.919*	0.886*	0.968*	0.849*	1.000*	0.777*	0.723*
BC		-2.0×10^{-5}	-1.5×10^{-5}	1.4×10^{-5}	-8.6×10^{-7}	0.000	-9.6×10^{-6}	-1.0×10^{-5}	-8.6×10^{-5}
Cocoa	-0.011*		-0.0001*	-2.3×10^{-6}	1.0×10^{-5}	0.0003	-6.0×10^{-6}	-0.0001*	-0.0003
DM	-0.020*	0.001*		0.0003**	-3.3×10^{-5}	0.0002	-9.1×10^{-6}	0.0001	0.001
EM	-0.004	-8.6×10^{-5}	-0.0001		-2.6×10^{-5}*	-0.0005	-0.0002*	-0.002	0.0007
EUR	-0.002	0.003*	0.0001	-0.0001**		0.0002	-8.2×10^{-5}	0.0001	0.0006
OIL	0.007*	-0.0004	-4.3×10^{-5}	-0.0003	8.5×10^{-6}		0.002	-0.0001*	0.0002
Gold	-0.009	0.001	-0.0001	-0.000	-1.7×10^{-5}	0.0002		-0.0002	0.0008
S&P 500	0.006	-0.003*	-0.0005*	-0.000	2.8×10^{-5}	-0.0010	0.0002*		-0.0007
Sugar	0.003	-0.001	-3.6×10^{-5}	0.000	-1.7×10^{-5}	-9.6×10^{-5}	2.4×10^{-5}	5.6×10^{-7}	
AIC	-3.481	-5.310	-6.535	-6.009	-8.053	-4.713	-6.652	-6.525	-5.285
SIC	-3.435	-5.265	-6.489	-5.963	-8.008	-4.667	-6.606	-6.479	-5.237

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

B. Results for the period before COVID-19

Tables 6 and 7 present the outcomes of the EGARCH and TGARCH models for the period before the COVID-19 pandemic. The results in Table 6 suggest the presence of shocks and volatility persistence, as evidenced by the significant values for the ARCH and GARCH coefficients. The coefficient representing the asymmetric effect (γ) is also significant, highlighting an asymmetric impact of news on financial market volatility. Additionally, the GARCH term reveals a high level of persistence in the volatility of these assets during this period.

However, the interconnections among the markets were relatively weak and less pronounced before the COVID-19 pandemic. There were limited linkages observed between bitcoins and cocoa. Notably, highly significant volatility spillovers were detected from the exchange market to bitcoin, developed and emerging stock markets, oil, gold, and sugar. The S&P 500 was found to explain volatility in developed stock markets, the exchange market, oil, and sugar. Furthermore, volatility transmissions were identified from the gold market to the oil and sugar markets.

The TGARCH model results provided in Table 7 emphasize the statistical significance of the GARCH term (β) for all financial assets, indicating the existence of volatility persistence. The values of this parameter vary, ranging from 0.465 for cocoa to 0.911 for developed market stocks. Additionally, the summation of the coefficients of the ARCH and GARCH terms (α + β) closely approximates 1, suggesting that the model demonstrates covariance stationarity, characterized by a notable degree of persistence and long memory in the conditional variances of these assets.

Table 6. *Empirical Results Based on EGARCH Model before the COVID-19 Pandemic (March 8, 2017- March 10, 2020)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	-1.189*	-4.925*	-0.454*	-0.574*	-19.25*	-13.20*	-0.011*	-0.884*	-15.99*
α	0.241*	0.159**	0.110*	0.217*	0.016	0.162*	-0.003*	0.272*	0.225*
γ	-0.030	-0.232*	-0.093*	-0.131*	-0.037	0.104*	0.062*	-0.257*	0.006
β	0.842*	0.401*	0.962*	0.955*	-0.740*	-0.658*	0.999*	0.931*	-0.916*
(α + β)	1.08	0.56	1.07	1.17	-0.72	-0.49	0.99	1.20	1.14
BC		-2.437**	-0.143	1.056	0.836	-0.691	0.132	0.093	1.101*
Cocoa	-9.006*		-3.132*	-1.198	0.779	4.086**	-1.978*	-3.47**	0.806
DM	3.759	-2.900		3.427	-5.934	14.02*	-0.705	-2.184	12.27*
EM	0.556	-2.582	-6.792*		-2.522	-2.661	-7.868*	-5.23**	-0.563
EUR	-31.04*	2.015	11.79**	15.48**		-39.96*	6.653*	-0.336	-5.173**
OIL	3.247*	-0.324	0.408	-0.154	1.541		0.358	-0.624	-1.900*
Gold	1.754	-6.343	-1.925	0.646	0.635	9.524*		-5.009	7.677*
S&P500	-0.736	-9.030	-16.36*	-2.496	14.21*	30.77*	0.673		-6.536*
Sugar	2.713	-9.862*	-0.391	2.093	-0.327	-3.234**	-0.912	1.306	
AIC	-3.644	-5.144	-7.096	-6.109	-8.178	-5.008	-6.987	-7.097	-5.305
SIC	-3.565	-5.064	-7.017	-6.030	-8.098	-4.928	-6.907	-7.017	-5.225

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

Table 7. *Empirical Results Based on TGARCH Model before COVID-19 Pandemic (March 8, 2017- March 10, 2020)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	0.001**	0.000*	0.000*	0.000*	0.000**	0.003*	1.3×10^{-5}*	4.6×10^{-5}*	0.001*
α	0.081**	-0.116*	0.016	0.037	0.046	-0.307*	0.147*	0.138	0.115*
γ	-0.051	0.321*	0.056**	0.201*	-0.063	-0.252	-0.046	0.058	-0.0001
β	0.515**	0.465*	0.911*	0.789*	0.769*	0.550*	0.677*	0.492*	0.515*
(α + β)	0.59	0.35	0.93	0.83	0.82	0.24	0.83	0.63	0.63
BC		-0.001*	0.000	0.0001*	0.000	-0.012	6.7×10^{-5}**	2.9×10^{-5}	-0.0004**
Cocoa	-0.016***		-0.000	0.000	0.000	-0.053*	8.7×10^{-6}	-0.001	-0.0008
DM	0.006	-0.002		-0.000	0.000	-0.055	-0.001*	-0.003*	0.0005
EM	-0.002	-0.000	-0.0003**		0.000*	0.019	0.0001**	-0.0003	0.002*
EUR	-0.028	0.002	0.0003	0.002**		-0.096	-0.001	-0.002**	-0.0049***
OIL	0.001*	-0.002**	0.000	0.0009*	-0.000		-7.4×10^{-5}	-0.0003	-0.0009
Gold	-0.011	-0.003**	-0.0002	0.001	-0.000	0.010		-0.0003	-0.0007
S&P 500	0.001	-0.003**	-0.0008*	-0.000	0.000	-0.062	-0.001*		-0.0043**
Sugar	0.007	-0.002*	-0.000	0.000	-0.000	-0.008	-0.001*	-2.7×10^{-5}	
AIC	-3.430	-5.145	-7.082	-6.122	-8.183	-2.799	-6.935	-6.720	-5.2515
SIC	-3.351	-5.065	-7.003	-6.042	-8.103	-2.719	-6.855	-6.641	-5.1719

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

Furthermore, the presence of the asymmetric term (γ) is both positive and statistically significant for cocoa, developed markets, and emerging markets. This signifies an asymmetric influence of news on the volatility of these financial assets. Pertinent findings include bidirectional volatility spillovers between cocoa and bitcoin, as well as cocoa and oil. Moreover, unidirectional volatility transmission is detected from the S&P 500 to gold and developed markets. Similarly, a unidirectional spillover is evident from the exchange market to emerging markets, the S&P 500, and sugar. Within the commodity market, shocks in sugar were specifically noteworthy, being statistically significant in explaining volatility within the cocoa and gold markets.

C. Results for the period during COVID-19

Tables 8 and 9 present the outcomes of the EGARCH and TGARCH models for the period during the COVID-19 pandemic. Table 8, provides the results of the EGARCH model while Table 9 reports the results of the TGARCH model during the COVID-19 health crisis period. Table 8 shows that the ARCH and GARCH coefficients (α) and (β) are highly significant for all financial markets, indicating the presence of strong shocks and significant volatility persistence. The asymmetric term (γ) is significant in almost all markets, with exceptions noted for bitcoin, the exchange rate, and sugar, highlighting the asymmetric impact of news on these markets during this tumultuous period.

Table 8. *Empirical results based on EGARCH model during COVID-19 Pandemic (March 11, 2020- March 17, 2023)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	-7.095*	-1.917**	-0.105*	-0.297**	-0.382*	-0.463*	-13.83*	-0.575*	-0.135*
α	0.274*	-0.040	-0.008	0.058**	0.146*	0.357*	-0.218*	0.221*	-0.053*
γ	-0.084***	0.018	-0.089*	-0.063*	-0.014	-0.048**	-0.026	-0.084*	0.013
β	-0.079	0.768*	0.988*	0.971*	0.975*	0.972*	-0.514*	0.955*	0.979*
(α + β)	0.20	0.73	0.98	1.03	1.12	1.33	0.73	1.18	0.93
BC		1.438	-0.539**	-0.349	0.386	-0.241	1.181	-0.447	-0.100
Cocoa	13.67*		-1.019	0.096	0.301	-0.800	2.882	0.685	-1.286
DM	-14.65*	4.969**		0.586	1.289	7.249*	-10.44*	1.049	2.017***
EM	0.881	-1.908	5.085*		1.425	11.27*	-1.509	-1.120	-0.392
EUR	27.62*	0.112	-0.875	0.479		-22.41*	13.31**	-2.512	6.100**
OIL	1.762*	0.869	0.339	-1.164*	-0.376		0.235	1.606*	-0.089
Gold	6.844*	3.548	0.249	-0.618	0.786	5.587**		-1.684	-1.154
S&P500	1.324	-3.939	-4.306*	-1.756	-1.655	-9.142*	0.036		1.304
Sugar	2.813	-2.316	1.682	2.111***	-3.107**	2.732	1.049	-3.184**	
AIC	-3.513	-5.519	-6.077	-5.908	-7.867	-4.233	-6.368	-6.009	-5.334
SIC	-3.434	-5.439	-5.998	-5.829	-7.788	-4.154	-6.288	-5.930	-5.255

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

Table 9. *Empirical Results Based on TGARCH Model During COVID-19 Pandemic (March 11, 2020- March 17, 2023)*

Particulars	BC	Cocoa	DM	EM	EUR	Oil	Gold	S&P500	Sugar
C	0.0014*	6.0×10^{-5}*	8.5×10^{-5}*	2.6×10^{-6}***	4.7×10^{-7}**	0.0018*	5.7×10^{-5}*	4.4×10^{-6}*	8.1×10^{-6}*
α	0.064	0.002	0.1153**	-0.0082	0.0537*	0.2525*	0.0297	0.0919**	0.0044
γ	0.158**	-0.044	0.1378***	0.0468*	0.0307	0.3223*	-0.0362	0.0903**	-0.0311
β	0.079	0.763*	0.4143*	0.9671*	0.9146*	0.2955*	0.4233*	0.8359*	0.9774*
(α + β)	0.14	0.77	0.53	0.96	0.97	0.55	0.45	0.93	0.98
BC		0.0003	0.0002	-4.9×10^{-5}	1.4×10^{-5}*	-0.0088*	0.0001**	-3.8×10^{-6}	2.5×10^{-5}
Cocoa	0.017*		-0.0004***	4.7×10^{-5}	8.9×10^{-6}**	-0.0180**	-0.0003	-6.9×10^{-5}	-0.0002
DM	-0.016*	0.0014*		0.0002	2.5×10^{-5}	0.0074	-0.0010*	0.0005*	0.0010
EM	0.006	-0.0004	0.0020*		-1.6×10^{-5}	0.0018	-0.0001	-0.0002	-0.0003
EUR	0.052*	0.0007	-0.0040*	-5.5×10^{-5}		-0.0951*	0.0014**	0.0006	0.0003
OIL	0.002*	0.0001*	-0.0006*	-0.0001*	6.2×10^{-6}		-3.0×10^{-5}	0.0002*	1.9×10^{-5}
Gold	0.002	0.0009	0.0005	2.9×10^{-5}	1.9×10^{-5}	0.0156		0.0003	-0.0005
S&P 500	-0.005	-0.0007	-0.0024*	-0.0006**	-1.1×10^{-5}	-0.0096	0.0005**		0.0009
Sugar	-0.001	-0.0006	-0.0006	0.0004**	-6.6×10^{-5}*	-0.0222*	0.0008*	-0.0003**	
AIC	-3.511	-5.5188	-5.9094	-5.9054	-7.8808	-3.4779	-6.3605	-5.9985	-5.3260
SIC	-3.432	-5.4396	-5.8303	-5.8263	-7.8016	-3.3988	-6.2814	-5.9193	-5.2468

Coefficients α and β captures ARCH and GARCH effects, whereas, γ represents the asymmetric effect in the GARCH model. An (*), (**), (***) indicates significance at the 1%, 5%, and 10% significance level.

During the COVID-19 pandemic, there was an increase in volatility transmissions among the various assets. Interestingly, the gold market appeared less connected to the rest of the assets, particularly to the stock markets, suggesting its role as a safe haven during crisis periods. Additionally, volatility spillovers intensified from the S&P 500 market to other developed and emerging markets. The exchange rate was a notable transmitter of volatility, affecting cocoa, developed and emerging markets stocks, oil, gold, and sugar.

Table 9 provides the outcomes of the TGARCH model during the COVID-19 pandemic. The ARCH coefficient (α) exhibits statistical significance for developed stock markets, the exchange market, crude oil, and the S&P 500, indicating the presence of the ARCH effect in these assets. The GARCH term (β) demonstrates statistical significance in all markets except the cryptocurrency market, signifying a high level of volatility persistence. The coefficient values span a range, with values as low as 0.079 for Bitcoin and as high as 0.9774 for the sugar market.

The presence of the asymmetric term (γ) is significant for all markets except cocoa, indicating that negative news had a more substantial impact on these assets compared to positive news. Notably, bidirectional volatility spillovers are observed between Bitcoin and the exchange rate, as well as between Bitcoin and crude oil. Additionally, the S&P 500 is found to transmit volatility to both developed and emerging markets, as well as to the gold market. Interestingly, the gold market appears to have weak connections with the stock markets during the COVID-19 pandemic. Regarding the volatility from stock markets to the gold market, there are observable time-varying unidirectional spillovers from the stock markets to the gold market. For instance, during the period before COVID-19, the emerging market significantly influenced the gold market, while the coefficient for the developed market became significant during the COVID-19 pandemic. These findings align with Chkili (2016), who noted low to negative correlations between gold and stock markets during major financial crises and argued that gold acted as a safe haven during the GFC. The numerical results obtained from the AIC and SIC suggest that the TGARCH model is considered the most suitable for describing volatilities in cocoa, emerging markets, and the exchange rate before the COVID-19 sub-sample. Conversely, for the remaining assets, the EGARCH model proves to be the best choice for modeling volatilities in the period before COVID-19, as indicated by the AIC and SIC values. During the COVID-19 period, the EGARCH model is the preferred option based on the AIC and SIC values, except in the case of the exchange market, where the TGARCH model is deemed the most appropriate for modeling the volatilities of the Euro return series.

The overall persistence of volatility, measured by (α + β), exhibited an increase during the COVID-19 period in comparison to the period preceding COVID-19. Specifically, this persistence heightened in the returns of cocoa, exchange rates, oil, S&P 500, and sugar, as illustrated in tables (6-9). Generally, higher (α + β) values were observed during the COVID-19 period compared to the pre-COVID-19 period. However, there were exceptions for cryptocurrency, developed markets, and gold, where the persistence decreased during the crisis period.

The significance of the asymmetric term (γ) became notably pronounced during the COVID-19 period, indicating the presence of asymmetric volatility spillovers. As shown in Table 9, the (γ) value was significant for cryptocurrency, developed markets, emerging markets, oil, and the U.S. stock markets during the COVID-19 crisis, whereas it was significant for cocoa, developed markets, and emerging markets only in the period before the COVID-19 crisis. This clearly demonstrates that asymmetric volatility spillovers intensified due to the impact of the deadly COVID-19 pandemic.

V. Conclusion

The financial markets experienced a profound impact due to the COVID-19 pandemic, as noted by Khan et al. (2023) and Ali et al. (2022). This crisis significantly altered the volatility patterns of financial returns. In light of this, this study delved into the market volatility of nine financial assets during the COVID-19 pandemic, employing two GARCH family models, namely EGARCH (1, 1) and TGARCH (1, 1). The findings of the study suggest that the EGARCH model is well-suited for all assets under scrutiny during the COVID-19 period, with the exception of EUR. These results align with Khan et al.'s (2023) research, which highlighted the superior performance of the EGARCH model over the traditional GARCH (1, 1) model and the GJR-GARCH (1, 1) model for modeling volatilities. During the COVID-19 pandemic, the measure of volatility persistence (β) exhibited a notably high level across all financial markets. Furthermore, this study corroborates the absence of a significant asymmetric effect in the volatility of Gold, EUR, and Sugar returns during this tumultuous period. However, crude oil, cryptocurrencies, and stock markets displayed a pronounced positive asymmetric effect amid the pandemic. These findings lend support to Shehzad et al.'s (2021) observations that crises like COVID-19 had a swift and substantial impact on both stock and oil markets.

The current study makes a significant contribution to the existing literature by highlighting the volatility behavior of all the major financial markets during the COVID-19 pandemic. The oil market experienced a massive crash during the COVID-19 pandemic. The findings also revealed that volatility among the markets varied during the two sub-periods investigated. A significant increase has been reported in the volatility of the financial assets during the COVID-19 pandemic. This can be explained by the irrational behavior of investors, which leads to speculations in the financial markets. In a speculative bubble situation, the news of prices can affect irrational investor's decisions, which leads to catastrophic results in the market.

The findings have important implications for investors, portfolio managers and policy makers. Understanding the interrelationships and the magnitude of volatility spillovers across the markets helps investors and portfolio managers to design the optimal portfolio and to adopt optimal diversification and hedging strategies. As for policymakers, they should take into account the time-varying interconnections across Bitcoin, commodity, exchange rate and stock markets while making decisions and designing regulatory structures to avoid negative consequences of volatility spillovers.

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