

# Gold Prices Volatility among Major Events and During the Current COVID-19 Outbreak

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## Abstract

This paper investigates the volatility of the gold spot and futures prices amid major international events for a sample period from January 1, 1979 to March 27, 2020. Events affecting gold price volatility were selected using the Bai–Perron structural break test. The results of the GARCH and T-GARCH modelling frameworks reveal that the returns series for the gold spot and futures demonstrate greater volatility spikes during the 1987 stock market crash, the first Gulf War, the 2001 terrorist attacks, and the COVID-19 outbreak. Conversely, for the Asian and global financial crises, the volatility in gold spot and futures prices show a high level of persistence. The results during the COVID-19 outbreak confirm investors' view of gold as a safe-haven asset during periods of great uncertainty.

**Keywords:** Gold prices, Volatility, Crises, COVID-19 outbreak.

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## **1. Introduction**

The global financial crisis that began in the United States triggered a great interest in the dynamics of the gold market. Indeed, gold has become a key element in investment diversification because it is considered a safe-haven asset that holds its value even when stock markets produce negative returns (Baur and Lucey, 2010; Coudert et al., 2011; Ciner et al., 2013). As a result, gold has attracted more investors, as well as central banks from 2007, leading to an increase in gold demand (Apergis and Eleftheriou, 2016). During the periods of high uncertainty and collapse in equity markets, gold is frequently considered a safe haven for investors due to its weak relationship with other asset classes. This special characteristic implies a distinctive volatility behavior where increases in gold prices may reflect past or future instability, indicating a greater volatility for gold prices (Baur, 2012; and Chiarella et al., 2016).

On the other hand, economic and political factors have led to several financial crises in recent decades, causing volatility spikes in the financial markets (Phillips and Yu, 2010). Hence, gold markets have faced significant price fluctuations and therefore greater volatility, leading to investors becoming interested in studying and understanding this pattern. This paper aims to reexamine the volatility pattern of the gold spot and futures market, as an element in the financial markets, during major international crises, particularly the ongoing COVID-19 crisis, to re-evaluate the safe-haven status of this market by employing two GARCH modelling frameworks. An awareness of the need to understand the dynamics of volatility in the financial markets has led to more empirical studies focused on modelling the volatility pattern in the gold market (Lucey and Tully, 2006; and Demidova-Menzel, 2007). Despite its importance, there is a lack of research in the literature that studies gold prices and volatility in the spot and futures market. Canarella and Pollard (2008) employed an asymmetric power autoregressive conditional heteroscedasticity (APARCH) model to examine the volatility behavior for the London gold market. The results revealed the existence of asymmetrical volatility responses toward market shocks, indicating that positive shocks (good news) have more influence over gold price volatilities than negative shocks (bad news).

The study of Arouri et al. (2012) investigated long memory and structural breaks behavior in the returns and volatility of precious metals, specifically gold, platinum, silver, and palladium. They applied an autoregressive fractional integral moving average and fractionally integrated generalized autoregressive conditional heteroscedasticity (ARFIMA and FIGARCH, respectively) models to estimate the returns and volatility of the precious metals, ultimately confirming that a long memory was present in the volatility of different series.

The existence of structural break points due to various factors implies a high level of risk in the market (Orbaneja et al., 2018). In this study, we care about structural breaks when modelling gold volatility, so we consider multiple break points confirmed through the Bai–Perron structural break test for events that have affected the global financial markets.

This study is motivated by a lack of studies focused on reexamining the phenomenon of gold spot and futures volatility during previous major crises of various natures that have significantly affected the financial markets, such as the stock market crash of 1987, the first Gulf War in 1990, the Asian crisis, the US terrorist attacks of 2001, and the more recent global financial crisis. Moreover, the ongoing COVID-19 outbreak represents an interesting period to include in our sample because coronavirus lockdowns were initiated throughout the world, increasing the fear of economic loss and stimulating the demand for gold as a safe-haven asset.

To accomplish the objectives of this paper, we investigate the existence or otherwise of volatility persistence in gold spot and futures prices throughout the crisis periods by apply a GARCH approach, which is commonly used to investigate gold price volatility (Hammoudeh and Yuan, 2008; Qadan and Yagil, 2012; and Trück, 2020). In addition, we follow the work of Zavadaska et al. (2018) and by employing a T-GARCH model to check for the presence of asymmetric effects and to discriminate the effects of positive and negative news given the crisis's nature. The research contributes to the body of knowledge by investigating different crises while concentrating on the behavior of the gold spot and futures volatility series over the entire period. In addition, we consider the periods before, during, and after each crisis, although not for the current COVID-19 crisis, which is still ongoing.

We structure the paper as follows: Section 2 discusses the methodology, while Section 3 presents the data and the empirical results. Section 4 then supplies this study's conclusion.

## 2. Methodology

We followed the work of Zavadaska et al. (2018) by, as a first step, estimating gold prices using the univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model developed by Bollerslev (1986). Next, we employed the Threshold Generalized Autoregressive Conditional Heteroscedasticity (T-GARCH) model of Zakoian (1994). The specification of the GARCH (p,q) model of Bollerslev (1986) is presented as follows:

$$h_t = \gamma_0 + \beta' + \varepsilon_t \quad (1)$$

Where,  $\varepsilon_t | \Omega_t - iid N(0, h_t)$ , and

$$h_t = \omega + \sum_{i=1}^p \alpha_i h_{t-i} + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2 \quad (2)$$

This implies that the variance scaling component value mutually depends upon previous values for the shocks, and it is caught by the lagged squared residual terms and its previous values captured by lagged terms. The most famous form of the GARCH (p, q) model is the GARCH (1, 1), which is frequently employed in

research related to gold markets, such as in the work of Bentes (2015), Jain and Biswal (2016), and Yaya et al. (2016). According to Salisu and Fasanya (2013), among others, this form demonstrates superiority when compared to GARCH models of a higher order. Its variance equation is presented below for  $\alpha + \beta < 1$ :

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (3)$$

The GARCH model is considered symmetric, but in most commodities and stock series, the negative and positive shocks have a significant effect on volatility. Hence, to examine the leverage effects and asymmetries in the conditional variance, we adopt the T-GARCH model, which seems to perform better for gold market volatility (Shaique et al., 2016). The conditional variance equation specification of the T-GARCH (1, 1) goes as follows:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \theta \varepsilon_{t-1}^2 d_{t-1} + \beta h_{t-1} \quad (4)$$

where  $\alpha$  and  $\beta$  represent the the coefficients of the parameters ARCH and GARCH, subject to the conditions that  $\alpha + \beta < 1$  and  $d_t$  is equal to 1 if  $\varepsilon_t < 0$ , and 0 if not. This implies that positive shocks have an  $\alpha$  impact, while negative shocks have an  $\alpha + \theta$  impact.

### 3. Data

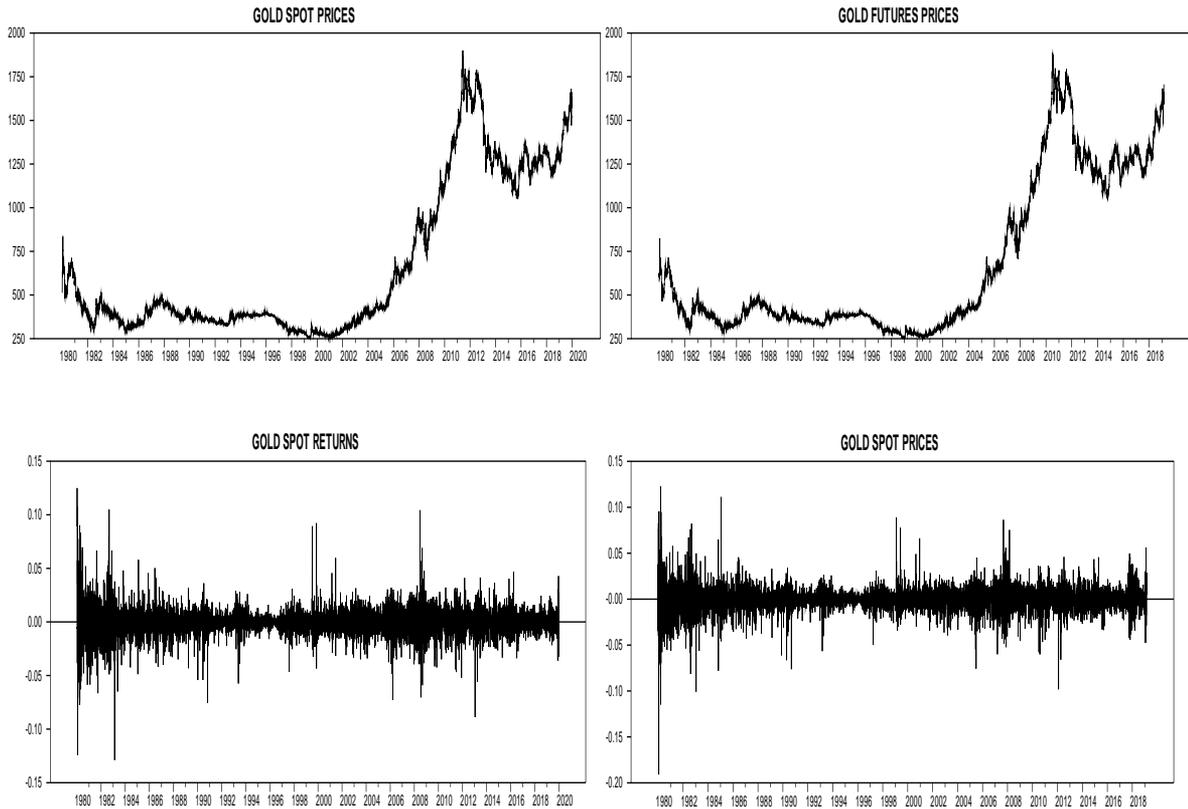
The data investigated in this paper comprise daily closing spot and futures prices for gold in US dollars per Troy ounce, with these being obtained from Bloomberg. Our data covers a 30-year period from January 2, 1980 to April 7, 2020, resulting in 10,214 daily observations. We used the Bai–Perron structural break test to identify the different break points. The plots for gold spot and futures prices are shown in Figure 1. An inspection of the price series' evolution over the whole period and the results of the Bai–Perron structural break test are given in Table 1. This reveals six break dates matching different significant historical events that affected gold prices.

**Table 1: Results of Bai–Perron Test**

Crisis	Whole Period	Break points		
		Pre-event	Event	Post-event
Stock market crash 1987	01/01/1980 29/12/1989	01/01/1980 02/09/1986	03/09/1986 31/12/1987	01/01/1988 29/12/1989
Gulf war	02/01/1990 12/05/1995	01/01/1990 27/09/1990	28/09/1990 01/04/1991	02/04/1991 12/05/1995
The Asian crisis	15/05/1995 04/07/2000	15/05/1995 30/06/1997	01/07/1997 13/01/2000	14/01/2000 04/07/2000
US terrorist attack	05/07/2000 13/03/2003	12/09/2000 16/09/2001	17/09/2001 08/02/2002	11/02/2002 13/03/2003
Global Financial crisis	14/03/2003 31/12/2015	01/01/2003 28/08/2007	29/08/2007 27/01/2012	31/01/2012 31/12/2015
COVID-19 Health crisis	-	01/01/2016 17/02/2020	18/02/2020 17/04/2020	-

The first relevant date is January 1987, which coincides with the establishment of the World Gold Council to stimulate and sustain the demand for gold. This major event in the gold market's history was followed by the Black Monday stock market crash of March 1987, leading to an increase in gold prices. The fluctuations between 1989 and 1991 are related to various economic or political events, such as the aggressive gold-management policies that were adopted by central banks, the first Gulf War, and the collapse of the Soviet Union, which resulted in reduced investor interest in gold and slow global economic growth. For the period from 1997 to 1998, the gold price reached its lowest level since 1979. The increase in prices may be partially explained by many central banks selling a great deal of gold to meet the currency standards required to join the European Union. In addition, it may relate to how the Asian crisis and the failure of several banks created considerable uncertainty in the markets. The break around 2001 can be attributed to the September 11 terrorist attacks. Next, the subprime financial crisis affected gold prices at the beginning of 2008, leading to a significant peak. Gold prices then decreased sharply and fluctuated, demonstrating how gold can be extremely volatile at the peak of a crisis. The next break is around October 2011, after gold prices increased from \$800 per ounce in 2009 to more than \$1,900 at the end of 2011, giving the impression of a bubble. Bauer and Lucey (2006) attribute the high demand for gold to three reasons: to reduce inflation risk, to hedge against economic uncertainty, and to reduce the effect of stock market booms. The spot gold price increased by 0.2% to \$1,674.20 an ounce, while gold futures increased by 0.4% to \$1,675.20. This high peak can be attributed to the above three reasons. The final peak relates to the ongoing COVID-19 major health crisis. This increase represents the biggest gain since October 2011 as investors fear that the COVID-19 pandemic may dramatically affect the global economy. In the same plots, the returns of the two gold prices show that gold futures demonstrate less volatility during periods of

significant historical events. The differences in the volatility persistence for each period will be discussed in the following section.



**Figure 1 : Plots of daily gold spot and futures prices.**

We present an analysis of descriptive statistics in Table 2 for the gold spot and futures prices, denoted  $P_t$ , and returns, denoted  $r_t$ , for the full sample. For the two series, the mean shows comparable behavior, although the spot prices seem to be marginally more volatile than the gold futures prices. The price series show positive skewness coefficients, indicating a right-skewed distribution, while the return series demonstrate a negative skewness coefficient with a left-skewed distribution. Furthermore, a leptokurtic distribution can be deduced from the excess kurtosis values for the prices and returns of the two series. For the Jarque–Bera statistics, we assume non-linear behavior and reject the hypothesis of normality.

Table 2: Descriptive statistics

Statistics	Gold spot market		Gold futures market	
	$P_t$	$r_t$	$P_t$	$r_t$
Mean	667.406	0.0001	672.004	0.0001
Std. Dev.	417.429	0.011	439.705	0.012
Skewness	1.001	-0.504	0.978	-0.377
Excess Kurtosis	2.495	12.792	2.438	15.296
Jarque-Bera	1854.13	711161.681	1763.22	99807.02
	(0.000) ***	(0.000) ***	(0.000) ***	(0.000) ***

Note: \*\*\* indicates the significance of Jarque-Berastatistic at 1% levels.

## 4. Empirical Results

### 4.1 GARCH (1, 1) results

Table 3 reports the results for the stock market crash period, and this reveals positive and statistically significant volatility coefficients for the two series over the whole period, as well as for other pre-crisis and in-crisis periods, with a long persistence. Conversely, during the post-crisis period, we observe greater volatility spikes in the gold futures series.

Table 3: Estimation results for the stock market crash

Models		Whole period		Pre-crisis		Crisis		Post-crisis	
		Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns
GARCH (1,1)	$\omega$	-0.0002 (0.274)	-0.0008 (0.1257)	-0.0002 (0.398)	-0.0012* (0.093)	0.0003 (0.559)	0.0014 (0.597)	-0.0003 (0.3499)	0.00008 (0.909)
	$\alpha$	0.1556*** (0.000)	0.0961*** (0.006)	0.1835*** (0.000)	0.0899** (0.0123)	0.16569 (0.598)	0.1049 (0.253)	0.080 (0.374)	0.1881 (0.118)
	$\beta$	0.915*** (0.000)	0.8694*** (0.000)	0.7708*** (0.000)	0.8874*** (0.000)	0.7046*** (0.0001)	0.8477*** (0.000)	0.8027** (0.0235)	0.4734* (0.058)
TGARCH (1,1)	$\omega$	2.4e-06** (0.036)	-0.0007 (0.191)	4.54e-06 (0.196)	-0.0009 (0.216)	1.6e-05** (0.001)	0.0016 (0.494)	4.2e-06* (0.062)	-0.0003 (0.678)
	$\alpha$	0.0918*** (0.002)	0.1102** (0.013)	0.1024** (0.038)	0.1127** (0.032)	0.1904*** (0.000)	0.1615 (0.531)	0.0948 (0.101)	0.045 (0.424)
	$\theta$	-0.026 (0.030)	-0.026 (0.418)	-0.0321 (0.227)	-0.0455 (0.251)	-0.2345 (0.000)	-0.0587 (0.781)	-0.0726 (0.174)	0.2032 (0.321)
	$\beta$	0.918*** (0.000)	0.8681*** (0.000)	0.9017*** (0.000)	0.8843*** (0.000)	0.7737*** (0.000)	0.8231*** (0.000)	0.879*** (0.000)	0.5459** (0.011)

Note: \*\*\*, \*\*, \* denotes statistical significance at 1%, 5% and 10% respectively.

As shown in Table 4, throughout the Gulf War period, the gold spot returns showed a high level of persistence for the pre-crisis and post-crisis periods. We also see high volatility spikes in both the gold spot and futures returns for the other crisis periods.

**Table 4: Estimation results for Gulf war**

Models		Whole period		Pre-crisis		Crisis		Post-crisis	
		Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns
GARCH (1,1)	$\omega$	-0.0001 (0.526)	-0.0005 (0.212)	0.0001 (0.8103)	-0.0002 (0.736)	0.00013 (0.370)	-0.0007 (0.439)	-0.0000 (0.8879)	-0.0005 (0.30)
	$\alpha$	0.2071*** (0.000)	0.3916* (0.051)	0.0148 (0.7309)	0.0381*** (0.007)	0.3059 (0.374)	0.2431 (0.133)	0.0420*** (0.000)	0.4339* (0.055)
	$\beta$	0.6871*** (0.000)	0.6319** (0.033)	0.9126*** (0.000)	0.6067** (0.0267)	0.6325* (0.0674)	0.6739** (0.047)	0.9501*** (0.000)	0.5325** (0.030)
TGARCH (1,1)	$\omega$	3.97e-05 (0.804)	-0.0001 (0.801)	7.02e-05 (0.930)	-0.0007 (0.217)	3.72e-05 (0.000)	-0.0012 (0.267)	1.02e-05 (0.951)	-8.35e-05 (0.879)
	$\alpha$	0.1633*** (0.000)	0.6275* (0.073)	0.0251*** (0.000)	-0.021*** (0.000)	0.2732 (0.129)	0.0667 (0.712)	0.045*** (0.000)	0.4689 (0.107)
	$\theta$	-0.0592 (0.000)	-0.4857 (0.029)	-0.0519 (0.000)	0.106 (0.411)	-0.0597 (0.606)	0.2943 (0.473)	-0.024 (0.008)	-0.4665 (0.080)
	$\beta$	0.6721*** (0.000)	0.098 (0.426)	0.9748*** (0.000)	0.721* (0.0632)	0.6267** (0.047)	0.6375** (0.038)	0.954*** (0.000)	0.5813** (0.047)

Note: \*\*\*, \*\*, \* denotes statistical significance at 99%, 95% and 90% respectively.

For the Asian crisis period, as shown in Table 5, the two returns series were found to have a high level of persistence except during the post-crisis period, where relevant volatility spikes can be distinguished. We can therefore reason that the gulf war period influenced volatility spikes more due to the high level of uncertainty when compared to the Asian crisis.

**Table 5: Estimation results for Asian Crisis**

Models	Whole period		Pre-crisis		Crisis		Post-crisis		
	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	
GARCH (1, 1)	$\omega$	-0.0005** (0.0396)	0.0004 (0.320)	-0.0001 (0.132)	0.0003 (0.704)	-0.0006* (0.070)	0.0008 (0.159)	-0.0006 (0.4338)	-0.0004 (0.535)
	$\alpha$	0.0367*** (0.000)	0.0508 (0.111)	0.0776*** (0.004)	0.0337* (0.0603)	0.0941 (0.224)	0.0817* (0.087)	0.2420** (0.001)	0.1965* (0.06)
	$\beta$	0.9621** (0.0405)	0.8684*** (0.000)	0.9073*** (0.000)	0.9575*** (0.002)	0.8476*** (0.000)	0.9144*** (0.0000)	0.7221*** (0.000)	0.7869** (0.0263)
TGARCH (1,1)	$\omega$	-0.0002** (0.034)	0.0006 (0.162)	-0.0001 (0.232)	0.0004 (0.666)	-0.0003 (0.274)	0.0008 (0.121)	-0.0001 (0.864)	0.0003 (0.634)
	$\alpha$	0.055*** (0.000)	0.0183*** (0.000)	0.0978*** (0.0000)	0.0148*** (0.000)	0.1232* (0.070)	0.0178*** (0.000)	0.1663** (0.000)	0.2103 (0.164)
	$\theta$	0.0135 (0.405)	-0.0512 (0.000)	-0.0354 (0.198)	-0.006 (0.138)	-0.1013 (0.053)	-0.0534 (0.001)	-0.4098 (0.002)	-0.2918 (0.047)
	$\beta$	0.944*** (0.000)	0.9816*** (0.000)	0.902*** (0.000)	0.9516*** (0.000)	0.8600** (0.000)	0.9821*** (0.000)	0.7663*** (0.008)	0.7839** (0.0112)

Note: \*\*\*, \*\*, \* denotes statistical significance at 99%, 95% and 90% respectively.

## 4.2 TGARCH (1, 1) results

The results of the T-GARCH model confirm the absence of a significant leverage effect or asymmetries for the periods of the stock market crash, the first Gulf War, the Asian crisis, and the global financial crisis. The results are also significant and demonstrate coherent results with the GARCH findings for the corresponding sub-periods.

As shown in Table 6, during the period of the September 11, 2001 terrorist attacks, the most relevant feature is how it had a direct effect on the gold market with persistency when compared to previous crisis periods, with high spikes, especially for gold spot prices, during the in crisis period.

Table 6 : Estimation results for US terrorist attack

Models		Whole period		Pre-crisis		Crisis		Post-crisis	
		Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns
GARCH (1, 1)	$\omega$	0.0002 (0.330)	-0.0006 (0.118)	0.000 (0.871)	-0.0005 (0.473)	0.0001 (0.819)	-0.0007 (0.416)	0.0004 (0.327)	-0.005 (0.303)
	$\alpha$	0.0551*** (0.0472)	0.0403 (0.455)	0.0511 (0.225)	-0.0886** (0.04)	0.1722 (0.145)	0.0731 (0.8543)	0.0504*** (0.005)	0.0482 (0.662)
	$\beta$	0.8547*** (0.000)	0.7706 (0.000)	0.7869*** (0.000)	0.866*** (0.000)	0.5430*** (0.003)	0.731* (0.053)	0.932*** (0.000)	0.7903** (0.014)
TGARCH (1,1)	$\omega$	0.0004 (0.107)	-0.0004 (0.341)	0.0005 (0.382)	-0.05*** (0.000)	0.0003 (0.591)	-0.0012 (0.285)	0.0005 (0.222)	-0.0001 (0.828)
	$\alpha$	0.1049* (0.062)	0.1425 (0.183)	0.1021*** (0.004)	-0.085*** (0.000)	0.3086 (0.151)	-0.134*** (0.006)	0.0772*** (0.000)	0.815** (0.034)
	$\theta$	-0.109 (0.064)	-0.1669 (0.074)	0.0284 (0.909)	-0.0863 (0.000)	-0.2744 (0.107)	0.1681*** (0.003)	-0.0489 (0.149)	-0.2549 (0.000)
	$\beta$	0.8927*** (0.000)	0.8141*** (0.000)	0.7534** (0.032)	0.8627* (0.063)	0.5545** (0.045)	0.781*** (0.008)	0.9227*** (0.000)	0.8151*** (0.000)

Note: \*\*\*, \*\*, \* denotes statistical significance at 99%, 95% and 90% respectively.

However, during the 2001 US crisis, the parameter  $\theta$  is positive and statistically significant for the futures returns series during the crisis period. The T-GARCH model also reveals the presence of a leverage effect. We therefore confirm the pattern that indicates that bad news may have a more significant effect on volatility than good news. Moreover, for the COVID-19 health crisis, the asymmetry parameter  $\theta$  is largely positive and statistically significant for the futures returns series during the crisis period, which agrees with the findings of Shaique et al. (2016).

As shown in Table 7 for the periods of the global financial crisis and the gold price bubble of 2011, the results can be considered positive and significant for spot and futures returns. However, during the pre-crisis period, the spot returns demonstrated greater volatility spikes than the futures returns. This implies that in quiet times, the futures returns are less volatile than spot returns.

**Table 7 : Estimation results for the Global Financial crisis**

Models		Whole period		Pre-crisis		Crisis		Post-crisis	
		Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns
GARCH (1, 1)	$\omega$	0.0003** (0.067)	-0.0001 (0.633)	0.0004* (0.093)	0.0516 (0.150)	0.001*** (0.001)	-0.0003 (0.431)	-0.0004 (0.146)	0.0002 (0.5272)
	$\alpha$	0.0445** (0.000)	0.070*** (0.003)	0.049*** (0.000)	0.0257 (0.368)	0.064*** (0.000)	0.0054 (0.5996)	0.0562 (0.531)	0.0537*** (0.008)
	$\beta$	0.945*** (0.000)	0.9251*** (0.000)	0.905*** (0.000)	0.965*** (0.000)	0.925*** (0.000)	0.911*** (0.000)	0.902*** (0.000)	0.9408*** (0.000)
TGARCH (1, 1)	$\omega$	0.0003*** (0.042)	-7.3e-05 (0.729)	0.0005** (0.067)	-2.72e-06 (0.995)	0.0011*** (0.001)	-0.0001 (0.758)	-0.0005** (0.068)	0.0002 (0.490)
	$\alpha$	0.0499*** (0.000)	0.0616* (0.003)	0.035*** (0.000)	0.0558** (0.049)	0.0715*** (0.000)	0.9071*** (0.000)	0.0051 (0.988)	0.0512*** (0.000)
	$\theta$	-0.0101 (0.480)	-0.0352 (0.049)	-0.0166 (0.032)	-0.0591 (0.100)	-0.0189 (0.076)	-0.9111 (0.000)	0.1507 (0.541)	-0.0272 (0.060)
	$\beta$	0.9454*** (0.000)	0.9383*** (0.000)	0.964*** (0.000)	0.9441*** (0.000)	0.9284*** (0.000)	0.9086** (0.041)	0.7758** (0.035)	0.9446*** (0.000)

Note: \*\*\*, \*\*, \* denotes statistical significance at 99%, 95% and 90% respectively.

The results allow us to state that in periods of uncertainty, the attractiveness of gold may increase because it offers investors a better sense of security during periods of financial market instability. In addition, as a safe-haven asset, the value of gold tends to increase in response to bad news or negative market shocks. The current COVID-19 pandemic is once again confirming this observation.

In the case of the ongoing COVID-19 pandemic, as shown in Table 8, we examine only the pre-crisis and in-crisis periods because it was still in progress at the time of writing. The results show that for both series, a high persistence exists during the pre-crisis period, but there are high volatility spikes during the crisis, implying that uncertainty currently persists in the market.

**Table 8 : Estimation results for COVID-19 outbreak**

Models		Whole period		Pre-crisis		Crisis	
		Spot returns	Futures returns	Spot returns	Futures returns	Spot returns	Futures returns
GARCH (1, 1)	$\omega$	0.0002 (0.244)	0.001 (0.867)	-0.0002 (0.742)	0.0003 (0.774)	0.0053 (0.765)	0.0009 (0.823)
	$\alpha$	0.0435*** (0.000)	0.0441*** (0.0000)	0.0495*** (0.000)	0.0309*** (0.000)	0.2252*** (0.007)	0.2365** (0.046)
	$\beta$	0.9478*** (0.000)	0.9576*** (0.000)	0.952*** (0.000)	0.9601*** (0.000)	0.7092*** (0.000)	0.7623*** (0.000)
TGARCH (1, 1)	$\omega$	0.0003 (0.156)	2.25e-05 (0.817)	-2.23E-05 (0.792)	2.78e-05 (0.790)	0.0007 (0.261)	0.0008*** (0.006)
	$\alpha$	0.0574*** (0.000)	0.0427* (0.074)	0.0414*** (0.000)	0.0335*** (0.000)	0.262*** (0.000)	0.2665*** (0.000)
	$\theta$	-0.0269 (0.118)	-0.0013 (0.770)	0.0049* (0.051)	0.0051* (0.084)	-0.0435 (0.636)	0.9956*** (0.000)
	$\beta$	0.9425*** (0.000)	0.9572*** (0.000)	0.9585*** (0.000)	0.9634*** (0.000)	0.7379*** (0.000)	0.7299*** (0.000)

Note: \*\*\*, \*\*, \* denotes statistical significance at 99%, 95% and 90% respectively.

## 5. Conclusion

In light of the current COVID-19 pandemic triggering an increase in gold prices, this paper revisits the volatility in gold prices for different crises. Based on progressive estimations over 30 years, we employed two GARCH-based models. The results demonstrate that the gold spot and futures returns series display higher volatility spikes during the stock crash, the first Gulf War, the 2001 terrorist attacks, and the COVID-19 outbreak. However, for the Asian and the global financial crises, the gold spot and futures volatility is characterized by a high level of persistence. Therefore, the nature of crisis is relevant to its influence on the behavior of gold spot and futures prices. The results also again indicate investors' perception of gold as a safe-haven asset during periods of elevated uncertainty.

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