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ORIGINAL ARTICLE

Re-examining the leverage effect and gold's safe haven properties with the utilization of the implied volatility of gold: a non-parametric quantile regression approach

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Abstract
Gold as a tradable financial asset has acquired the reputation of a safe haven from market turbulence. The objective of this study is to investigate empirically the relationship between gold prices and implied volatility in the futures markets of gold, re-examine the leverage hypothesis and attempt to make inferences about gold's safe haven properties. In doing so, it utilizes the recently developed econometric tool of non-parametric quantile regressions. This is the first work to apply the flexible non-parametric quantile regressions on the exchange-traded funds (ETFs) of gold. The data used are daily returns of options of gold shares and implied volatility changes from June of 2008 to December of 2018. The empirical findings indicate that, for the total sample period as well as for almost all of the five sub-periods examined, changes in the implied volatility of gold are insensitive, and not statistically significant, to changes in the price returns of gold. The leverage hypothesis holds for a wide range in the third sub-period. Accordingly, investors in other ETFs (currency or oil) may choose to use gold as shelter during (extreme) economic downturns.

Keywords Gold prices · Implied volatility · Safe haven · Non-parametric quantiles

JEL Classification G15 · C12 · C14

Introduction

Amid the spread of Covid-19 around the globe, stock and bond markets worldwide have experienced significant losses and unprecedented volatility (Brodeur et al. 2020). As a consequence, due to the increasing uncertainty of financial markets and

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the instability of the economic environment, portfolio diversification has become more and more important for investors (O'Connor et al. 2015).

Gold prices often can act as an indicator of the health of the economy (Beckmann et al. 2015). A rise in the price of gold may be a signal that the economy is not performing well (Beckmann et al. 2015; Baur and McDermott 2016). Hence, in times of an economic/financial crisis or high rates of inflation, many investors turn to gold to "seek for shelter" (Joy 2011; Reboredo 2013b). On the other hand, in periods of economic stability and/or growth, investors are more likely to turn to more speculative investments, such as stocks, bonds and real estate. During these times, the price of gold usually falls (Hood and Malik 2013).

Investors seek out to diversify their portfolio and include investments that will act as a safe haven during times of crisis. The latter is extremely useful for portfolio managers who want to maintain a diversified portfolio and who want investment protection against downside risk. Gold, along with other precious metals, is known to be frequently uncorrelated with other assets (Hood and Malik 2013; Bredin et al. 2017). In the relevant literature, gold's safe haven and/or hedge status has been examined with regards to other assets (stocks, oil and currencies). Bredin et al. (2017) showed that precious metals mitigate the downside risk when combined with equities. Their empirical findings indicate that gold, silver and platinum contribute to downside risk reduction in the short-run. Furthermore, their results indicate that, in the short-run, risk reduction opportunities from gold are larger than previously found by the literature. Lastly, the authors report marginal risk reduction contributions from precious metals variance (variability) at all intervals studied. In their study, risk is measured using both volatility and the 99% value-at-risk for the different intervals. In a previous work, Hood and Malik (2013) evaluated the role of gold, silver and platinum relative to the Volatility Index (VIX) as a hedge and safe haven. The empirical findings indicate that gold serves as a hedge and a weak safe haven for different volatility values in the US stock market. Beckmann et al. (2015) considers investors who hold a portfolio of stocks and gold and analyze trading strategy described by changes of the portfolio composition depending on the two scenarios, hedge and safe haven. Overall, their findings reveal that the gold market is of special importance for policymakers and investors, since it provides a useful ingredient for portfolio diversification due to its hedge and/or safe haven status[1]. Reboredo (2013a) considers portfolio risk managers using gold to preserve or to stabilize the purchasing power of oil exporters. Results indicate that gold can act as an effective safe haven against extreme oil price volatility.

There is a large number of studies that have examined the usefulness of gold as a hedge and/or a safe haven against inflation (Chua and Woodward 1982; Jaffe 1989; McCown and Zimmerman 2006; Blose 2010; Tully and Lucey 2007; Worthington and Pahlavani 2007; Iqbal 2017). Other studies have examined if gold is a safe haven

[1] To be in accord with previous studies, in the Online Appendix section, we provide an empirical implementation of gold's safe haven status against another investment, namely the returns of the exchange-traded fund of USA oil prices (USO). Results indicate that gold is a strong safe haven in periods of extreme market declines in the USO prices.

with respect to stock market movements (Beckmann et al. 2015; Baur and Lucey 2010; Hood and Malik 2013). Some studies have considered the role of gold as hedge or safe haven investment against currency depreciation (Reboredo 2013b; Joy 2011; Reboredo and Rivera-Castro 2014) as well as oil price changes (Ciner et al. 2013; Reboredo 2013a). Hood and Malik (2013) evaluate the role of gold relative to the volatility Index (VIX) as a hedge and/or as a safe haven. The majority (if not all of them) of the aforementioned works finds that gold serves as a hedge as well as a safe haven against other investments as well as against inflation and currency depreciation. Lastly, Baur (2012a) and Immanuvel and Lazar (2020) test for the leverage hypothesis. The latter study (Immanuvel and Lazar 2020) tests if the leverage effect exists in world gold markets. According to the results, the leverage effect suggests that positive information causes more volatility in the London Bullion Market Association prices than negative information.

Empirical research on gold's properties has been undertaken with a variety of statistical tools and econometric techniques. The simple ordinary least squares (OLS) with asymmetric GARCH process for the OLS errors (Baur and Lucey 2010), the smooth transition approach (Beckmann et al. 2015), the threshold tail and average dependence (Reboredo and Rivera-Castro 2014), the Granger causality in a Vector Error Correction Model (Anand and Madhogaria 2012), the multivariate GARCH model of dynamic conditional correlations (Joy 2011; Ciner et al. 2013), the EGARCH model (Immanuvel and Lazar 2020) as well as the statistical tool of parametric copulas (Reboredo 2013b), are among the tools utilized to assess gold's hedge/safe haven status as well the leverage effect.

In the light of the preceding, the present work re-examines the leverage hypothesis in the case of gold and attempts to make inferences about gold's safe haven properties with the utilization of the implied volatility of gold shares options. In doing so, it employs the recently proposed econometric tool of the non-parametric quantile regressions (NPQR) (Belloni et al. 2019). To the best of our knowledge, this is the first work that utilizes the implied volatility of gold prices along with the NPQR approach in order to assess gold's safe haven status[2]. The NPQR has all the advantages of the parametric linear quantile regression (LQR) but it is far less vulnerable to the problem of misspecification. Accordingly, the objective of the present work is three fold. First of all, it estimates the co-movement between prices of gold shares options and implied volatility in the futures markets of gold. Second, it utilizes the newly developed econometric tool of the non-parametric quantile regression. As Fousekis (2019) points out, the NPQR approach allows the data to speak for itself. Third, based on the empirical findings, this study makes inferences about gold's leverage effect and safe haven properties in the global financial system. The latter is extremely useful for portfolio managers who want to maintain a diversified portfolio and who want investment protection against downside risk. In addition, it is useful for policy makers, given the association between gold and macroeconomic

[2] The most recent work that has employed the NPQR approach by Fousekis (2019) to assess the relationship between the daily prices of the US Oil Fund and the Chicago Board Options Exchange (CBOE) crude oil price implied volatility index.

variables, such as interest rates and exchange rates (Reboredo 2013a; Soytas et al. 2009).

In financial economics, safe haven status has always been examined with respect to something, for example stock markets, inflation, precious metals and others. The goal of the present study is to utilize the econometric tool of NPQR to approach the relation between returns and volatility from a different statistical point of view and attempt to make inferences about the leverage effect (Black 1976) and its association to gold's safe haven properties.

In what follows, the next section presents the implied volatility of gold, the third section, the methodology, and the fourth section offers the description of data. The fifth section presents the Kendall's *tau* and the breakpoint test. The sixth section offers the empirical results and discussion. The seventh section offers conclusions and suggestions for future research.

Implied volatility of gold

The Gold Volatility Index (Gold VIX- GVZ) measures the market's expectation of 30-day volatility of gold prices. The GVZ is derived by applying the VIX methodology to options on SPDR Gold Shares (GLD). GLD is an exchange-traded fund (ETF) that represents fractional, undivided interest in the SPDR Gold Trust, which primarily holds gold bullion. Accordingly, the performance of GLD is intended to reflect the spot price of gold, less fund expenses.

The VIX methodology was developed by the Chicago board options exchange (CBOE) and it measures the market's expectation of short-run (30 days) forward looking volatility of an exchange traded fund[3]. VIX provides a measure of market's risk as well as the investors' sentiment. Applying technical analysis on the volatility can improve confidence in identifying inflection points in the spot value of gold. Accordingly, future volatility is one of the most significant parameters in the option pricing model. Implied volatility is often referred as the investors' fear gauge. Accordingly, volatility levels are largely fear driven: higher levels of fear imply higher levels of volatility. Furthermore, implied volatility is forward looking and it is implied by the market price of the underlying stock.

In the relevant literature of financial economics, it is well documented the negative correlation between stock market prices and the associated volatility (Badshah 2013; Fousekis and Grigoriadis 2018). However, there is disagreement among researchers regarding the findings of stock market indices and volatility indices moving in opposite directions. The leading explanations are the leverage hypothesis (Black 1976), the volatility feedback hypothesis (Wu 2001) and the representativeness and affect heuristics hypothesis (Boussaidi 2013; Badshah 2013).

[3] Cboe also calculates the Crude Oil Volatility Index (OVX) based on United States Oil Fund (USO) option prices as well as the Euro Currency Volatility Index (EVZ) based on options on the Currency Shares Euro Trust (FXE).

The leverage hypothesis attributes the negative relationship between stock market returns and volatility returns to the financial leverage of firms. The leverage hypothesis suggests that changes in stock returns lead changes in volatility. The volatility feedback suggests that an increase in the expected volatility causes current stock prices to fall, for the investors to be compensated for the additional risk. Finally, the representativeness and affect heuristics hypothesis is a psychological bias which means that, under uncertainty, investors are prone to believe that a history of a high performance of a specific firm is representative of a general performance (Boussaidi 2013). In addition, investors believe that the firm will continue to generate earnings in the future. In general, under the representativeness heuristics hypothesis investors tend to expect higher returns with lower risk from stocks of financially stable firms or they link, without any high-level of reasoning, benefits with whatever they perceive as positive and risks with something negative (Fousekis and Grigoriadis 2018).

The aforementioned hypotheses are questioned by a number of researchers (Badshah 2013; Thaler 2005) who put forward the so-called behavioral explanations. As Low (2004) and Fousekis (2019) point out, the behavioral explanations are specifically developed for implied volatility and they attribute the relationship between prices and volatility to fear, exuberance, and loss aversion.

Methodology

Quantile regressions (QR) capture the marginal effects of an explanatory variable on the dependent variable in a specific quantile. More specifically, QR is the principal method for analyzing the impact of covariates on outcomes. This impact is characterized by the quantile function of the conditional distribution of the outcome given covariates and its functionals (Belloni et al. 2019; Arias et al. 2002). Therefore, QR make it possible to analyze the levels of the impact of the independent variable on the explained variable, at different quantile levels.

Let us assume that Y is the dependent variable of interest (outcome) and X is a vector of independent variables (covariates):

$$F_{Y|X}(\tau|x) = h(\tau, w) + \omega'\delta(\tau). \quad (1)$$

In the quantile regression approach, the τ sample quantile can be obtained by solving the following minimization problem:

$$F_{Y|X}(\tau|x) \approx G(x)'\beta(\tau), \quad (2)$$

where $\beta(\tau) = (\alpha(\tau)', \delta(\tau)')$ and $G(x) = (G(w)', u')'$ are the series that approximate the non-parametric quantile regression. The first average partial derivatives (APDs) of $F_{Y|X}(\tau|x)$ with respect to w are the main linear functionals of interest for the present study. The APDs are derived as follows:

$$\mathrm{APD} = \int \frac{\partial h(\tau, w)}{\partial w} \mathrm{d}\mu \approx \int \frac{\partial h(\tau, w)}{\partial 10w} \mathrm{d}\mu, \tag{3}$$

where μ is a given measure.

Given a sample of observations $(Y_i,\ X_i)$ with $i = 1, 2, \ldots N$ as well as the distribution function of Y, the estimated value of the coefficient vector $\beta(\tau)$ can be obtained by solving:

$$\hat{\beta}(\tau) = \min_{\beta \in R^k} \sum_{i=1}^{N} \rho_\tau (Y_i - Z(X_i)')\, \beta, \tag{4}$$

where ρ_τ is the tilted absolute value function and $k = \dim(\beta(\tau))$.

In the parametric quantile regression approach, the coefficient vector $\beta(\tau)$ has a limiting distribution given by (Cai and Xu 2008)

$$\sqrt{N}(\hat{\beta}(\tau) - \beta(\tau)) \xrightarrow{d} N(0,\ \tau(1-\tau)\, D^{-1}\Omega_x D^{-1}), \tag{5}$$

where

$$D = E(f_y(X\beta)XX') \text{ and } \Omega_x = E(X'X), \tag{6}$$

with f_y being the probability distribution function.

On the other hand, inference in non-parametric quantile regressions presents many difficulties due to the non-reduction of the approximation error as the sample size increases. As a consequence, the stochastic process $\sqrt{N}(\hat{\beta}(\tau) - \beta(\tau))$ does not, in general, have a limiting distribution even after an appropriate normalization. Belloni et al. (2019) address the problem using the notion of coupling. The coupling is a construction of two processes on the same probability space that are uniformly close to each other with high probability. Usually, one of the processes is the process of interest and the other one is a process whose distribution is known up to a relatively small number of parameters that can be consistently estimated from the data. Being able to construct an appropriate coupling means that the distribution of the process of interest can be approximated by simulating the distribution of the coupling process from the data.

Belloni et al. (2019) develop two couplings, the pivotal and the Gaussian. More specifically, for each sample size N, the authors construct a pivotal process and a Gaussian process on the same probability space as the data that are uniformly close to the process $\sqrt{N}(\hat{\beta}(\tau) - \beta(\tau))$ with high probability. In addition, Belloni et al. (2019) have developed four re-sampling methods (pivotal, the gradient bootstrap, the Gaussian bootstrap, and the weighted bootstrap) to approximately simulate the distribution of the pivotal (first two methods) and the Gaussian (last two methods) processes. These results provide an inference theory for the coefficient vector $\beta(\tau)$ and contribute in developing a feasible inference theory for linear functionals of the conditional quantile functions, namely the partial derivatives of $F_{Y|X}(\tau|x)$.

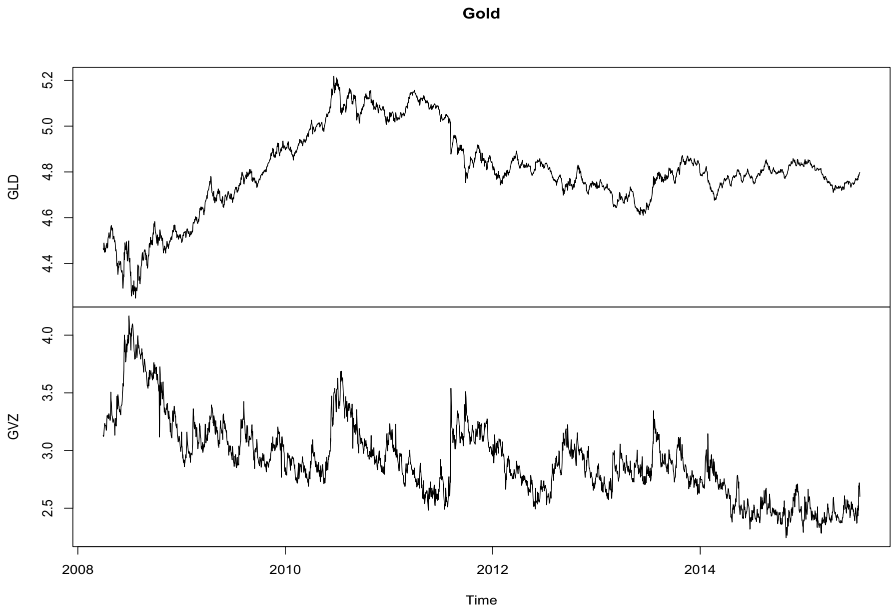

Fig. 1 Natural logarithms of GLD and GVZ (vertical axis) between June 3rd, 2008 and December 31st, 2018. Time is measured along the horizontal axis

Data description, Kendall's *tau* and breakpoint test

Data description

The data for the empirical analysis are the price per gold share of GLD options and the associated, with the GLD, implied volatility index (GVZ). Data cover the period from June 3rd, 2008 to December 31st, 2018 (2664 daily observations)[4].

Figure 1 presents the evolution of the natural logarithms of the GLD and the GVZ for the time between June 3rd, 2008 to December 31st, 2018. It appears that the two time series generally move in opposite directions but there are some periods where co-movement is positive. Furthermore, the GVZ returns appear to be more volatile relative to the GLD ones.

Table 1 presents the descriptive statistics and tests on the distributions of the percentage changes (rates of change) for GLD and GVZ. The rates of change (or returns) in GLD are defined as $\text{dln(GLD)} = \ln(\text{GLD})_t - \ln(\text{GLD})_{t-1}$, and the rates of change in GVZ is defined as $\text{dln(GVZ)} = \ln(\text{GVZ})_t - \ln(\text{GVZ})_{t-1}$.

The empirical results for the statistical significance of skewness, kurtosis and normality have been obtained with the use of the tests by D'Agostino (1970), Anscombe

[4] SPDR Gold Shares began trading on the New York Stock Exchange in November 2004. June of 2008 is the date where CBOE started calculating and distributing the Gold VIX. Data have been obtained from Quandl (www.quandl.com) and from Yahoo Finance (www.finance.yahoo.com).

Table 1 Descriptive statistics for dln(GLD) and dln(GVZ)

Statistics	dln(GLD)	dln(GVZ)
Min	− 0.0919	−0.4459
Max	0.1069	0.4807
Mean	0.0001	− 0.0002
Median	0.0003	− 0.0048
St.dev	0.0115	0.0556
Skewness	− 0.1738	0.8710
Kurtosis	7.8799	8.8592
Tests	p values	p values
Skewness	< 0.01	< 0.01
Kurtosis	< 0.01	< 0.01
Normality	< 0.01	< 0.01

Table 2 Values of the Kendall's *tau* test

Variables	0	+ 1	+ 2	+ 3
GLD leads	− 0.0280 (0.0290)	0.0400 (0.0020)	0.0010 (0.9780)	0.0010 (0.9280)
GVZ leads	− 0.0280 (0.0290)	0.0130 (0.2970)	0.0090 (0.4670)	0.0070 (0.6060)

p values in parentheses

and Glynn (1983) and Shapiro and Wilk (1965), respectively. Both GLD and GVZ returns exhibit a positive and statistically significant kurtosis, pointing to leptokurtic distributions. The distribution of GLD returns exhibits negative skewness whereas that of GVZ exhibits positive skewness. For both time series (returns of GLD and GVZ) the null of normality is strongly rejected at any reasonable level of significance.

Kendall's tau (τ_N)

To measure and evaluate the type of co-movement between GLD and GVZ (contemporaneous co-movement or lag–lead relationship), the present study employs Kendall's tau. Kendall's tau provides information on the co-movement across the entire joint distribution function, both at the center and at the tails of it. It is calculated from the number of concordant and discordant pairs of observations in the following way:

$$\tau_N = \frac{P_N - Q_N}{\binom{N}{2}} = \frac{4P_N}{N(N-1)} - 1, \tag{7}$$

Table 3 Results of the breakpoint test on the natural logarithms of GVZ

Breakpoints	BIC criterion	RSS criterion	Break dates	Sub-periods
1	524.1	187.7	30-Dec-2009	1
2	− 665.4	119.4	9-Feb-2012	2
3	− 939.0	107.1	9-Jan-2014	3
4	− 996.0	104.2	14-Feb-2017	4
5	− 978.7	104.3		5

where N represents the number of observations, and P_N and Q_N denote the number of concordant and discordant pairs, respectively.[5]

Table 2 shows the values of τ_N. Column 2, presents the values of Kendall's tau for the contemporaneous co-movement between GLD and GVZ. The contemporaneous co-movement between GLD and GVZ is statistically significant. Columns 3, 4 and 5 present the values of Kendall's tau for the co-movement between GLD and GVZ at lag lengths equal to + 1, + 2, + 3, respectively, when GLD leads and when GVZ leads. The lag–lead co-movement is statistically significant in only one case where the lagged by + 1 changes in GLD appear to lead changes in GVZ. This empirical finding is in favor of the leverage hypothesis. According to this fundamental hypothesis, changes in returns lead changes in volatility.

Breakpoint test

Earlier empirical works (Giot 2005; Fousekis 2019) have already suggested that the strength and the pattern of the relationship between stock market prices and volatility indices might depend on volatility levels. The present study tests for this possibility in the GLD–GVZ relationship, by applying the multiple breakpoint test to the natural logarithms of the volatility index (GVZ). To decide on the number of breaks the present work minimizes the Bayesian information criterion (BIC) and the residual sum of squares criterion (RSS). Table 3 presents the results. Both the BIC and the RSS criteria detect four break points which indicate five sub-periods within the whole sample[6]. Figure 2 presents graphically the values of the BIC and the RSS criteria.

[5] Two pairs (x_j, y_j), (x_k, y_k), $j, k = 1, 2, \ldots, N$, are defined as concordant (discordant) when $(x_j - x_k)$,$(y_j - y_k) > 0\ (< 0)$.

[6] Previous studies (Fousekis 2019) employ the Bai and Perron (2003) test.

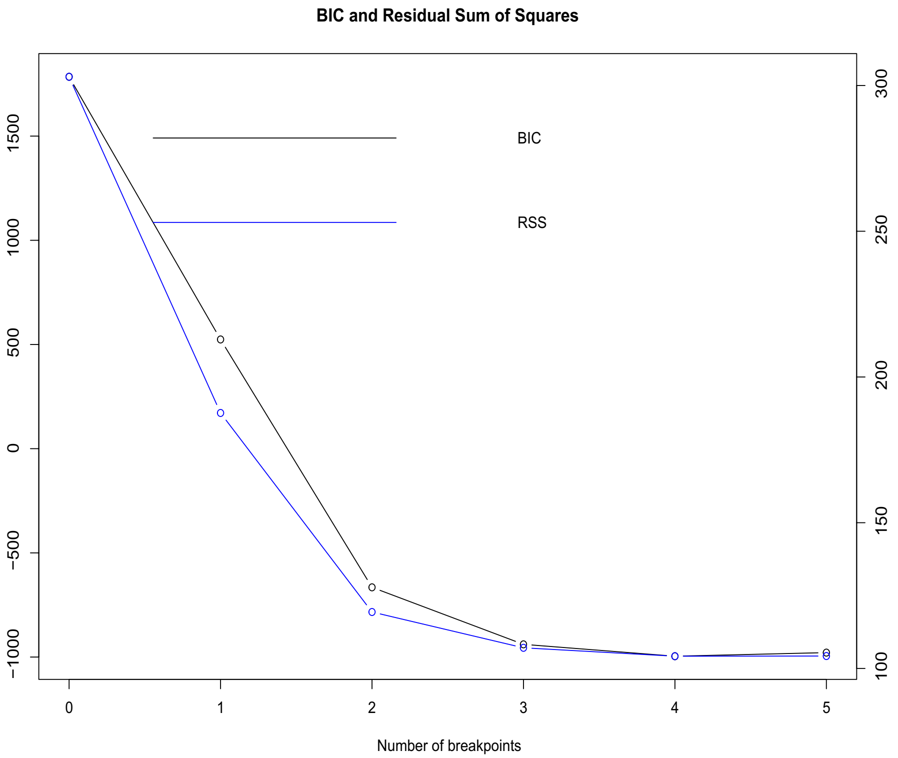

Fig. 2 BIC and RSS criteria

Empirical results

The present section employs the non-parametric quantile regressions methodology, for the total period as well as for each of the five sub-periods, to estimate the co-movement between gold prices and gold's implied volatility. The estimations are carried out using the R package quantreg.nonpar (Lipsitz et al. 2016).

Table 4 presents the estimated values of the average partial derivatives of the GVZ changes with respect to the GLD returns at 19 quantiles along with their respective standard errors for the whole sample (3 June 2008 to 31 December 2018). Figure 3 presents diagrammatically the estimated values of the APDs along with their 95intervals. Each one of the following figures in the present study includes two horizontal lines: a dotted one, at zero level and a dashed one, at a level equal to the minimum value of the estimated APDs. The horizontal line at zero is within the 95confidence interval at every given quantile, suggesting that all estimated APDs

Table 4 The estimated values of the APDs for the whole sample

Quantile	Point estimate	Standard error	(95% Confidence	Interval)
0.05	− 0.5800	0.2289	− 1.1920	0.0317
0.1	− 0.3047	0.2019	− 0.8443	0.2349
0.15	− 0.4304	0.1740	− 0.8956	0.0347
0.2	− 0.2187	0.1572	− 0.6389	0.2016
0.25	− 0.2069	0.1514	− 0.6116	0.1977
0.3	− 0.1406	0.1551	− 0.5550	0.2738
0.35	− 0.0809	0.1523	− 0.4879	0.3261
0.4	− 0.0293	0.1521	− 0.4358	0.3771
0.45	− 0.0914	0.1505	− 0.4935	0.3107
0.5	− 0.2240	0.1457	− 0.6135	0.1654
0.55	− 0.2120	0.1461	− 0.6025	0.1785
0.6	− 0.1126	0.1472	− 0.5061	0.2809
0.65	− 0.1318	0.1489	− 0.5297	0.2661
0.7	− 0.0494	0.1542	− 0.4614	0.3626
0.75	0.0616	0.1574	− 0.3592	0.4824
0.8	− 0.0693	0.2013	− 0.6072	0.4687
0.85	− 0.0175	0.2059	− 0.5678	0.5320
0.9	0.3038	0.2489	− 0.3615	0.9690
0.95	0.6629	0.3684	− 0.3217	1.6480

Standard errors were computed using pivotal bootstrapping with 5000 replications

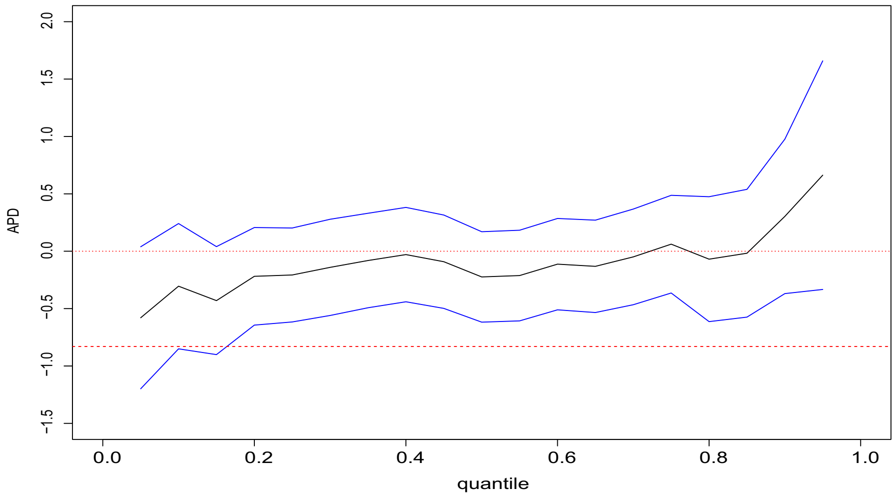

Fig. 3 The estimated values of the average partial derivatives (APD) for the whole sample (3 June 2008 to 31 December 2018). APD are measured along the vertical axis and quantiles are measured along the horizontal axis

Table 5 The estimated values of the APDs for the first sub-period

Quantile	Point estimate	Standard error	(95% Confidence	Interval)
0.05	0.6497	0.7790	− 1.2760	2.5760
0.1	1.6700	0.7704	− 0.2351	3.5750
0.15	1.8080	0.7833	− 0.1285	3.7450
0.2	1.6630	0.7610	− 0.2188	3.5450
0.25	1.3590	0.5260	0.0579	2.6590
0.3	1.4230	0.5331	0.1047	2.7410
0.35	1.3760	0.5263	0.0749	2.6780
0.4	1.2580	0.4945	0.0355	2.4810
0.45	1.3910	0.5360	0.0653	2.7160
0.5	0.9810	0.6187	− 0.5489	2.5110
0.55	0.9252	0.4957	− 0.3004	2.1510
0.6	0.8943	0.4892	− 0.3153	2.1040
0.65	0.7680	0.4809	− 0.4212	1.9570
0.7	0.5499	0.4739	− 0.6219	1.7220
0.75	0.3675	0.4851	− 0.8320	1.5670
0.8	0.6464	0.4792	− 0.5385	1.8310
0.85	0.6152	0.4894	− 0.5950	1.8250
0.9	0.7127	0.5664	− 0.6879	2.1130
0.95	0.0051	0.8451	− 2.0850	2.0950

Standard errors were computed using pivotal bootstrapping with 5000 replications

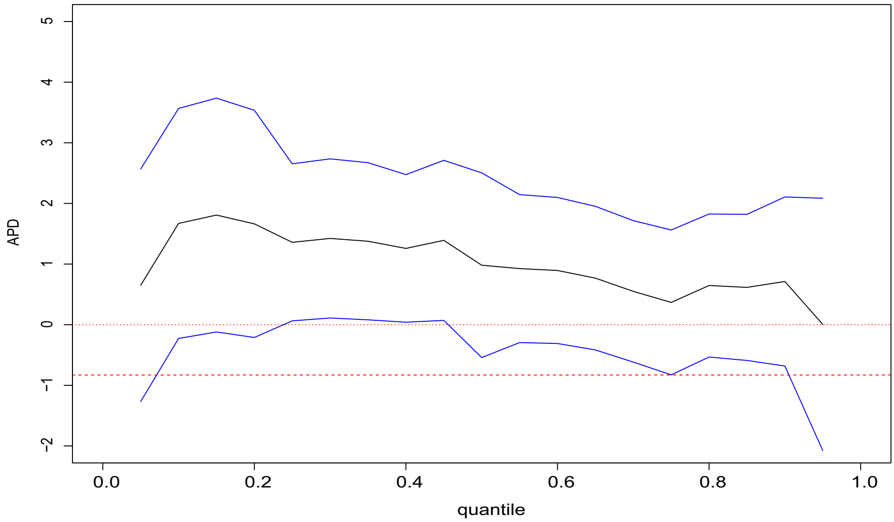

Fig. 4 The estimated values of the average partial derivatives (APD) for the first sub-period (3 June 2008 to 30 December 2009). APD are measured along the vertical axis and quantiles are measured along the horizontal axis

Table 6 The estimated values of the APDs for the third sub-period

Quantile	Point estimate	Standard error	(95% Confidence	Interval)
0.05	− 1.710	1.6070	− 6.8760	3.4550
0.1	− 2.0850	0.4784	− 3.6220	− 0.5472
0.15	− 2.1880	0.4080	− 3.4990	− 0.8765
0.2	− 1.9880	0.3868	− 3.2310	− 0.7445
0.25	− 1.9840	0.3928	− 3.2470	− 0.7219
0.3	− 1.9890	0.4118	− 3.3120	− 0.6649
0.35	− 1.7940	0.4265	−3.1650	−0.4230
0.4	− 1.9690	0.4236	− 3.3310	− 0.6075
0.45	− 1.9890	0.4136	− 3.3180	− 0.6596
0.5	− 2.0690	0.4401	− 3.4840	− 0.6542
0.55	− 1.8810	0.4589	− 3.3560	− 0.4058
0.6	− 1.7430	0.4496	− 3.1880	− 0.2974
0.65	− 1.6520	0.4353	− 3.0510	−0.2525
0.7	− 1.5610	0.4354	− 2.9600	− 0.1613
0.75	− 1.2690	0.4940	− 2.8560	0.3193
0.8	− 1.3820	0.4890	− 2.9540	0.1894
0.85	− 1.4150	0.5172	− 3.0780	0.2474
0.9	− 1.4550	0.5457	− 3.2090	0.2990
0.95	− 0.8742	0.8118	− 3.4840	1.7350

Standard errors were computed using pivotal bootstrapping with 5000 replications

are not statistically different than zero[7]. Hence, GVZ returns are insensitive to GLD changes at any given quantile, namely changes in GLD returns do not affect the level of gold's implied volatility (GVZ).

The first sub-period of the present study (3 June 2008 to 30 December 2009) coincides (almost) with the beginning of the most recent 2008 financial crisis. The 2008 financial crisis, also known as the global financial crisis, was a severe world-wide economic crisis and is considered to have been the most serious financial crisis since the Great Depression of the 1930s. During the 2008 financial crisis different classes of assets suffered significant losses. On the other hand, gold prices were not affected by the economic crisis. On the contrary, gold gained in value[8]. Hence, many investors sought in gold for shelter. The empirical findings of this study for the specific time period (Table 5, Fig. 4), seem to be in agreement with the aforementioned facts: the estimated values of the APDs are not statistically different than zero or they assume values very close to zero. The results are in agreement with the findings

[7] Apart from the fact that the 95% confidence interval include the value of zero, the absolute values of the point estimates at the lower tails (0.05 and 0.10) and at the upper tails (0.90 and 0.095) are very similar indicating symmetric reaction.

[8] Since the beginning of the financial crisis and until the end of the period examined here, the nominal gold price increased in value by 40%.

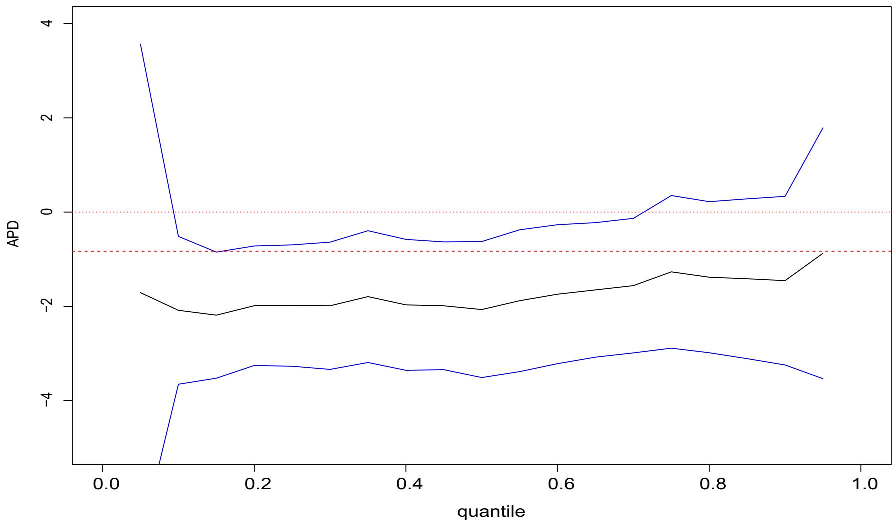

Fig. 5 The estimated values of the average partial derivatives (APD) for the third sub-period (10 February 2012 to 9 January 2014). APD are measured along the vertical axis and quantiles are measured along the horizontal axis

by Hood and Malik (2013) and by Beckmann et al. (2015). Hence, as McCown and Zimmerman (2006) point out in their analysis, gold shows the characteristics of a zero beta asset, bearing no market risk for the investors during economic downturns.

For the third sub-period (10 February 2012 to 9 January 2014), according to the empirical results (Table 6, Fig. 5), GVZ returns are sensitive to GLD changes for a quite wide range of quantile levels. The latter indicates that changes in GLD returns can affect the level of gold's implied volatility (GVZ). At the extremes, changes in GVZ are insensitive to GLD returns.

The pattern of the plot of the APDs for the third sub-period, and for the quantile range between 0.10 and 0.75, resembles a U-shaped curve. The latter indicates that risk/fear decreases at the lower quantile range (0.10) and increases at the upper quantile range (0.75) (Fousekis 2019). A possible explanation for these findings may lie in the recent debt crisis within the European Union. The European financial crisis was a multi-year debt crisis that had been taking place in since the end of 2009. Member states such as Greece, Portugal, Ireland, Spain and Cyprus were unable to repay or refinance their government debt or to bail out over-indebted banks. The third sub-period of this work coincides with a very particular part of the European debt crisis. The European Central Bank (ECB) contributed to solve the crisis by lowering interest rates and providing cheap loans of more than one trillion euro. On September 6th, 2012, the ECB calmed financial markets by announcing free and unlimited support for all countries in the Eurozone. Return to economic growth and improved structural deficits enabled Ireland and Portugal to exit their bailout programmes in July of 2014. Greece and Cyprus managed to partly regain market access in 2014. As a result investors started regaining faith to assets other than gold and/or withdrawing funds from gold causing changes in the returns and the volatility of gold prices[9]. Due to the fact that implied volatility is forward looking and is implied by the market price of the underlying stock, the findings of this work for the third sub-period most likely capture the investors' underlying behavior. The empirical findings for the third sub-period are in agreement with the results by Baur (2012b), Immanuvel and Lazar (2020) and Reboredo (2013a).

For the second sub-period (31 December 2009 to 9 February 2012), the fourth sub-period (10 January 2014 to 14 February 2017) and the fifth sub-period (15 February 2017 to 31 December 2018) the empirical results (Tables 7, 8 and 9, respectively, in the Online Appendix A) indicate that all estimated APDs are not statistically significant, indicating that changes in GVZ are insensitive to GLD returns.

According to the empirical results, the implied volatility of gold is insensitive to changes in GLD and is not statistically different than zero. The only exception is the 0.10–0.75 quantile range of the third sub-period, where findings support the leverage hypothesis, namely changes in GLD returns lead changes in GVZ. The latter validates the findings in "Data description, Kendall's tau and breakpoint test", where according to Kendall's *tau*, GLD returns lag–lead by one (+ 1) changes in GVZ. Due to the fact that the implied volatility is the market's expectation about the future realized volatility of the asset under examination, the findings of the present work are in agreement (with almost all) the previous studies that have indicated that gold is a safe haven asset. Whereas there is no theoretical model which explains why gold is usually referred to as a safe haven asset, one possible explanation could be that gold was among the first forms of money and was traditionally used as an inflation hedge. Furthermore, gold is found to be uncorrelated with other classes of assets, which is an important characteristic in a globalized financial system in which correlations and inter-dependence have increased dramatically among most asset classes.

Conclusions

Amid the coronavirus pandemic, stock markets around the globe have been experiencing high volatility and unexpected declining returns. As a prime example, on Monday, April 20th of 2020, the price of futures of WTI crude oil went negative for the first time in history. Implied volatility is a significant parameter in risk prediction and investment hedging as well as in the pricing of the asset of interest. The present study examines the relationship between implied volatility and prices in the future markets of gold, using data on daily GLD returns and GVZ changes from June, 2008 to December, 2018. The empirical analysis is performed with the use of the econometric tool of non-parametric quantile regressions. Results are obtained for the total period as well as for a number of sub-periods which are determined on the basis of statistically significant breaks in the implied volatility level. Based on the empirical findings for the nature of dependence between GLD and GVZ, this work attempts to

[9] Gold finished the year of 2013 as one of the worst-performing asset classes. In reality, gold suffered its sharpest fall in 30 years for the year of 2013.

cast light upon the leverage hypothesis as well as the role gold plays as a safe haven investment.

According to Kendall's *tau*, GLD returns lag–lead by one (+ 1) changes in GVZ. This empirical finding is in favor of the leverage hypothesis. For the total sample period, changes in GLD returns do not affect the level of gold's implied volatility (GVZ). More specifically, GVZ changes are not statistically different than zero. For the individual sub-periods, with the exception of the third sub-period, the pattern of dependence is quite similar with that of the total sample period. The derivatives do not vary much along the GVZ change distribution and changes in the implied volatility of gold are not statistically significant. For the third sub-period (10 February 2012 to 9 January 2014), changes in GVZ are insensitive to GLD changes at the lower and the upper extremes. For the quantile levels between 0.10 and 0.75, the estimated values of the APDs are statistically significant and they assume negative values. Lastly, the derivatives do not vary along the GVZ change distribution for the total period as well as for the five sub-periods. In addition, changes in the implied volatility of gold are not statistically significant. Hence, the implied volatility of gold prices is not statistically different than zero under market up-swings and market down-swings and one can conclude that gold can be used as a financial shelter during economic turbulence.

The relationship between the implied volatility of gold (GVZ) and other commodity exchange-traded funds, like oil and/or the Eurocurrency, can be a possible future research path to shed more light about gold's hedge and/or safe haven properties when it comes to the aforementioned ETFs. The non-parametric quantile regression can be a useful econometric tool to assess the aforementioned relationships.

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Declarations

Conflict of interest On behalf of all the authors, the corresponding author states that there is no conflict of interest.

Informed consent All participants provided written informed consent prior to enrollment in the study.

Ethical approval To ensure objectivity and transparency in research, all the ethical and professional conduct manners have been followed.

References

Anand R, Madhogaria S (2012) Is gold a 'safe-haven'?-an econometric analysis. Proc Econ Financ 1:24–33

Anscombe FJ, Glynn WJ (1983) Distribution of the kurtosis statistic b 2 for normal samples. Biometrika 70(1):227–234

Arias O, Hallock KF, Sosa-Escudero W (2002) Individual heterogeneity in the returns to schooling: instrumental variables quantile regression using twins data. In: Economic applications of quantile regression. Springer, pp 7–40

Badshah IU (2013) Quantile regression analysis of the asymmetric return-volatility relation. J Futures Mark 33(3):235–265

Bai J, Perron P (2003) Critical values for multiple structural change tests. Econometr J 6(1):72–78

Baur DG (2012a) Asymmetric volatility in the gold market. J Altern Invest 14(4):26–38

Baur DG (2012b) Asymmetric volatility in the gold market. J Altern Invest 14(4):26–38

Baur DG, Lucey BM (2010) Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ Rev 45(2):217–229

Baur DG, McDermott TK (2016) Why is gold a safe haven? J Behav Exp Financ 10:63–71

Beckmann J, Berger T, Czudaj R (2015) Does gold act as a hedge or a safe haven for stocks? a smooth transition approach. Econ Model 48:16–24

Belloni A, Chernozhukov V, Chetverikov D, Fernández-Val I (2019) Conditional quantile processes based on series or many regressors. J Econometr

Black F (1976) Studies of stock market volatility changes. In: 1976 Proceedings of the American statistical association bisiness and economic statistics section

Blose LE (2010) Gold prices, cost of carry, and expected inflation. J Econ Bus 62(1):35–47

Boussaidi R (2013) Representativeness heuristic, investor sentiment and overreaction to accounting earnings: the case of the tunisian stock market. Proc Soc Behav Sci 81:9–21

Bredin D, Conlon T, Potì V (2017) The price of shelter-downside risk reduction with precious metals. Int Rev Financ Anal 49:48–58

Brodeur A, Gray DM, Islam A, Bhuiyan S (2020) A literature review of the economics of covid-19. IZA, Institute of Labor Economics, DP No. 13411

Cai Z, Xu X (2008) Nonparametric quantile estimations for dynamic smooth coefficient models. J Am Stat Assoc 103(484):1595–1608

Chua J, Woodward RS (1982) Gold as an inflation hedge: a comparative study of six major industrial countries. J Bus Financ Acc 9(2):191–197

Ciner C, Gurdgiev C, Lucey BM (2013) Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates. Int Rev Financ Anal 29:202–211

D’Agostino RB (1970) Transformation to normality of the null distribution of g1. Biometrika 57(3):679–681

Fousekis P (2019) Crude oil price and implied volatility: insights from non-parametric quantile regressions. Stud Econ Financ 36(2):168–182. https://doi.org/10.1108/SEF-04-2018-0117

Fousekis P, Grigoriadis V (2018) Causality between stock market and “fear gauge” indices: an empirical analysis with e-statistics. Appl Financ Lett 7(1):13–21

Giot P (2005) Relationships between implied volatility indexes and stock index returns. J Portf Manag 31(3):92–100

Hood M, Malik F (2013) Is gold the best hedge and a safe haven under changing stock market volatility? Rev Financ Econ 22(2):47–52

Immanuvel SM, Lazar D (2020) Does information spillover and leverage effect exist in world gold markets? Glob Bus Rev. https://doi.org/10.1177/0972150919885472

Iqbal J (2017) Does gold hedge stock market, inflation and exchange rate risks? An econometric investigation. Int Rev Econ Financ 48:1–17

Jaffe JF (1989) Gold and gold stocks as investments for institutional portfolios. Financ Anal J 45(2):53–59

Joy M (2011) Gold and the us dollar: Hedge or haven? Financ Res Lett 8(3):120–131

Lipsitz M, Belloni A, Chernozhukov V, Fernández-Val I (2016) Quantreg.nonpar: an r package for performing nonparametric series quantile regression. arXiv preprint arXiv:1610.08329

Low C (2004) The fear and exuberance from implied volatility of s&p 100 index options. J Bus 77(3):527–546

McCown JR, Zimmerman JR (2006) Is gold a zero-beta asset? analysis of the investment potential of precious metals. Anal Invest Potential Precious Met. https://doi.org/10.2139/ssrn.920496

O’Connor FA, Lucey BM, Batten JA, Baur DG (2015) The financial economics of gold—a survey. Int Rev Financ Anal 41:186–205

Reboredo JC (2013a) Is gold a hedge or safe haven against oil price movements? Resourc Policy 38(2):130–137

Reboredo JC (2013b) Is gold a safe haven or a hedge for the us dollar? Implications for risk management. J Bank Financ 37(8):2665–2676

Reboredo JC, Rivera-Castro MA (2014) Can gold hedge and preserve value when the us dollar depreciates? Econ Model 39:168–173

Shapiro SS, Wilk MB (1965) An analysis of variance test for normality (complete samples). Biometrika 52(3/4):591–611

Soytas U, Sari R, Hammoudeh S, Hacihasanoglu E (2009) World oil prices, precious metal prices and macroeconomy in turkey. Energy Policy 37(12):5557–5566

Thaler RH (2005) Advances in behavioral finance, vol 2. Princeton University Press, Princeton

Tully E, Lucey BM (2007) A power garch examination of the gold market. Res Int Bus Financ 21(2):316–325

Worthington AC, Pahlavani M (2007) Gold investment as an inflationary hedge: cointegration evidence with allowance for endogenous structural breaks. Appl Financ Econ Lett 3(4):259–262

Wu G (2001) The determinants of asymmetric volatility. Rev Financ Stud 14(3):837–859