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Do volatility indices diminish gold’s appeal as a safe haven to investors before and during the COVID-19 pandemic?

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This study addresses the research question of whether volatility indices of different asset classes reduce gold’s appeal as a safe-haven asset before and during the COVID-19 pandemic. We use daily data for seven volatility indices and gold prices and apply the suitable nonlinear autoregressive distributed lag method to analyze the data. Our results indicate that during COVID-19, only the negative Eurocurrency volatility has diminished gold prices in the long term, whereas in the short term, the positive gold, silver, emerging market, and (lagged) financial market volatilities have diminished gold prices. During the pre-COVID-19 normal period, volatilities in the financial, energy, gold, silver, and eurocurrency markets improved gold prices, whereas in the short term, only lagged negative oil volatility diminished gold prices. A robustness test for the 2011–2015 pre-COVID-19 period reveals that this period is to an extent comparable to that of COVID-19. This study reveals no direct effects from emerging markets volatility on gold prices. Notwithstanding, a long memory in gold prices persists and uneven spillover effects exist. Finally, those volatilities predominantly increase gold prices under the normal economic conditions but decrease gold’s appeal as a safe haven during crises in the comparable periods. We delineate the implications for investors.

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\textbf{1. Introduction}

International investors had shifted their portfolios toward investing in commodity markets following the global financial crisis and its preceding jitters in the financial market, which coincided with volatile macroeconomic and financial environments and heightened geopolitical risks (Bampinas and Panagiotidis, 2015). The years following the global financial crisis had seen gold becoming a particularly popular substitute hedge instrument in portfolio diversification decisions (Kirkulak Uludag and Lkhamazhapov, 2014). Gold is thus considered a safe-haven commodity for all types of investors, particularly during times of crises, as it aids them in coping with macroeconomic and financial risks (See Agyei-
Ampomah et al. 2014, Balcilar et al. 2016, Baur and Lucey 2010, Baur and McDermott 2010, Beckmann et al. 2015, 2019, Bilgin et al. 2018, Bouoiyour et al. 2018, Gürgün and Ünalıuş 2014, Reboredo 2013, Tanin et al. 2021b, 2021c).

In the meantime, investment profitability in the commodity markets is becoming growingly more uncertain with the fall in demand, supply, and prices of the commodities because of the ongoing COVID-19 pandemic (Rajput et al., 2020). An overview of the initial months of this COVID-19 crisis reveals that its adverse effects have been significantly more intense, comprehensive, and widespread than those of the global financial crisis, causing a substantial economic and social destruction to global institutions and financial and commodity markets (Baker et al., 2020; Goodell, 2020). Given all these changes, we hypothesize that the COVID-19 pandemic has led international investors to seek flight-to-safety by acquiring gold as a safe-haven asset during this pandemic. In particular, we examine the research questions of whether: (1) different volatility indices, influenced by various financial and commodity markets, have impacted gold prices; and (2) gold serves as a safe-haven asset before or during the ongoing COVID-19 pandemic.

Investors and market participants (e.g., bank depositors) are most likely to be concerned about the economy’s long-term viability, particularly at the onset of COVID-19 (Huynh et al., 2021). For example, Anastasiou and Drakos (2021) find that a crisis-linked sentiment (i.e., a behavior) intensifies fear among European bank depositors, leading them to massively withdraw their bank deposits. Although those authors argue that depositors’ crisis-related sentiments are linked to a herding or irrational behavior, we however call it a flight-to-safety as those depositors feel that their deposits may disappear during the crisis, thus leading to a bank default. We contend that these depositors are potential investors in the financial markets, and they search for a safe haven refuge during a crisis such as COVID-19. In a similar vein, Huynh et al. (2021) find that in the equity markets of the 17 largest economies, investor sentiment positively predicts the stock volatility, while it negatively predicts the stock return upon the arrival of the COVID-19 crisis. This view sheds light on the investing strategies favoring the safest options (gold, for example), especially during a crisis period.

We follow a basic theoretical framework from psychological economics, which tells us that humans make their decisions by focusing on emotions (Ester, 1998; Loewenstein, 2000), preferences (Lucey and Dowling, 2005; Romer, 2000; Zajonc, 1980) as well as on risk and heuristics (Finucane et al., 2000; Nasir, 2020). Although economic humans (i.e., investors) conventionally make investment decisions by calculating risk-return trade-offs, their decisions may be driven by feelings (Huynh et al., 2021), which are persistent and heterogeneous (Cole and Milani, 2021). Concerning the financial literature, Kaplanski and Levy (2010) in cases such as aircraft disasters and stock returns discover a connection between anxiety and negative sentiments due to Lee et al. (1991), thereby finding that people are not entirely rational when they are anxious. In short, an extreme event has the power to drive investors’ behaviors, causing them to respond impulsively to the “bad news.” Hirshleifer et al. (2020) provide further empirical evidence stating that mood seasonality predicts stock returns, implying that greater mood parameters could lead to higher returns. Kostopoulos and Meyer (2018) find that investors buy more when they are in a good mood, especially when investing in risky and riskier stocks. Moreover, Kim and Kim (2014) uncover evidence demonstrating that previous stock price performance positively impacts investor sentiments (or behaviors).

According to behavioral finance studies (e.g., Forlani 2002, Kahneman 2003), some investors are not entirely rational, and their demands for risky assets are influenced by their views or feelings that are not entirely supported by fundamental facts. Concerning commodity markets, Bampinas et al. (2019) show evidence that in times of market instability, irrational investor behavior, or panic reactions, gold acts as a safe haven due to its intrinsic characteristics.

The above studies give us enough information to link investors’ behaviors with gold markets or prices. We could then argue that crises significantly impact investors’ feelings, moods, behaviors, and, of course, affect their investment decisions. With that, crisis periods such as COVID-19 make those sentiments distinguishable from those of a normal or a calm period. Caporale et al. (2017) argue that volatility in gold prices is particularly sensitive to macroeconomic news and that the global financial crisis has increased such links. It is worth mentioning that the volatility of gold is a salient factor in investors’ and consumers’ behaviors and has significant implications for the financial markets and the economy (Bampinas et al., 2019).

Most studies analyzing the volatility spillover effects on gold take a few commodities, currencies, or financial markets into consideration. For example, Bampinas et al. (2019) have examined the volatility of gold and oil, while Tiwari et al. (2019) have investigated the dependence of the gold market on emerging stock markets. Dutta (2018) has investigated the impacts of oil volatility on precious metals such as gold, silver, and copper, whereas Papadamou and Markopoulos (2014) have explored the volatility between gold, silver, and three currencies: the euro, the British pound, and the Japanese yen. Jubinski and Lipton (2013) have studied the financial market volatility with relation to gold, silver, and oil, while Khalifa et al. (2011) have forecast volatility between gold, silver, and copper.

The above studies have contributed to the important analysis of relationships between volatility variables prior to the COVID-19 pandemic period. The worldwide financial and commodity markets’ panic and economic collapse (Gopinath, 2020; World Bank, 2020) following the COVID-19 pandemic have motivated us to accommodate additional variables (i.e., volatility indices of different asset classes) into the analysis, and thereby produce more updated, accurate, and meaningful results. We presume that volatility indices influence gold prices in nonlinear and asymmetric manners, especially during the COVID-19 pandemic. Because the prices of commodities, including gold, have exhibited large swings and frequent instabilities in...

1 The United States, Germany, France, Italy, Spain, the United Kingdom, China, South Africa, Australia, Japan, India, Russia, South Korea, Turkey, Argentina, Brazil, and Indonesia.
recent decades (Arouri et al., 2012; Vivian and Wohar, 2012), it is plausible that their volatility reacts to shocks in a nonlinear manner (Chkili et al., 2014). In implementing the BDS test, we also find that the data (i.e., volatility indices and gold prices) are nonlinear. In addition, several recent studies (Bouri et al., 2018; Chkili et al., 2014; Raza et al., 2016) have demonstrated that volatilities nonlinearly impact gold prices.

In contrast, volatility asymmetry is unearthed when negative shocks show a stronger influence on the volatility process compared to positive shocks, and it usually manifests itself at times of extreme financial conditions, such as the 2008 global financial crisis (Chkili et al., 2014). Nelson (1991) was the first to empirically test the asymmetric relation between asset classes (e.g., stock prices) and changes in volatility in response to the negative and positive news while highlighting that asymmetry plays a pivotal role in the variance/volatility and asset risk premia of those assets. The asymmetry has a significant impact on asset pricing. Therefore, an exploration of the relationships between volatility indices and gold prices, with the latest available data and in the presence of COVID-19, will serve as a valuable contribution to the literature.

Consistent with the aforementioned research questions, this study investigates how the seven volatility indices under consideration impact gold prices before and during the COVID-19 pandemic and affect its status as a safe haven. These indices are the financial market volatility (VIX), crude oil volatility (OVX), overall energy volatility (EVX), gold volatility (GVX), silver volatility (SVX), emerging market volatility (EMVX), and eurocurrency volatility (ECVX). To this end, we sourced daily data from before the pandemic (March 2011–December 2019) and during the pandemic (January 2020–Mach 2021). This data on gold prices obtained from the Intercontinental Exchange Benchmark Administration Ltd. and data on the seven volatility indices acquired from the Chicago Board Options Exchange.

We argue that there are at least five crucial reasons for examining the relationships between the volatility indices and gold prices in a nonlinear and asymmetric setting. First, authors such as Apergis and Eleftheriou (2016) have recently proposed that business cycles asymmetrically affect gold prices. Second, asymmetry and structural breaks such as major credit events and bankruptcy are examples of nonlinearities that impact market dynamics, particularly when the sample period includes major financial crises, such as the global financial crisis (Raza et al., 2016). In other words, time-series data generally show nonlinear patterns, such as those of high volatility and crises of assets such as gold, thereby leading to an urge of employing nonlinear methods. Third, the nonlinear autoregressive distributed lag (NARDL) model (Shin et al., 2014) can disentangle hidden cointegration as postulated by Granger and Yoon (2002). The data are considered to have a hidden cointegration if its respective positive and negative aspects are cointegrated, whereas traditional cointegration tests such as the Engle and Granger (1987) and Johansen (1988) cointegration tests are unable to discover cointegrating relationships between level data. Fourth, Jain and Biswal (2016) suggest that linear models may no longer be appropriate due to commodity prices’ increasing tendency to behave like financial assets. Fifth, Demirer et al. (2010) find that the linear model fails to capture the dynamics between investor herding behavior and stock markets, while nonlinear models shine and yield consistent results.

Therefore, we apply the NARDL method because it can help analyze the nonlinear and asymmetric relationships between the indices, and it can distinguish between investor heterogeneity (short-term versus long-term). One of the merits of the NARDL method is that it can detect long memory. Chkili et al. (2014) demonstrate that a nonlinear method that accommodates the long memory and asymmetric features can better describe the volatility of gold (returns).

When long memory is present, past prices of a commodity may distort future prices in the long term. When the price series exhibit long memory, it reveals that the observed prices are not independent over time. If prices are not independent, then past prices can help predict future prices, thereby violating the market efficiency hypothesis. It poses a serious challenge to the supporters of the random walk behavior of the stock as it violates the efficient market assumption as well as enhancing the likelihood of investors making speculative profits (Kirkulak Uldug and Lkhamazhapov, 2014), which opposes the random walk or martingale behavior (Fama, 1970). The presence of long memory indicates the predictability of gold prices, casting doubt on the weak-form competence of the gold market (Kirkulak Uldug and Lkhamazhapov, 2014). Therefore, whether the presence of long memory in the gold market is spurious is worth the investigation. Spurious long memory is likely to appear as a result of structural breaks or sudden changes in extreme market conditions, namely financial crises, wars, and policy changes. Asserting the existence of long memory created by structural breaks would enable stakeholders to capture the nature of gold volatility more precisely.

This study’s novel contributions are six-fold. First, to the best of our knowledge, this is the first study to examine the effects of seven volatility indices related to financial and commodity markets on gold prices before or during the COVID-19 crisis. Second, this study indicates that volatility indices are unlikely to negatively affect gold prices in the long term, confirming gold as a hedging instrument and a safe-haven commodity at least in the long term. Third, when crises unfold (e.g., as in the case of the post-global financial crisis, the European sovereign debt crisis, the gold market crash in 2013, or the COVID-19 pandemic), the seven volatility indices gain the power to considerably decrease gold prices, thus inhibiting this metal’s appeal in some instances in the short term. Fourth, the results highlight that because of the COVID-19 crisis, the negative effects of the volatility indices are comparatively higher than their positive counterpart on gold prices, signifying uneven spillover effects (volatility→gold prices). Fifth, this study is not consistent with the finding of Kirkulak Uldug and Lkhamazhapov (2014), who highlighted that long memory in gold prices is not spurious but rather a valid and intrinsic property of the data. Finally, supported by empirical evidence, we infer that those volatilities predominantly increase gold prices under normal economic conditions.

The remainder of this study is organized as follows. Section 2 presents the data and the research methods. Section 3 provides and discusses the results. Section 4 concludes this study with policy implications.
2. Data and research methods

2.1. Data

In selecting subperiods prior to and during COVID-19, we followed Wang et al. (2021), who consider January 1, 2007–December 31, 2019, as the pre-COVID-19 period and January 1, 2020–December 31, 2020, as the COVID-19 period. In our case, the available time-series data span the daily period from May 17, 2011 (based on the data’s availability for all the seven volatility indices) to March 26, 2021. The gold prices (y) and the volatility indices (x) are transformed into natural logarithmic forms to achieve uniform data. To offer robust findings, we have used the NARDL method to cluster the data into five-day weeks and then estimated the dynamics of the volatility indices and the gold prices.

Table 1 summarizes the details of the dependent and independent variables of this study.

Fig. 1a–x delineate an initial understanding of the raw data. The main estimation is divided into two periods, before and during the COVID-19 pandemic, coupled with a robustness test of the subsample 2011–2015. There were at least three crises during the subsample: the post-global financial crisis, the European sovereign debt crisis, and the gold market crisis in 2013 (Fletcher and Rankin, 2013). Gold prices floated between USD 1000 (approximately) and USD 2000, yet a few extreme fluctuations were seen during the COVID-19 period and the 2011–2015 years. At the end of June 2013, gold prices descended sharply in the commodity’s worst performance since 1968, fueled by fears of the discount in quantitative easing, a strengthening of the US dollar, and a fall in demand for gold among Indian and Chinese investors (Fletcher and Rankin, 2013). The scenario of the massive decline in gold prices stayed until the end of 2015. Between March 2011 and March 2021, the seven volatility indices studied showed intense fluctuations, as the following graphs illustrate. However, the volatility indices manifested the highest degree of fluctuation between March and April 2021 owing to the intensified panic of the COVID-19 crisis (Fig. 1b–h).

2.2. Model specification

The NARDL model allows for an investigation of the nonlinear and asymmetric relationship between the dependent (y) and the independent (x) variables, anticipating asymmetric adjustments throughout the business cycle (De Long and Summers, 1986; Falk, 1986; Neftci, 1984). Chkili et al. (2014), Raza et al. (2016), Bouri et al. (2018), and Dutta et al. (2019) empirically demonstrate that gold exhibits common characteristics of asymmetry and nonlinearity regarding volatility. Having those findings in hand, it is clear that the nexus between volatilities and gold prices is asymmetric and nonlinear. Nevertheless, to double-check the nonlinearity, we apply the BDS test (Broock et al., 1996) to our data and find that the data are

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Notes: (1) “Data is collected via Thomson Reuters Eikon. (2) “Do” refers to “the same as above.”

Table 1

| Variables | Definitions | Notations | Data type | Data source* |
|-----------|-------------|-----------|-----------|--------------|
| Dependent Variable: | | | | |
| Gold Prices | Prices of Gold, London Bullion Market in USD, Per metric ton ounce | GLDP | Natural logarithm | ICE Benchmark Administration Ltd. |
| Independent Variable(s): | | | | |
| Financial Market Volatility | CBOE Standard and Poor’s (S&P) 500 Index (SPX) Volatility (United States) | VIX | Natural logarithm | Chicago Board Options Exchange (CBOE) |
| Crude Oil Volatility | CBOE Crude Oil Volatility Index | OVX | Do | Do |
| Energy Volatility | CBOE Energy Exchange-traded Fund (ETF) Volatility Index | EVX | Do | Do |
| Gold Volatility | CBOE Gold Volatility Index | GVX | Do | Do |
| Silver Volatility | CBOE Silver Exchange-traded Fund (ETF) Volatility Index | SVX | Do | Do |
| Emerging Markets Volatility | CBOE Emerging Markets Volatility Index | EMVX | Do | Do |
| Eurocurrency Volatility | CBOE Eurocurrency Volatility Index | ECVX | Do | Do |

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2 Huynh et al. (2021) also consider January 1, 2020, as the starting point of COVID-19.
3 Among the seven volatility indices under study, six of them (financial market volatility, oil volatility, overall energy volatility, gold volatility, silver volatility, and eurocurrency volatility) are the most commonly used measures of volatility in the literature (Badshah et al., 2013; Benedetto et al., 2020; Dutta et al., 2020; Gogzor et al., 2016; Liu et al., 2013; Umar, 2015). However, we might be the first to test the effect of the emerging markets volatility index.
4 We divide the pre-COVID-19 2011–2019 period into two subperiods: (a) 2011–2015, when the worldwide markets have experienced various crises, and (b) 2016–2019, when we observe no major crisis. Therefore, we consider the second subperiod 2016–2019 (or pre-COVID-19 normal period) as part of the main estimation while we use the first subperiod 2011–2015 (or the pre-COVID-19 period) for a robustness test.
The Ongoing COVID-19 Period: January 01, 2020 – March 26, 2021

Fig. 1. Volatility and Gold Prices. Note: GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.

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The Pre-COVID-19 Normal Period: January 01, 2016 – December 31, 2019

Fig. 1. Continued
The Robustness Test (Pre-COVID-19 Period): March 17, 2011 – December 31, 2015

Fig. 1. Continued
nonlinear (Appendix A1). Hence, we directly proceed with the estimation employing the NARDL method (Shin et al., 2014), which captures nonlinear, dynamic, and asymmetric effects while differentiating between the short- and long-term impacts of the exogenous/independent variables (i.e., the volatility indices) on the dependent variable (gold prices). The short- and long-term impacts distinguish between investor heterogeneity (short-term versus long-term).

The nonlinear threshold vector error correction model was a potential candidate for use in this analysis. However, because this model exhibits the convergence problem when the parameters proliferate, we ultimately elected to use the NARDL model described below, which is free from such issues and relaxes the typical restriction of requiring the same order of integration for a time-series of variables (Apergis and Cooray, 2015). Further, the NARDL model is capable of choosing the best lag order, which helps to solve the multicollinearity problem (Shin et al., 2014). Further, a bounds-testing approach such as NARDL can offer robust empirical results (Narayan, 2005). The long-term equations for the NARDL, as suggested by Shin et al. (2014), are as follows:

\[ y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \]  

\[ \Delta x_t = \nu_t, \]  

where \( y_t \) (gold prices) and \( x_t \) (volatility indices) are scalar variables and where \( x_t \) is decomposed as \( x_t = x_0 + x_t^+ + x_t^- \), where \( x_t^+ \) and \( x_t^- \) are partial sum processes of the positive and negative changes in \( x_t \), consecutively:

\[ x_t^+ = \sum_{j=1}^{t} \Delta x_{j}^+ = \sum_{j=1}^{t} \max(\Delta x_{j}, 0), \quad x_t^- = \sum_{j=1}^{t} \Delta x_{j}^- = \sum_{j=1}^{t} \min(\Delta x_{j}, 0). \]  

We inspected the symmetric short-term coefficients using the Wald statistic, following an asymptotic \( \chi^2 \) distribution. To test the short-term dynamic asymmetries in the response of volatility indices to a fall in gold prices, we have indirectly imposed long-term symmetry restrictions \( \theta^+ = \theta^- = \theta \), which can be simplified as

\[ \Delta y_t = \rho y_{t-1} + \theta x_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \sum_{i=0}^{q-1} (\pi_i^+ \Delta x_{t-i}^+ + \pi_i^- \Delta x_{t-i}^-) + e_t. \]  

Short-term symmetry constraints can take two forms: (i) \( \pi_i^+ = \pi_i^- \) for all \( i = 0, \ldots, q-1 \) or (ii) \( \sum_{i=0}^{q-1} \pi_i^+ = \sum_{i=0}^{q-1} \pi_i^- \). When allowing such restrictions in the existence of an asymmetric long-term relationship, we obtain

\[ \Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \sum_{i=0}^{q-1} \pi_i \Delta x_{t-i} + e_t. \]  

We trimmed the insignificant lags of the first-differenced terms in formulating the final NARDL, as suggested by the principles of the NARDL model. The most restricted NARDL model is attained when assuming a nonlinearity of the long-term relationship in combination with short-term asymmetric adjustments (Shin et al., 2014):

\[ \Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \sum_{i=0}^{q-1} \pi_i \Delta x_{t-i} + e_t. \]  

Finally, to visually illustrate the asymmetry, we presented the cumulative dynamic multipliers of a change in \( x_t^+ \) and \( x_t^- \) to graphically expose the nexus between asymmetric gold prices \( (y_t) \) and volatility indices \( (x_t) \). The asymmetric and cumulative dynamic multiplier effects of \( x_t^+ \) and \( x_t^- \) on \( y_t \) are the following:

\[ m_h^+ = h \sum_{j=0}^{h} \frac{\partial y_t}{\partial x_{t-j}^+} = \sum_{j=0}^{h} \lambda_j^+, \quad m_h^- = h \sum_{j=0}^{h} \frac{\partial y_t}{\partial x_{t-j}^-} = \sum_{j=0}^{h} \lambda_j^-, \quad h = 0, 1, 2 \ldots \]  

\[ h \rightarrow \infty, \quad m_h^+ \rightarrow \beta^+ \text{ and } m_h^- \rightarrow \beta^-. \]  

where \( \beta^+ = -\theta^+/\rho \) and \( \beta^- = -\theta^-/\rho \) are the asymmetric long-term coefficients, \( p, q \) is the lag order, and \( h \) denotes the horizon. The NARDL automatically chooses a lag order of three.

We have applied three steps for the NARDL estimation. First, we ran unit root tests to confirm whether our variables are I(1). Second, informed by the results of the unrestricted NARDL estimation, we followed a general-to-specific procedure (Sukmana and Ibrahim, 2017) to trim out insignificant lags from models to determine the final specification (presented in Tables 3 and 4). This step helps determine whether the short- and long-term relationships exist between gold prices and the volatility indices. Finally, we presented the cumulative dynamic multiplier effects of a 1% change in \( \Delta x_t^+ \) and \( \Delta x_t^- \) to visually determine the asymmetric relationship between \( x \) (volatility indices) and \( y \) (gold prices) (Shin et al., 2014) in Fig. 2.
The Ongoing COVID-19 Period: January 01, 2020 – March 26, 2021

Fig. 2. Cumulative Dynamic Multipliers (Volatility → Gold Prices). Notes: (1) The 95% bootstrap CI is based on 1000 replications. (2) GLDP is the dependent variable, whereas the rest (e.g., VIX, OVX, and EVX) are the independent variables. (3) The periods are in weeks (i.e., 40 weeks). (4) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.
The Pre-COVID-19 Normal Period: January 01, 2016 – December 31, 2019

Fig. 2. Continued
The Robustness Test (Pre-COVID-19 Period): March 17, 2011 – December 31, 2015

Fig. 2. Continued
3. Results and discussion

3.1. Unit root test

We first conducted unit root tests to determine whether we could move forward with the estimation. The tests confirmed that gold prices and volatility indices are stationary, which is the prerequisite for a causality analysis. Both the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests (Table 2) confirmed that all variables are stationary in all horizons. This indicated that we could proceed with testing the gold prices and the seven volatility indices empirically.

3.2. Short- and long-term relationships

3.2.1. During crisis period

Table 3 reports the results obtained for the COVID-19 period. In the long term, we see no significant impact of the seven volatility indices on the gold prices. Concerning the short-term impact, the lagged and positive financial market volatility (VIX) decreased gold prices. Thus, the financial markets are tied to the gold market; and hence, they impact gold prices (Choudhry et al., 2015; Mensi et al., 2013). Choudhry et al. (2015) argue that gold may not perform well during financial crises as a result of a bidirectional interdependence between the gold prices and stock prices, along with the stock market volatility. While a positive gold volatility (GVX) diminished gold prices, a three-week prior and positive GVX enhanced them. These results make sense due to the fact that, by nature, an increase in volatility in the gold market should reduce the gold prices. Despite the volatility, over time, investors might have gained confidence in gold as a reliable investment instrument, which then translated to make the three-week prior and the positive GVX to increase gold prices.

In the same short term, positive silver volatility (SVX) also diminished gold prices. Gold and silver typically behave like twins or cousins, and thus, may show similar sensitivities toward changes in volatility. This result, however, contrasts with the findings of Troster et al. (2019), who witnessed no causality between silver and gold market volatilities during moderate volatility regimes (Quantile 0.50 and 0.60), though this finding may be attributed to their quantile regression method. Additionally, the positive emerging market volatility (EMVX) diminished gold prices, a finding potentially explained by the crisis period of COVID-19 and the succeeding shocks in EMVX. The results of Tiwari et al. (2019) partially agree with our result that gold does not serve as a safe-haven commodity under all market conditions for emerging countries (E7).

The lagged gold prices enhanced gold prices only in the short term and in the case of O VX. We, however, find no impact of the lagged gold prices in the long term. As mentioned before, the short-term effects of the lagged gold prices indicate the presence of long memory, yet we find no such long memory, as supported by our empirical estimations. Although this contrasts with the study of Kirkulak Uludag and Lkhamazhapov (2014), it is consistent with the efficient market assumption and comes in line with the random walk or martingale behavior (Fama, 1970). Analyzing the period before the ongoing COVID-19 pandemic allows us to determine whether the ongoing pandemic has caused no long memory.

3.2.2. Pre-COVID-19 normal period

We further tested the period before COVID-19 (January 2016–December 2019) and presented the results of these tests in Table 4. These results mostly oppose our findings from data during the ongoing COVID-19 crisis, indicating that the COVID-19 findings could be exclusive to the crisis period and a result of the pandemic situation. First, only the negative eurocurrency volatility (ECVX) diminished gold prices in the long term. It is worth mentioning that European Currencies dominated gold prices in the 1980s (Sjaastad and Scacciavillani, 1996). Can we therefore conclude that the euro is able to drive gold prices, especially during the pre-crisis period and in the long term?

Positive financial market volatility (VIX) impacted gold prices positively in the short term. This finding endorses the discovery of Choudhry et al. (2015) that under normal circumstances, volatility in the financial market enhances gold prices. The positive energy volatility (EVX) and gold volatility (GVX) also enhanced gold prices between 2016 and 2019. As discussed previously, gold is seen as a safe haven (Beckmann et al., 2019; Harris and Shen, 2017; Ji et al., 2020; Mensi et al., 2017), leading international investors to buy gold as a hedging instrument (Singhal et al., 2019). When the economy fails (Jain and Biswal, 2016) or when the global prices of oil, a major energy source (Pandey and Vipul, 2018), is highly volatile (Bouri et al., 2017), investors desire to shift over to gold investments. These facts may justify the results, with the exception of the finding concerning GVX. By nature, an increase in gold volatility should diminish gold prices.

A rise in ECVX has also been found to impact gold prices positively in the short term. As mentioned, the euro may be able to drive gold prices during the pre-crisis period, which may validate the study of Sjaastad and Scacciavillani (1996). With this finding, we may assume that during the relatively calm period of 2016–2019, an increase in ECVX has positively affected gold prices, whereas in the stressed period of the COVID-19 crisis, ECVX has no impacts on gold prices, as illustrated in Table 3.

Unlike in the ongoing COVID-19 period, negative changes in silver volatility (SVX) in the period before the COVID-19 pandemic enhanced gold prices, which again contrasts with the findings of Troster et al. (2019). However, the lagged and negative oil volatility (OVX) diminished gold prices, a finding that contrasts with the outcome of the COVID-19 period, as can be witnessed in Table 3. Perhaps the extreme uncertain situations associated with negative oil prices for the first time in history during COVID-19 (Wallace, 2020) may have caused the pandemic period to be distinctive from the normal (i.e., the pre-COVID-19 period). Nevertheless, Dutta (2018) finds no evidence that oil volatility impacts, either positively or negatively,
### Table 2
Unit root test.

|                  | ADF      | PP      |
|------------------|----------|---------|
|                  | Variable | Z(t) t-stat. | 1% C. V. | p-value | Result | Z(p) t-stat. | 1% C. V. | Result |
| Level Form       | GLDP     | 1.496    | -3.459  | 0.536   | NS      | -3.920    | -20.306 | NS     |
|                  | VIX      | -2.371   | 0.150   | NS      | -8.079  | NS        | NS      |         |
|                  | OVX      | -3.187   | 0.021   | NS      | -8.779  | NS        | NS      |         |
|                  | EVX      | -2.422   | 0.136   | NS      | -6.266  | NS        | NS      |         |
|                  | GVX      | -2.940   | 0.041   | NS      | -10.316 | NS        | NS      |         |
|                  | SVX      | -2.730   | 0.069   | NS      | -11.063 | NS        | NS      |         |
|                  | EMVX     | -2.259   | 0.186   | NS      | -9.095  | NS        | NS      |         |
|                  | ECVX     | -2.498   | 0.116   | NS      | -7.736  | NS        | NS      |         |
| 1st Difference Form | ΔGLDP   | -1.469   | -3.479  | 0.004   | S       | -206.854  | -20.110 | S      |
|                  | ΔVIX     | -1.622   | 0.000   | S       | -230.388 | S        |         |
|                  | ΔOVX     | -1.457   | 0.000   | S       | -207.299 | S        |         |
|                  | ΔEVX     | -1.238   | 0.000   | S       | -187.464 | S        |         |
|                  | ΔGVX     | -1.451   | 0.000   | S       | -199.238 | S        |         |
|                  | ΔSVX     | -1.204   | 0.000   | S       | -173.224 | S        |         |
|                  | ΔEMVX    | -1.390   | 0.000   | S       | -207.651 | S        |         |
|                  | ΔECVX    | -1.667   | 0.000   | S       | -220.841 | S        |         |

Notes: (1) NS and S denote the non-stationary and stationary notations, respectively. (2) Δ represents first-differenced variables. (3) MacKinnon approximate p-value for Z(t). (4) C. V. = Critical Value. (5) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.

### The Pre-COVID-19 Normal Period: January 01, 2016–December 31, 2019

|                  | ADF      | PP      |
|------------------|----------|---------|
|                  | Variable | Z(t) t-stat. | 1% C. V. | p-value | Result | Z(p) t-stat. | 1% C. V. | Result |
| Level Form       | GLDP     | -1.273   | -3.430  | 0.000   | NS      | -3.906    | -20.700 | NS     |
|                  | VIX      | -5.320   | 0.000   | S       | -41.970  | S        |         |
|                  | OVX      | -3.422   | 0.010   | NS      | -17.499  | NS       | NS      |         |
|                  | EVX      | -3.750   | 0.004   | S       | -23.476  | S        |         |
|                  | GVX      | -1.819   | 0.371   | NS      | -6.535   | NS       | NS      |         |
|                  | SVX      | -2.425   | 0.135   | NS      | -11.382  | NS       | NS      |         |
|                  | EMVX     | -4.181   | 0.001   | S       | -28.589  | NS       | NS      |         |
|                  | ECVX     | -2.378   | -3.430  | 0.000   | S       | -9.955   | NS       | NS     |
| 1st Difference Form | ΔGLDP   | -24.322  | 0.000   | S       | -636.682 | -20.700  | S       |
|                  | ΔVIX     | -26.615  | 0.000   | S       | -636.398 | S        |         |
|                  | ΔOVX     | -26.616  | 0.000   | S       | -680.487 | S        |         |
|                  | ΔEVX     | -23.887  | 0.000   | S       | -604.186 | S        |         |
|                  | ΔGVX     | -28.846  | 0.000   | S       | -721.155 | S        |         |
|                  | ΔSVX     | -27.989  | 0.000   | S       | -671.723 | S        |         |
|                  | ΔEMVX    | -27.643  | 0.000   | S       | -666.673 | S        |         |
|                  | ΔECVX    | -28.217  | 0.000   | S       | -651.136 | S        |         |

Notes: (1) NS and S denote the non-stationary and stationary notations, respectively. (2) Δ represents first-differenced variables. (3) MacKinnon approximate p-value for Z(t). (4) C. V. = Critical Value. (5) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.

### The Robustness Test (Pre-COVID-19 Period): March 17, 2011–December 31, 2015

|                  | ADF      | PP      |
|------------------|----------|---------|
|                  | Variable | Z(t) t-stat. | 1% C. V. | p-value | Result | Z(p) t-stat. | 1% C. V. | Result |
| Level Form       | GLDP     | -0.462   | -3.430  | 0.8992  | NS      | -0.765    | -20.700 | NS     |
|                  | VIX      | -4.417   | 0.0003  | S       | -32.603  | S        |         |
|                  | OVX      | -1.857   | 0.3524  | NS      | -6.806   | NS       | NS      |         |
|                  | EVX      | -3.437   | 0.0097  | S       | -19.019  | NS       | NS      |         |
|                  | GVX      | -4.051   | 0.0012  | S       | -26.688  | S        |         |
|                  | SVX      | -3.503   | 0.0079  | S       | -18.684  | NS       | NS      |         |
|                  | EMVX     | -3.429   | 0.0100  | NS      | -22.262  | S        |         |
|                  | ECVX     | -3.254   | 0.0171  | NS      | -13.592  | NS       | NS      |         |
| 1st Difference Form | ΔGLDP   | -27.143  | -3.430  | 0.000   | S       | -759.661  | -20.700 | S      |
|                  | ΔVIX     | -28.364  | 0.000   | S       | -803.088 | S        |         |
|                  | ΔOVX     | -26.139  | 0.000   | S       | -773.482 | S        |         |
|                  | ΔEVX     | -27.015  | 0.000   | S       | -758.269 | S        |         |
|                  | ΔGVX     | -25.786  | 0.000   | S       | -722.139 | S        |         |
|                  | ΔSVX     | -27.098  | 0.000   | S       | -783.452 | S        |         |
|                  | ΔEMVX    | -26.275  | 0.000   | S       | -703.517 | S        |         |
|                  | ΔECVX    | -24.684  | 0.000   | S       | -688.624 | S        |         |

Notes: (1) NS and S denote the non-stationary and stationary notations, respectively. (2) Δ represents the first-differenced variables. (3) MacKinnon approximate p-value for Z(t). (4) C. V. = Critical Value. (5) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.
gold prices, and his result might be attributed to his study period, which ranges from May 2007–June 2016, while we investigated the period from January 2016–December 2019, which is a (or normal) subperiod here.

Interestingly, the negative and lagged VIX, EVX, and ECVX enhanced gold prices in the period before the COVID-19 pandemic. In this global era, markets and commodities are typically linked. Thus, the natural assumption is that a decrease in volatility in one market or commodity would enhance prices of another under normal circumstances, that is, before the COVID-19 pandemic. Our results may point toward this assumption.

The lagged gold prices in the period before COVID-19 appeared to decrease gold prices only in the short term and on one occasion. This finding confirms that the long memory of gold prices is not a property of the data, contrasting the martingale behavior (Fama, 1970) while signaling a strong-form efficiency of the gold market. Nevertheless, Kirkulak Uludag and Lkhamaazhavop (2014) have presented the opposite findings for the case of the Turkish gold market.

### 3.4. Robustness test: the pre-COVID-19 period

We checked the robustness of our findings by examining a period of crises and post-crisis adjustments (Fig. 1q–x). We see at least three crises during March 2011–December 2015: the post-global financial crisis, the European sovereign debt crisis, and the worst crash in the gold market at the end of June 2013 since 1968 (Fletcher and Rankin, 2013). In line with the inherent nature of gold and its bond with silver, we find here that an upsurge in gold (GVX) and silver (SVX) volatility diminished gold prices (Table 5). However, a decrease in energy (EVX), silver, emerging market (EMVX), and eurocurrency (ECVX) volatility diminished gold prices.

Although these findings regarding gold prices contrast with previous findings for the years 2016–2019, these mostly match the findings of the COVID-19 period and Fletcher and Rankin (2013) concerning the middle of 2013, when gold experienced its worst quarterly performance of the past forty-five years. The effects of the post-global financial crisis, the European sovereign debt crisis, and the post-crisis adjustments may have contributed to the results. However, the ongoing
Table 4
NARDL estimation (volatility → gold prices).

|                        | (1)                      | (2)                      | (3)                      | (4)                      | (5)                      | (6)                      | (7)                      |
|------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| x                      | VIX                      | O VX                     | EVX                      | GVX                      | SVX                      | EMVX                     | EC VX                    |
| y_{t-1}                | −0.003                   | −0.006                   | −0.007                   | −0.005                   | −0.005                   | −0.007                   | −0.008                   |
| x_{t-1}                | 0.014 [0.01]             | 0.003 [0.01]             | −0.011 [0.02]            | −0.048** [0.02]          |                         |                          |                          |
| Δy_{t-1}              |                         |                          |                          |                          | −0.144* [0.09]           |                          |                          |
| Δx_{t-1}              | 0.023** [0.01]           | 0.024 [0.02]             | 0.028* [0.02]           | 0.032* [0.02]           | 0.032                    | 0.028                    | 0.023* [0.01]           |
| Δx_{t-2}              | 0.006 [0.01]             | 0.024 [0.02]             | 0.015 [0.02]             | 0.031                    |                          |                          |                          |
| Δx_{t-3}              | 0.011 [0.02]             |                          |                          |                          | −0.003                   |                          |                          |
| Δx_{t-4}              |                          |                          |                          |                          |                          | 0.009                    |                          |
| Δx_{t-5}              |                          |                          |                          |                          |                          |                          | −0.006                   |
| Δx_{t-6}              |                          |                          |                          |                          |                          |                        |                          |
| Δx_{t-7}              | 0.017 [0.02]             | −0.025                   | 0.007                   | 0.016                   | 0.054** [0.02]          | 0.008                    | −0.006                   |
| Δx_{t-8}              | −0.023                   | −0.048** [0.02]          | −0.030                   | −0.008                   | 0.002                    |                          |                          |
| Δx_{t-9}              | 0.029** [0.01]           | 0.022                    | 0.055** [0.03]          |                          |                          |                          |                          |
| Δx_{t-10}            |                          |                          |                          |                          |                          |                        |                          |
| Constant              | 0.020 [0.06]             | 0.040 [0.06]             | 0.053                   | 0.033                   | 0.036 [0.06]             | 0.036                    | 0.049 [0.06]             |
| Observations (weeks)  |                          |                          |                          |                          | 0.057                    |                          |                          |
| F–Statistic           | 3.394** [0.02]           | 1.543                    | 2.534** [0.012]         | 1.467                   | 1.949* [0.088]          | 0.967                    | 1.788                    |
| RMSE                  | 0.008                    | 0.008                    | 0.008                   | 0.008                   | 0.008                    | 0.008                    | 0.008                    |

Notes: (1) Standard errors are presented in brackets. (2) p-values are noted in parentheses. (3) *p < 0.1, **p < 0.05, ***p < 0.01. (4) k = 4. (5) The superscripts + and − denote positive and negative variations, respectively. (6) STATA omitted insignificant coefficients because we have constrained them to zero. (7) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility. (8) GLDP is a dependent variable, whereas the rest (e.g., VIX and OVX) are independent variables, and each independent variable is framed under a separate equation, in line with the dependent variable (i.e., GLDP). (9) Observations are in weeks.

COVID-19 period shows some exclusive findings (Table 3). We argue that the crisis periods generally show an almost similar pattern when it comes to affecting gold prices by volatility indices.

We again find no long memory similar to the findings during- and pre-COVID-19 periods, as presented in Tables 4 and 5. A summary of the findings provided in Tables 3–5 is presented in Table 6.

3.5. Cumulative dynamic effects

Fig. 2a–u illustrate the findings of this study, presenting the asymmetric dynamic multipliers for the examined periods before and during the ongoing COVID-19 pandemic. These multipliers paint temporal adjustments to gold prices as part of a new long-term equilibrium contributed to by positive or negative shocks to the volatility indices over forty-week horizons. These multipliers have been determined following the best possible estimates offered by the constrained NARDL models. The positive and negative changes presented have been generated through bootstrapping based on one thousand replications.

Fig. 2a–g show that the impact of the negative changes in the volatility indices has holistically outweighed the impact of positive changes in the same volatility during the ongoing COVID-19 period. While the impact of positive changes in the volatility indices is higher than that of negative changes in the VIX, the opposite holds true for six other volatility indices. However, the duration of the asymmetry lasts forty weeks for all the volatility indices. The cumulative dynamic multiplier effects of the period before the COVID-19 pandemic (Fig. 2h–n) are mostly the opposite of those during the COVID-19 period. Positive changes in the volatility indices supersede the negative ones (except 2i–j and 2n). The asymmetries, however, lasted for forty weeks in all cases. The graphs (Fig. 2o–u) depicting the robustness test, on the other hand, exhibit similar results to the COVID-19 period, having asymmetry periods of forty weeks. This again highlights that crisis periods and succeeding volatilities usually behave identically, impacting financial and commodity markets.

These results validate the prior findings obtained in Tables 3–5, thereby underscoring our findings’ reliability in formulating strategies and making investment decisions.
Table 5
NARDL estimation (volatility → gold prices).

|                  | (1)          | (2)          | (3)          | (4)          | (5)          | (6)          | (7)          |
|------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| \( x : \)        | VIX          | OVX          | EVX          | GVX          | SVX          | EMVX         | ECVX         |
| \( y_{t-1} \)    | 0.003        | 0.002        | 0.002        | 0.003        | 0.002        | 0.003        | 0.003        |
| [0.00]           | [0.00]       | [0.00]       | [0.00]       | [0.00]       | [0.00]       | [0.00]       | [0.00]       |
| \( \Delta x_t \) | 0.021        | 0.009        | 0.016        | -0.086**     | -0.076***    | 0.008        | 0.004        |
| [0.02]           | [0.02]       | [0.03]       | [0.02]       | [0.02]       | [0.02]       | [0.02]       | [0.04]       |
| \( \Delta x_{t-1} \) | 0.006        | -0.014       | 0.023        | -0.018       | -0.021       | -0.019       |
| [0.01]           | [0.03]       | [0.03]       | [0.02]       | [0.02]       | [0.02]       | [0.03]       |
| \( \Delta x_{t-2} \) | -0.026       | -0.019       | -0.055**     | -0.020       | -0.061**     | -0.046**     | -0.064**     |
| [0.02]           | [0.03]       | [0.02]       | [0.02]       | [0.03]       | [0.02]       | [0.03]       |
| \( \Delta x_{t-3} \) | -0.001       | 0.003        | 0.003        | -0.024       | -0.022       | -0.016       | -0.024       |
| [0.03]           | [0.03]       | [0.03]       | [0.03]       | [0.03]       | [0.03]       | [0.03]       |
| Constant         | -0.009       | -0.015       | -0.013       | 0.024        | 0.022        | 0.028        |
| [0.02]           | [0.03]       | [0.03]       | [0.03]       | [0.03]       | [0.03]       | [0.04]       |
| Observations     | 249          | 249          | 249          | 249          | 249          | 249          | 249          |
| (weeks)          |              |              |              |              |              |              |              |
| F-Statistic      | 0.726        | 0.179        | 1.263        | 6.289***     | 6.974***     | 1.292        | 1.645        |
| (0.604)          | (0.970)      | (0.281)      | (0.000)      | (0.000)      | (0.268)      | (0.149)      |
| RMSE             | 0.011        | 0.011        | 0.011        | 0.010        | 0.010        | 0.011        | 0.011        |

Notes: (1) The Standard errors are presented in the brackets. (2) The p-values are noted in the parentheses. (3) \(* p < 0.1, ** p < 0.05, *** p < 0.01\) (4) \(k = 4\). (5) The superscripts + and − denote the positive and negative variables, respectively. (6) STATA omitted insignificant coefficients because we have constrained them to zero. (7) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility. (8) GLDP is the dependent variable, whereas the rest (e.g., VIX and OVX) are the independent variables, and each independent variable is framed under a separate equation, in line with the dependent variable (i.e., GLDP). (9) Observations are in weeks.

4. Conclusion

We have examined the nexuses between seven volatility indices and gold prices using daily data from March 2011 to March 2021, decomposed into pre-COVID-19 and during COVID-19 subperiods. The results show that during the ongoing COVID-19 subperiod, the positive gold volatility diminished gold prices. Further, positive silver and emerging market volatility and lagged and positive financial market volatility diminished gold prices. Our analysis of the pre-COVID-19 normal period from 2016 to 2019 suggests that the positive financial market, energy, gold, and eurocurrency volatility enhanced gold prices, while the negative silver volatility enhanced gold prices. However, the financial (equity) market and energy volatility enhanced gold prices regardless of whether the change was positive or negative. While lagged and negative financial market volatility diminished gold prices, the lagged and negative eurocurrency volatility increased gold prices. All these outcomes were evident in the short-term period only. In the long-term period, however, only negative eurocurrency volatility decreased gold prices and only during the 2016–2019 pre-COVID-19 period.

A robustness test of data from 2011 to 2015 (or the pre-COVID-19 period) confirms our findings on the COVID-19 subperiod, while it indicates that the uneven results during the ongoing COVID-19 pandemic are predominant because of the ongoing crisis. The effects of the post-global financial crisis, the European sovereign debt crisis, and the most significant decline in the gold performance of the past forty-five years occurred in June 2013 and over the following adjustments might have contributed to the negative results during the years 2011–2015. Concerning the similarity of the 2011–2015 and COVID-19 subperiods, we infer that the crisis periods generally show an almost similar pattern when it comes to affecting gold prices by volatility indices. Although, to some extent, the ongoing COVID-19 subperiod also reveals the same effects as 2011–2015, a three-week prior positive gold volatility increased prices, underlining the uniqueness of the ongoing COVID-19 than the pre-COVID-19 subperiod.

Notwithstanding the time horizons, whether before or during the COVID-19 pandemic, the lagged gold prices rarely impact gold prices in the short term and highly unlikely in the long term. During the ongoing COVID-19 crisis, however, the lagged gold prices have enhanced gold prices in the short term, indicating that this effect is due to the ongoing pandemic.

In disagreeing with Dutta (2018), we have found evidence showing that negative oil volatility negatively impacts gold prices, although it is only for one occasion in the short term, and solely during the 2016–2019 pre-COVID-19 normal period. Our findings suggest that during the economic turmoil, irrational investors’ behavior or panic reactions (Bampinas et al., 2019), such as during the COVID-19 years, and in the long term, gold is unlikely to be negatively affected by the examined
Table 6
Summary of the results.

| Term | Indices | Sign | (Jan '20–Mar '21) | 2016–2019 | 2011–2015 | Term | Indices | Sign | (Jan '20–Mar '21) | 2016–2019 | 2011–2015 |
|------|---------|------|-------------------|-----------|-----------|------|---------|------|-------------------|-----------|-----------|
| Volatility | Long-term | VIX | Positive | Negatively | | | Short-term (Volatility) | VIX | Positive | Negatively | | |
| | | OVX | Positive | Negatively | | | | OVX | Positive | Negatively | | |
| | | EVX | Positive | Negatively | | | | EVX | Positive | Negatively | | Positively |
| | | GVX | Positive | Negatively | | | | GVX | Positive | Negatively | Positively | Negatively |
| | | SVX | Positive | Negatively | | | | SVX | Positive | Negatively | Positively | Negatively |
| | | EMVX | Positive | Negatively | | | | EMVX | Positive | Negatively | Positively | Negatively |
| | | ECVX | Positive | Negatively | | | | ECVX | Positive | Negatively | Positively | Negatively |
| Lagged | Long-term | VIX | Positive | Negatively | | | Lagged VIX | Positive | Negatively | | |
| GLDP → GLDP | | OVX | | Lagged OVX | Positive | Negatively | | |
| | | EVX | | Lagged EVX | Positive | Negatively | | |
| | | GVX | | Lagged GVX | Positive | Positively | | |
| | | SVX | | | | | |
| | | EMVX | | | | | |
| | | ECVX | | | | | |
| Short-term | VIX | | Positively | | | | Lagged SVX | Positive | Negatively | | |
| | OVX | | | Lagged EMVX | Positive | Negatively | | |
| | EVX | | | Lagged ECVX | Positive | Positively | | |
| | GVX | | | | | | |
| | SVX | | | | | | |
| | EMVX | | | | | | |
| | ECVX | | | | | | |

Notes: (1) This table presents only the significant impacts of volatility indices on gold prices. (2) GLDP = Gold prices, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility.
seven volatility indices, and can therefore serve as a safe haven at least in the long term. Our findings partially contrast with the results of the study of Kirkulak Uludag and Lkhamazhapov (2014), who found that in the aftermath of the global financial crisis, gold became more disposed to high volatility and wide swings. Rather, we find that their statement is valid for the period 2011–2015 (owing to the post-global financial crisis, the European sovereign debt crisis, and the 2013 crisis in the gold market and the following adjustments) and during the ongoing COVID-19 subperiod, but not during the normal 2016–2019 years.

Our findings contrast with the results of study of Bredin et al. (2015), who have suggested that gold can serve as a hedging instrument for a period of one year. We contend that gold prices are most likely to benefit from (either increased or decreased) volatility in other markets during the normal subperiod (e.g., 2016–2019). By partially supporting the study of Singhal et al. (2019), we argue that under both stressed (in the long term) and unstressed economic conditions, gold functions as a safe asset (yet the safe-haven attribute of this metal is slightly pronounced during the short-term of the stressed economic conditions, as our results suggest), leading investors to buy gold as a hedging tool.

The decision to invest in gold over the short term could also plausibly give opportunities for investors to invest in this yellow metal as a safe-haven asset, yet investors need to act smartly and diligently to reap the benefits of such an investment in the short term. In other words, to some extent, gold can be considered a safe haven in the short term. This study is expected to benefit not only international investors and patrons but also policymakers and enthusiastic researchers who wish to make optimum investment decisions for both calm and turbulent situations. For example, out of the seven volatility indices, crude oil volatility impacts gold’s safe-haven status the least in the short term, highlighting that we may include crude oil in a diversified portfolio to diversify the risk in the short term. One may also wish to investigate whether other assets, such as United States Treasury securities (e.g., US T-bonds) and/or cryptocurrencies (e.g., bitcoin), can serve as a safe haven in the short term, especially during the COVID-19 crisis.

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**Appendix**

A1. BDS test for nonlinearity checks

| m | GLDP | 1.1133 | 1.6699 | 2.2265 |
|---|---|---|---|---|
| 2 | 2.8519*** (0.00) | −0.9401 (0.35) | 1.2480 (0.21) | 0.4108 (0.68) |
| 3 | 1.1484 (0.25) | −2.3928** (0.02) | 0.7401 (0.46) | 0.4446 (0.66) |
| 4 | 2.1172** (0.03) | −1.8314** (0.07) | 0.9574 (0.34) | 0.9470 (0.34) |
| 5 | 5.3758*** (0.00) | −1.8034** (0.07) | 1.1805 (0.24) | 1.4511 (0.15) |
| 6 | 9.7761*** (0.00) | −1.5241 (0.13) | 1.2760 (0.20) | 1.6981* (0.09) |

0.422 0.8439 1.2659 1.6878

(continued on next page)
| m     | VIX   | 0.5566 | 1.1133 | 1.6099 | 2.2265 |
|-------|-------|--------|--------|--------|--------|
| 2     | 0.5227 | (0.60) | 0.3145 | (0.75) | 0.2671 | (0.79) | 0.9923 | (0.32) |
| 3     | 2.3070** | (0.02) | 0.9527 | (0.34) | 0.5120 | (0.61) | 1.2000 | (0.23) |
| 4     | 4.1582*** | (0.00) | 1.2510 | (0.21) | 0.4923 | (0.62) | 1.0566 | (0.29) |
| 5     | 8.6633*** | (0.00) | 1.5018 | (0.13) | 0.4799 | (0.63) | 0.9760 | (0.33) |
| 6     | 11.9594*** | (0.00) | 1.4150 | (0.16) | 0.2935 | (0.77) | 0.6937 | (0.49) |
|       | 0.4639 |        | 0.9278 |        | 1.3916 |        | 1.8555 |        |
| OVX   | 2     | 1.2494 | (0.21) | 0.7982 | (0.42) | −0.9097 | (0.36) | −0.3651 | (0.72) |
| 3     | 2.6001** | (0.01) | 1.5625 | (0.12) | 0.8203 | (0.41) | 1.8358** | (0.07) |
| 4     | 2.4130** | (0.02) | 2.5922** | (0.01) | 1.2342 | (0.22) | 2.0153** | (0.04) |
| 5     | 6.0077*** | (0.00) | 3.4066*** | (0.00) | 1.4241 | (0.15) | 2.0295** | (0.04) |
| 6     | 4.9281*** | (0.00) | 3.6638*** | (0.00) | 1.5955 | (0.11) | 2.0559** | (0.04) |
|       | 0.4843 |        | 0.9685 |        | 1.4528 |        | 1.9371 |        |
| EVX   | 2     | 0.9978 | (0.32) | 2.3343** | (0.02) | 2.0335** | (0.04) | 1.4083 | (0.16) |
| 3     | −0.6228 | (0.53) | 2.0610** | (0.04) | 1.0487 | (0.29) | 0.4535 | (0.65) |
| 4     | −0.9341 | (0.35) | 1.0202 | (0.31) | 0.5404 | (0.59) | 0.3065 | (0.76) |
| 5     | −3.9629*** | (0.00) | 0.4043 | (0.69) | 0.5548 | (0.58) | 0.4589 | (0.65) |
| 6     | −6.6098*** | (0.00) | −0.8643 | (0.39) | 0.0907 | (0.93) | 0.2105 | (0.83) |
|       | 0.5298 |        | 1.0596 |        | 1.5894 |        | 2.1191 |        |
| GVX   | 2     | 2.2714** | (0.02) | 1.9710** | (0.05) | 1.6051 | (0.11) | 2.7439** | (0.01) |
| 3     | 7.1128*** | (0.00) | 1.4965 | (0.13) | 1.4313 | (0.15) | 3.4001*** | (0.00) |
| 4     | 4.2879*** | (0.00) | 1.8608* | (0.06) | 1.1503 | (0.25) | 3.5547*** | (0.00) |
| 5     | 2.0622*** | (0.04) | 2.3435** | (0.02) | 0.9656 | (0.33) | 3.4688*** | (0.00) |
| 6     | −1.5806 | (0.11) | 2.2613** | (0.02) | 0.9510 | (0.34) | 3.3435*** | (0.00) |
|       | 0.4764 |        | 0.9527 |        | 1.4291 |        | 1.9055 |        |
| SVX   | 2     | −1.1077 | (0.27) | −0.1320 | (0.90) | −0.7663 | (0.44) | −0.8151 | (0.42) |
| 3     | −1.0259 | (0.31) | 0.2861 | (0.77) | −0.4620 | (0.64) | −0.0382 | (0.97) |
| 4     | −0.5010 | (0.62) | −0.0552 | (0.96) | −0.8918 | (0.37) | −0.2344 | (0.81) |
| 5     | 2.9527*** | (0.00) | −0.0389 | (0.97) | −0.7694 | (0.44) | −0.0407 | (0.97) |
| 6     | 2.0825** | (0.04) | 0.5915 | (0.55) | −0.7768 | (0.44) | 0.0337 | (0.97) |
|       | 0.4454 |        | 0.8909 |        | 1.3363 |        | 1.7818 |        |
| EMX   | 2     | 2.3665** | (0.02) | 0.3518 | (0.73) | −0.1480 | (0.88) | −1.0261 | (0.30) |
| 3     | 2.9262*** | (0.00) | 0.6762 | (0.50) | 0.3678 | (0.71) | −0.3729 | (0.71) |
| 4     | 4.0939*** | (0.00) | 0.5503 | (0.58) | 0.6499 | (0.52) | −0.1190 | (0.91) |
| 5     | 2.6544** | (0.01) | 0.3149 | (0.75) | 0.6008 | (0.55) | −0.2478 | (0.80) |
| 6     | −4.1120*** | (0.00) | −0.2451 | (0.81) | 0.1725 | (0.86) | −0.4049 | (0.69) |
|       | 0.4911 |        | 0.9822 |        | 1.4732 |        | 1.9643 |        |
| ECX   | 2     | 1.7288 | (0.08) | 0.8161 | (0.41) | 0.3158 | (0.75) | 0.0475 | (0.96) |
| 3     | 0.9622 | (0.34) | 0.3947 | (0.69) | 0.0965 | (0.92) | −0.1029 | (0.92) |
| 4     | 0.0770 | (0.94) | −0.1550 | (0.88) | −0.4799 | (0.63) | −0.6396 | (0.52) |
| 5     | 3.3468*** | (0.00) | −0.3496 | (0.73) | −0.5970 | (0.55) | −0.8698 | (0.38) |
| 6     | 4.3010*** | (0.00) | −1.0033 | (0.32) | −0.6715 | (0.50) | −0.8883 | (0.37) |

Notes: (1) 'm' denotes Embedding dimension. (2) Epsilon for the close points is in the BOLD Font. (3) p-values (of the BDM Test) are noted in parentheses. (4) *p < 0.1, **p < 0.05, ***p < 0.01. (5) GDLP = Gold Returns, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMX = Emerging markets volatility, and ECX = Eurocurrency volatility.
A2. Descriptive statistics (summary of raw data)

| Variable | Obs.  | Mean   | Std. Dev. | Min.   | Max.   | Pearson Correlation* | p-value |
|----------|-------|--------|-----------|--------|--------|-----------------------|---------|
| GLDP     | 1043  | 1292.443 | 89.468 | 1062.380 | 1548.980 | 1.000 | 1.000 |
| VIX      | 1043  | 14.766  | 4.211 | 9.140  | 37.320  | -0.0159 | 0.6078 |
| OVX      | 1043  | 34.290  | 9.850 | 17.860  | 78.970  | -0.1771 | 0.0000 |
| EVX      | 1043  | 21.564  | 5.484 | 11.710  | 47.550  | -0.1698 | 0.0000 |
| GVX      | 1043  | 13.614  | 3.179 | 8.880  | 28.370  | -0.0479 | 0.1220 |
| SVX      | 1043  | 22.112  | 4.435 | 14.890  | 37.690  | 0.0163 | 0.5984 |
| EMVX     | 1043  | 20.310  | 4.412 | 13.280  | 39.310  | -0.2890 | 0.0000 |
| ECVX     | 1043  | 7.972   | 1.890 | 4.240  | 14.490  | -0.5425 | 0.0000 |

Notes: (1) ‘Dependent variable (e.g., GLDP) versus independent variable (e.g., VIX, OVX, and EVX).’ (2) p-values (of Pearson Correlation) are noted in parentheses. (3) *p < 0.1, **p < 0.05, ***p < 0.01. (4) GLDP = Gold Returns, VIX = Financial market volatility, OVX = Oil volatility, EVX = Energy volatility, GVX = Gold volatility, SVX = Silver volatility, EMVX = Emerging markets volatility, and ECVX = Eurocurrency volatility. (5) Observations are in weeks. (6) GLDP is the dependent variable, whereas the rest (e.g., VIX, OVX, and SVX) are the independent variables, and each independent variable is framed under a separate equation, in line with our dependent variable (i.e., GLDP).

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