Does strategic commodities price respond to U.S. Partisan Conflict? Evidence from a parametric test of Granger causality in quantiles

Yong Jiang
Business School, Hunan University, Changsha 410082, China

Abstract
Currently, U.S. politics have been characterized by a high degree of partisan conflict, which has led to increasing polarization and high policy uncertainty. Given the importance of U.S. in the global commodity market, we investigate whether U.S. partisan conflict affects the price performance (returns and volatility) of two strategic commodities (oil and gold). To this end, we employ a parametric test of Granger causality in quantiles proposed by Troster (2016), which can discriminate between causality affecting the median and the tails of the conditional distribution. Meanwhile, this approach allows us to investigate whether there exist different effects of U.S. partisan conflict index on the oil market and gold market under different market conditions. The empirical results suggest that U.S. partisan conflict can affect the returns of oil and gold, with the effects cluster around the tail of the conditional distribution of returns. More specifically, the partisan conflict mainly affects the oil returns when the crude oil market is in a bearish state (lower quantiles). By contrast, partisan conflict matters for gold returns only when the gold market is in a bullish scenario (higher quantiles). In addition, for the volatility of oil and gold, the predictability of partisan conflict index virtually covers the entire distribution of volatility. This study provides valuable implications for academics, policymakers, and investors.

Keywords: Strategic commodities; Oil and gold prices; Partisan Conflict; Granger causality in quantiles
1. Introduction

Oil and gold are the two most important commodities in the world, and improving the understanding of drivers of their prices is a longstanding research objective. To date, a large number of studies have investigated the impact factors of commodity prices. In general, as an internationally traded commodity, oil and gold be deemed to have the similar properties to ordinary commodities whose prices are mainly influenced by the supply-side factors and demand-side factors (Cai et al., 2001; Tully and Lucey, 2007; Kilian, 2009; Gallo et al., 2010; Coleman, 2012; Kim and Vera, 2018). In recent years, with the turbulence in the international situation and the slowdown in the global economic recovery process, strategic commodities especially for oil, whose economic importance and the geographical imbalance between availability and consumption make it become a politically sensitive commodity. Likewise, in regard to gold, it always is used by investors as a hedge in portfolio diversification and a safe haven in times of extreme economic, inflation and political turbulence and severe market turmoil (Baur and McDermott, 2010; Lau et al., 2017; O’Connor et al., 2015; Aye et al., 2016). Up to now, a vast body of literature provides evidence that the crude oil and gold price may tend to be sharply influenced by the non-fundamentals such as the economic policy uncertainty (EPU), investor attention and political risk (Coleman, 2012; Chen et al., 2016; Wang et al., 2017; Yao et al., 2017; Uddin et al., 2018). For example, evidence in Lombardi and Van Robays (2011) suggests that investors' risk perceptions and speculative behaviors have a strong influence over the movements of oil prices. Jones and Sackley (2016) incorporate the U.S. economic policy uncertainty index into a gold-pricing model and find that gold prices are positively related to EPU.

The U.S. is the largest consumer of crude oil and the second largest net importer of crude oil in the world (British Petroleum (BP), 2017). BP statistics show that the U.S. consumed 19631 thousand barrels per day in 2016, accounting for 20.3% of the world's consumption of crude oil. Since 2009, with the progress of shale oil recovery techniques, crude oil production in the US has gradually intensified, the U.S. has become the world’s second-largest oil producer, just after Saudi Arabia. In 2016, it produced 12.354 million barrels, accounting for a global share of 13.4%. It can be seen that the United States has an important position in the crude oil market, both in
supply and in demand aspects. Meanwhile, the US has the largest gold reserve in the world, reaching 8133.5 tons in 2017, accounting for 72.65% of its foreign exchange reserves. To sum up, given the importance of US in the global commodity market, it cannot ignore the role that the US has played in the price mechanism of international strategic commodities. Some evidence of U.S. factors such as U.S. EPU affecting oil price from structural vector autoregressive (SVAR) models applied to monthly data has been found in Kang and Ratti (2013a, 2013b) and Antonakakis et al. (2014). For gold market, Balcilar et al. (2017) find that there exists a causality running from U.S. EPU to gold returns.

Recent years, U.S. politics have been characterized by a high degree of partisan conflict. The combination of increasing polarization and the divided government may lead to the deepening panic for investors in the financial market. For example, Azzimonti (2018) has proven that U.S. partisan conflict affects the private investment. Gupta et al. (2017, 2018) provide evidence that the U.S. partisan conflict has a critical impact on the U.S. stock market. Fig.1 displays the dynamics of oil prices, gold prices and U.S. partisan conflict index. We use US refiner’s acquisition cost of crude oil as the measure of the global crude oil prices and gold price is obtained from London Bullion Market. As can be seen that, the partisan conflict index tends to increase near elections and during debates over such contentious policies as the debt ceiling and health-care reform (Azzimonti, 2018). For instance, the rise in partisan conflict accelerated during the Great Recession, peaking with the 2013 government shutdown. During the Trump-Clinton election in 2016, the index up to a peak again. What is more, it notes that after the financial crisis of 2008-2009, the US partisan conflict index has a significant upward trend. At the same time, it shows that the prices of crude oil and gold also have a corresponding upward trend, respectively. Through simple statistics based on Spearman's rank correlation coefficient approach, using the entire sample data we preliminarily estimate the correlation coefficient of the partisan conflict index and the crude oil price is 0.3, with the price of gold is 0.68. It indicates that there exists a link between the partisan conflict index and the price of crude oil and gold. However, how does the U.S. partisan conflict index affect the price movements of gold and oil, linear or nonlinear? Does the effect of the partisan conflict index on the returns and volatility of the two strategic commodities be homogeneous in different market conditions? It is of significance to answer these questions for managing risk, hedging and making investment decisions.
Fig. 1 Oil and gold prices and U.S. partisan conflict index from January 1981 to October 2017. Notes: Right axis is U.S. partisan conflict index. The shaded regions represent NBER recessions.

To address these issues, this paper obtains an index of U.S. partisan conflict (PCI) recently developed by Azzimonti (2018) as the proxy of U.S. partisan conflict condition, using a parametric test of Granger causality in quantiles recently proposed by Troster (2016) to study whether the U.S. partisan conflict can predict the returns and volatility of strategic commodities price. Our empirical analysis uses monthly data of oil and gold prices and of the U.S. partisan conflict indices spanning the January 1981 to October 2017. This paper makes several important contributions to
the literature as follows.

First, this paper contributes to the literature that examining the predictive effect of U.S. partisan conflict on the returns and volatility for oil and gold. Though some studies have considered the effect of non-fundamentals such as the EPU and investor sentiment, to date, there is little research has examined whether the U.S. partisan conflicts have an impact on the returns and volatility for oil and gold. By doing this, we provide a new indicator that can easily be observed for investors to track the dynamic characteristics such as returns and volatility on the price of crude oil and gold. To our knowledge, this is the first study to test this empirically and thus presents a contribution to the literature to date.

Second, concerning the volatility estimation of oil and gold, contrary to previous papers characterize the volatility of oil and gold prices by using some time-varying volatility models such as GARCH and SV models (Hammoudeh and Yuan, 2008; Ewing and Malik, 2016) but cannot identify which one is better among so many GARCH and SV models. By means of efficient approach, we compare a number of GARCH and SV models in a formal Bayesian model comparison exercise. The competing models include the standard models of GARCH (1,1) and SV with an AR(1) log-volatility process, as well as flexible models with jumps, volatility in mean, leverage effects, t distributed and moving average innovations (see Chan and Grant, 2016). To our knowledge, to date, only Chan and Grant (2016) have investigated and selected the best volatility model for oil price in their article. However, no study has explored which model can better describe the price volatility of gold.

Third, rather than focusing on specific episodes of market periods, this paper employs a parametric quantile causality testing approach which is powerful enough to consider all market conditions jointly (e.g., bearish, bullish, low volatility and high volatility). Therefore, we can examine the predictive ability of U.S. partisan conflict index for the oil market and gold market under different market conditions. This will allow us to see under what conditions the U.S. partisan conflict index could predict the oil and gold or does not.

Fourth and last, we are the first to use the parametric test of Granger causality in quantiles recently proposed by Troster (2016) to study whether U.S. partisan conflicts can cause the returns and volatility of oil and gold. The causality in quantile test approach has two novel aspects: first, the approach takes different locations and scales of the conditional distribution into account, which can provide more rich information
on causality between U.S. partisan conflicts and commodities prices than the traditional mean causality. Next, the approach can address the problem of structural break and sample segmentation. Existing studies have proved that oil and gold prices have nonlinear and structural mutation characteristics (Chen et al., 2014; Uludag and Lkhmazhapov, 2014; Gil-Alana et al., 2015) and which may have an adverse impact on linear model estimation (Troster, 2016). Traditionally, most literature such as Fan and Xu (2011), Pershin et al. (2016), chooses to segment the sample, but the sample segmentation will lose the sample information. The approach allows us to examine causal relationships at any chosen conditional quantiles without pre-selecting some arbitrary sub-samples (Jeong et al., 2012).

We provide evidence that there is no significant evidence supporting a causal link between the U.S. partisan conflict index and the oil and gold returns at the median of the conditional distribution. The explanatory power of U.S. partisan conflict index on the oil and gold returns tends to cluster around at the tails of the conditional distribution. More specifically, the partisan conflict has a strong predictive power on the oil returns when the crude oil market is in a bearish state, however, under a bullish state, the impact of the partisan conflict on oil returns is not significant. By contrast, partisan conflict matters for gold returns only when the gold market is in a bullish market. It is found that for gold returns at lower quantiles, the partisan conflict index has limited predictive power on the gold returns, with the 0.2 quantiles being an exception. In addition, it is proven that the U.S. partisan conflict index significantly affects the volatility of oil and gold prices over the entire conditional distribution, i.e., at various phases of the oil and gold market.

The remainder of the paper is organized as the following: Section 2 provides a brief relevant literature review. Section 3 presents the data and preliminary analysis. Section 4 introduces the empirical methodologies and research framework. Section 5 discusses the empirical results. Section 6 summarizes the major conclusions of this study and some policy implications.

2. Literature

The continued financialization in commodities markets over the last decade together with their use as a diversifier, hedge and safe haven for different traditional investments have generated a great deal of interest in the predictability of commodities returns and volatilities. Especially oil and gold are the world's most
important two commodities, and improving the understanding of drivers of their prices is a longstanding research objective. Recent years, with the deeper of financialization of the crude oil and gold market, a larger body of literature focuses on the non-fundamental factors such as EPU, investor attention, and political risk, and so on. In this section, we collate the recent studies on the impact of non-fundamental factors on the price of crude oil and gold.

For oil market, Hamilton (2009) analyzes the cause and influence of oil price shocks between 2007 and 2008 and concludes that most of the shocks are triggered by the politics-induced oil production halts. Aloui et al. (2016) use a copula approach have investigated the effect of equity and EPU on crude-oil returns, find that higher uncertainty, as measured by equity and EPU indices, significantly increase crude-oil returns only during certain periods of time. Balcilar et al. (2017) use a nonparametric quantile causality test and argue that U.S. EPU and equity market uncertainty have strong predictive power for oil returns over the entire distribution barring regions around the median, for oil volatility the predictability virtually covers the entire distribution. Chen et al. (2016) use the SVAR model and investigate the impacts of OPEC's political risk on the Brent crude oil prices, and find that the political risk of OPEC countries does have a significant and positive influence on Brent crude. Uddin et al. (2018) select the EPU index of US and Europe, implied US bond volatility index, the US VIX index, market sentiment and speculation index of US as the geopolitical risks, using an entropy-based wavelet method study the impact of geopolitical risks on the oil price changes. Yao et al. (2017), Han et al. (2017) and Afkhami et al. (2017) provide evidence that investor attention for the oil market has strong predictive power on oil prices. Qadan and Nama (2018) show that investor sentiment, captured by nine different proxies such as U.S. EPU and consumer confidence index has a significant effect on the returns and volatility of oil prices.

With regard to gold market, Jones and Sackley (2016) incorporate an index of the U.S. and European EPU into a gold-pricing model and find that gold prices are positively related to EPU. The results suggest that the safe haven status of gold induces an increase of its price in times of high uncertainty. Using a nonparametric causality-in-quantiles test, Balcilar et al. (2016) have confirmed that the policy and equity-market uncertainty can affect gold-price returns and volatility. Baur and Dimpfl, (2016) choose the internet search queries for gold as the investor's attention to gold price movements and find a positive relationship between the gold price
volatility and search queries. Li and Lucey (2017) find that EPU is a positive determinant of gold being an investment safe haven. Balcilar et al. (2017) find that the effect of investor sentiment is more prevalent on intraday volatility in the gold market, rather than daily returns. Bilgin et al. (2018) use U.S. partisan conflict index as the proxy of policy uncertainty and find that worsening EPU contributes to increases in the price of gold. Raza et al. (2018) find that EPU causes gold prices in all the examined countries (G7 and China)

To sum up, while a substantial number of studies examine the determinants of oil and gold prices from the non-fundamental factors such as geopolitical risk, investor sentiment or attention and EPU, little research has considered the effect of U.S. partisan conflict on the gold price. In this paper, we try to fill this gap.

3. Methodology

This section presents our empirical framework that is twofold. First, we introduce two classes of time-varying volatility models: the generalized autoregressive conditional heteroscedastic (GARCH) models and the stochastic volatility (SV) models to estimate the conditional volatility of oil and gold. Meanwhile, we examine which one model is the best to model the price volatility of oil and gold by comparing the Bayes factor. Then, we employ a novel parametric test of Granger causality in quantiles proposed by Troster (2016) to investigate the ability of U.S. partisan conflict index in predicting the returns and volatility of oil and gold prices, respectively.

3.1. Time-varying volatility models: GARCH and SV models

In this section, we discuss the two classes of time-varying volatility models used in the model comparison exercise. The competing models include the standard models of GARCH (1,1) and SV with an AR (1) log-volatility process, as well as flexible models with jumps, volatility in mean, leverage effects, and t distributed and moving average innovations (for detailed model descriptions see Chan and Grant, 2016).

Both the GARCH and SV models are estimated using Bayesian techniques. One key step in estimating the SV models is the joint sampling of the log volatilities. That step is done by using the acceptance-rejection Metropolis-Hastings algorithm described in Chan (2017), which is based on the precision sampler of Chan and Jeliazkov (2009). A novel feature of this algorithm is its use of fast band matrix
routines rather than using the conventional Kalman filter. In general, the former approach is more efficient than the latter.

We follow Chan and Grant (2016) and introduce an overview of Bayesian model comparison via the Bayes factor and outline an efficient approach to compute the Bayes factor using importance sampling. Since the Bayes factor is simply a ratio of two marginal likelihoods, researchers often only report the marginal likelihoods of the set of competing models (Chan and Grant, 2016). In this paper, we also list the marginal likelihoods of different volatility models. Hence, if the observed data are likely under the model $M_1$, the associated marginal likelihood would be “largest” among these competing models.

**Table 1** GARCH models and SV models

| Pane 1: GARCH models |   |
|----------------------|---|
| GARCH                | GARCH(1,1) model where $\sigma^2_2$ follows a stationary AR(1) |
| GARCH-2              | Same as GARCH but follows $\sigma^2_2$ a stationary AR(2) |
| GARCH-J              | Same as GARCH but the price equation has a “jump” component |
| GARCH-M              | Same as GARCH but $\sigma^2_2$ enters the prices equation as a covariate |
| GARCH-MA             | Same as GARCH but the observation error follows an MA(1) |
| GARCH-t              | Same as GARCH but the observation error follows a t distribution |
| GARCH-GJR            | GARCH with a leverage effect |

| Pane 2: SV models    |   |
|----------------------|---|
| SV                   | SV model where $h_t$ follows a stationary AR(1) |
| SV-2                 | Same as SV but $h_t$ follows a stationary AR(2) |
| SV-J                 | Same as SV but the price equation has a "jump" component |
| SV-M                 | Same as SV but $h_t$ enters the prices equation as a covariate |
| SV-MA                | Same as SV but the observation error follows an MA(1) |
| SV-t                 | Same as SV but the observation error follows a t distribution |
| SV-L                 | SV with a leverage effect |

Notes: $\sigma^2_2$ and $h_t$ denote the conditional variance. For detailed model descriptions, see Chan and Grant (2016).

### 3.2. Granger causality in quantiles

A novel methodology is presented here, as proposed by Troster (2016), which can be employed to examine the ability of U.S. partisan conflict index in predicting the returns and volatility of oil and gold prices across different conditional quantiles. In this paper, we denote U.S. partisan Conflict index as $Z_t$ and the returns and volatility of the oil and gold price as $Y_t$, respectively.

According to Granger (1969), a series $Z_t$ does not Granger-cause another
series \( Y \), if past \( Z \) does not help to predict future \( Y \) given past \( Y \). Suppose explanatory vector \( I_t := \left( I_t^Y, I_t^Z \right) \in R^d \), \( d = s + q \), where \( I_t^Y := \left( Y_{t-1}, ..., Y_{t-s} \right) \in R^s \) and \( I_t^Z := \left( Z_{t-1}, ..., Z_{t-q} \right) \in R^q \). We characterize the null hypothesis of Granger non-causality from \( Z \) to \( Y \) as follows:

\[
H_0 \Rightarrow \quad y_t \mid I_t^Y, I_t^Z = F_y \left( y_t \mid I_t^Y \right), \quad \text{for all } Y \in R. \tag{1}
\]

Where \( F_y \left( y_t \mid I_t^Y, I_t^Z \right) \) and \( F_y \left( y_t \mid I_t^Y \right) \) be the conditional distribution functions of \( Y \) given \( \left( I_t^Y, I_t^Z \right) \) and \( I_t^Y \), respectively. We denote the null hypothesis of (1) as Granger non-causality in distribution. Since the estimation of the conditional distribution may be complicated in practice, many articles have tested Granger non-causality in mean, which is only a necessary condition for (1). In this case, \( Z \) does not Granger cause \( Y \) in mean if

\[
E \left( Y \mid I_t^Y, I_t^Z \right) = E \left( Y \mid I_t^Y \right) \quad \text{a. s.,} \tag{2}
\]

where \( E \left( Y \mid I_t^Y, I_t^Z \right) \) and \( E \left( Y \mid I_t^Y \right) \) are the mean of \( F_y \left( \cdot \mid I_t^Y, I_t^Z \right) \) and \( F_y \left( \cdot \mid I_t^Y \right) \), respectively. Granger non-causality in mean of (2) can be easily extended to higher order moments. However, causality in mean overlooks the dependence that may appear in conditional tails of the distribution. Besides, the Granger non-causality distribution of (1) does not inform us about the level where the causality exists, if (1) is rejected. Thus, we propose to test Granger non-causality in conditional quantiles, since it allows us to determine the pattern of causality and it provides a sufficient condition for testing Granger non-causality in the distribution of (1), as the quantiles completely characterize a distribution. Let \( Q_{\tau}^{Y,Z} \left( I_t^Y, I_t^Z \right) \) be the \( \tau \)-quantiles of \( F_y \left( \cdot \mid I_t^Y, I_t^Z \right) \), we can rewrite Eq. (1) as follows:

\[
H_0^{QC} \Rightarrow \quad \tau \left( y_t \mid I_t^Y, I_t^Z \right) = Q_{\tau}^{Y} \left( Y_t \mid I_t^Y \right), \quad \text{a. s. for all } \tau \in \Gamma, \tag{3}
\]

where \( \Gamma \) is a compact set such that \( \Gamma \subset [0,1] \) and the conditional \( \tau \)-quantiles of \( Y \) satisfy the following restrictions:

\[
\Pr \left( Y_t \leq Q_{\tau}^{Y} \left( Y_t \mid I_t^Y \right) \right) = \tau, \quad \text{a. s. for all } \tau \in \Gamma, \tag{4}
\]

\[
\Pr \left( Y_t \leq Q_{\tau}^{Y,Z} \left( Y_t \mid I_t^Y, I_t^Z \right) \right) = \tau, \quad \text{a. s. for all } \tau \in \Gamma
\]
Given an explanatory vector \( I_t \), we have
\[
\Pr \{ Y_t \leq Q_t(Y_t | I_t) | I_t \} = E \{ I \{ Y_t \leq Q_t(Y_t | I_t) \} | I_t \},
\]
where \( I(Y_t \leq y) \) is an indicator function of the event that \( a \) is less or equal than \( y \). Thus (3) is equivalent to
\[
\left\{ 1 \{ Y_t \leq Q_t^{r,z}(Y_t | I^r_t, I^z_t) | I^r_t, I^z_t \} \right\} = E \left\{ 1 \{ Y_t \leq Q_t(Y_t | I_t) \} | I^r_t, I^z_t \right\},
\]
a.s. for all \( \tau \in T \), \hspace{1cm} (5)
where the left-hand side of (5) is equal to the \( \tau \) -quantile of \( F_t(Y_t | I^r_t, I^z_t) \) by definition. Following Troster (2016), we postulate a parametric model to estimate the \( \tau \) th quantile of \( F_t(Y_t | I^r_t, I^z_t) \), where we assume that \( Q_t(Y_t | I_t) \) is correctly specified by a parametric model \( m(\cdot, \theta(\tau)) \) belonging to a family of functions \( M = \{ m(\cdot, \theta(\tau)) | \theta(\cdot) \tau \mapsto \theta^\rho, \text{ for } \tau \in T \subset [0,1] \} \). Let \( B \subset M \) be a family of uniformly bounded functions \( \tau \mapsto \theta(\tau) \) such that \( \theta(\tau) \in \Theta \subset R^\rho \). Then, under the null hypothesis in (3), the \( \tau \) -conditional quantile \( Q_t^\tau(Y_t | I^r_t) \) is correctly specified by a parametric model \( m(I^r_t, \theta_0(\tau)) \), for some \( \theta_0 \in B \), using only the restricted information set \( I^r_t \), and we redefine our testing problem in (3) as
\[
H_0^{\tau} : \{ 1 \{ Y_t \leq m(I^r_t, \theta_0(\tau)) \} | I^r_t, I^z_t \} = \tau, \text{ a. s. for all } \tau \in T, \hspace{1cm} (6)
\]
versus:
\[
H_A^{\tau} : \{ 1 \{ Y_t \leq m(I^r_t, \theta_0(\tau)) \} | I^r_t, I^z_t \} \neq \tau, \text{ for some } \tau \in T, \hspace{1cm} (7)
\]
where \( m(I^r_t, \theta_0(\tau)) \) correctly specifies the true conditional quantile \( Q_t^\tau(Y_t | I^r_t) \), for all \( \tau \in T \). We rewrite (6) as \( H_0^{\tau} \). ~ \{ 1 \{ Y_t - m(I^r_t, \theta_0(\tau)) \leq \tau \} | I^r_t, I^z_t \} = 0 \) almost surely, for all \( \tau \in \Gamma \). Then we can characterize the null hypothesis (6) by a sequence of unconditional moment restrictions:
\[
H_0^{\tau} : \{ 1 \{ Y_t - m(I^r_t, \theta_0(\tau)) \leq \tau \} | i \omega I_t \} = 0, \hspace{1cm} (8)
\]
where \( \exp(i \omega I_t) = \exp \left[ i \left( \sigma_1(Y_{t-1}, Z_{t-1}) + \ldots + \sigma_r(Y_{t-r}, Z_{t-r}) \right) \right] \) is a weighting function, for all \( \sigma \in R^d \) with \( r \leq d \), and \( i = \sqrt{-1} \) is the imaginary root. The rest
statistic is a sample analog of \( E \left[ \left[ I \left( Y_t - m^T \left( I^T \theta_0 (\tau) \right) \right) \leq 0 \right] - \tau \right] \exp (i \omega I_t) \) :

\[
v_T (\omega, \tau) := \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \left[ I \left( Y_t - m^T \left( I^T \theta_0 (\tau) \right) \right) \leq 0 \right] - \tau \right] \exp (i \omega I_t)
\] (9)

where \( \theta_\tau \) is a \( \sqrt{T} \)-consistent estimator of \( \theta_0 (\tau) \), for all \( \tau \in T \). Then, we apply the test statistic proposed by Troster (2016):

\[
S_T := \int \int v_T (\omega, \tau) \right\}^2 \text{d}F_x (\omega) \text{d}F (\tau)
\] (10)

where \( F_x (\cdot) \) is the conditional distribution function of the ad-variate standard normal random vector, \( F (\cdot) \) as a uniform discrete distribution over a grid of \( T \) in \( n \) equi-distributed points, \( T = \{ \tau \}^n_{j=1} \). And the vector of weights \( \omega \in R^d \) is drawn from a standard normal distribution. The test statistic in (10) can be estimated using its sample counterpart. Let \( \Psi \) be the \( T \times n \) matrix \( \Psi \) with elements \( \psi_{ij} = \Psi (Y_t - m^T \left( I^T \theta_\tau (\tau) \right)) \). Then, the test statistic \( S_T \) has the form

\[
S_T = \frac{1}{Tn} \sum_{j=1}^{n} \left| \psi_j \right| W \psi_j
\] (11)

where \( W \) is the \( T \times T \) matrix with elements \( w_{i,s} = \exp \left[ -0.5 \left( I_i - I_s \right)^2 \right] \), and \( \psi_j \) denotes the \( j \)th column of \( \Psi \). It rejects the null hypothesis whenever it observes “large” values of \( S_T \).

We use the subsampling procedure of Troster (2016) to calculate critical values for \( ST \) in Eq. (14). Given our series \( \{ X_t = (Y_t, Z_t) \} \) of sample size \( T \), we generate \( B = T - b + 1 \) subsamples of size \( b \) (taken without replacement from the original data) of the form \( \{ X_t, \ldots \} \). Then, the test statistic \( S_T \) in Eq. (11) is calculated for each subsample; we obtain p-values by averaging the subsample test statistics over the \( B \) subsamples. Following Troster (2016), we choose a subsample of size \( b = [kT^{2/5}] \), where \( [\cdot] \) is the integer part of a number, and \( k \) is a constant parameter. To apply the ST test in Eq. (14), we specify three different QAR models \( m(\cdot) \), for all \( \tau \in \Gamma \subset [0,1] \), under the null hypothesis of non-Granger-causality in Eq. (9) as follows:

\[
QAR(1): m^T (I^T \theta (\tau)) = \mu_1 (\tau) + \mu_2 (\tau) Y_{t-1} + \sigma_\psi \Phi^{-1} (\tau)
\]
\[ QAR(2) : m^2(I^Y_t, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \sigma_i^2 \Phi_u^{-1}(\tau) \]

\[ QAR(3) : m^3(I^Y_t, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_4(\tau)Y_{t-2} + \mu_5(\tau)Y_{t-3} + \sigma_i^2 \Phi_u^{-1}(\tau) \] (12)

Where the parameters \( \theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_i) \) are estimated by maximum likelihood in an equally spaced grid of quantiles, and \( \Phi_u^{-1}(\cdot) \) is the inverse of a standard normal distribution function. To verify the signature of the causal relationship between the variables, we estimate the quantile autoregressive models in Eq. (12) including lagged variables of another variable. For simplicity, we present the results using only a QAR (3) model with the lagged values of the other variable as follows:

\[ Q^Y_t(\gamma | I^Y_t, I^\gamma_t) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_4(\tau)Y_{t-2} + \mu_5(\tau)Y_{t-3} + \beta(\tau)Z_{t-1} + \sigma_i^2 \Phi_u^{-1}(\tau) \] (13)

4. Data

This paper empirically investigates the ability of U.S. partisan conflict index in predicting the returns and volatility of oil and gold prices, using monthly data covering the time period from January 1981 to October 2017, with the start and end dates being purely driven by data availability. We use the U.S. partisan conflict index, developed by Azzimonti (2018), which is obtained from the website of Federal Reserve Bank of Philadelphia\(^2\). This index tracks the degree of political disagreement among U.S. politicians at the federal level by measuring the frequency of newspaper articles reporting disagreement in a given month. Higher index values indicate greater conflict among political parties, Congress, and the President.

We use the US refiner’s acquisition cost of crude oil as the measure of the global crude oil prices which can be obtained from the US Energy Information Administration (EIA) in the United States Department of Energy\(^3\). While the gold price used in this paper is the Gold Fixing Price at 3:00 P.M. (London time) in the London Bullion Market, based in U.S. Dollars, which is obtained from the FRED database of the Federal Reserve Bank of St. Louis\(^4\). The oil and gold prices are divided by the US consumer price index (CPI) from the Bureau of Labor Statistics to obtain the real price. The returns are measured in terms of the first-differenced natural logarithm of the real oil and gold prices.

\(^2\) https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index
\(^3\) www.eia.gov/.
\(^4\) https://research.stlouisfed.org/fred2/
The summary statistics of the variables have been reported in Table 1. As can be seen, oil returns have higher volatility than gold returns. Oil returns are skewed to the left, and gold returns and U.S. partisan conflict index skewed to the right, with all the variables having excess kurtosis. The Jarque–Bera test overwhelmingly rejects the null of normality, and this evidence of fat tails in the variables provides us the preliminary motivation to use causality-in-quantile test rather than standard linear Granger causality test based on the conditional mean.

Table 1 summary statistics

|                      | Gold returns | Oil returns | Log Partisan conflict index |
|----------------------|--------------|-------------|----------------------------|
| Mean                 | -0.064       | -0.119      | 4.627                      |
| Median               | -0.322       | 0.196       | 4.572                      |
| Maximum              | 17.587       | 36.641      | 5.603                      |
| Minimum              | -15.194      | -33.942     | 4.081                      |
| Std. Dev.            | 3.895        | 7.437       | 0.266                      |
| Skewness             | 0.162        | -0.552      | 0.811                      |
| Kurtosis             | 5.180        | 6.743       | 3.580                      |
| Jarque-Bera          | 89.468***    | 280.452***  | 54.598***                  |
| Observations         | 442          | 442         | 442                        |

Notes: Std.Dev denotes standard deviation; *** denotes the rejection of the null of normality of the Jarque-Bera test at 1% level of significance.

With regard to the evaluation of price volatility for oil and gold, all the time-varying volatility models used in this paper are estimated by Bayesian techniques (see Chan and Grant, 2016) in this paper. The marginal likelihoods are computed using the improved cross-entropy method of Chan and Eisenstat (2015). The model comparison results are reported in Table 3. Overall, it suggests that the best model for modeling the price volatility of oil and gold is the SV-MA model. The marginal likelihood of the SV-MA model for estimating the volatility of crude oil and gold prices is the largest, -1393.9 and -1196.2, respectively. Therefore, in this paper, we employ the SV-MA model to measure the price volatility of the crude oil and gold. This finding of oil volatility estimation is in line with Chan and Grant (2016) who have proved that the SV-MA model is the best one for estimating oil price volatility.

Furthermore, we also investigate which features are important in modeling the dynamic volatility of oil and gold prices by comparing the different GARCH and SV models. By comparing the GARCH with the GARCH-2 and the SV with the SV-2, we conclude that the richer AR (2) volatility process provides a higher marginal
likelihood of a model. Thus, for modeling volatility of oil and gold prices, the volatility models with the AR (2) volatility process are better than the models with AR (1) volatility process.

Next, we examine the importance of volatility feedback for modeling price volatility of oil and gold. We find that adding the volatility feedback component markedly increases the marginal likelihood of SV model for oil and gold. By comparison, the model-fit cannot be improved by adding the volatility feedback component in the GARCH for the gold prices.

To investigate the relevance of the moving average component, we compare the GARCH with the GARCH-MA and the SV with the SV-MA. For SV models, adding the MA component improves the model-fit for the crude oil and gold prices. However, for GARCH models, the marginal likelihood cannot be improved by adding the MA component for the crude oil and gold.

We also examine whether the GARCH model and SV model with the “jump” can better shape the price volatility of crude oil and gold than the conventional GARCH and SV model. It shows that the marginal likelihood has improved when adding the jump component into GARCH and SV models. Therefore, it is essential to consider the jump component in the GARCH model and SV model when modeling the price volatility of crude oil and gold.

Finally, by comparing the GARCH with the GARCH-GJR and the SV with the SV-L, we conclude that the leverage effect is important for modeling price volatility of the crude oil and gold compared to the conventional GARCH and SV model without the specification of leverage. As we know, the leverage effects are important for stock returns and crude oil price (Chan and Grant, 2016). These results support the fashionable argument of ‘financialization’ of the crude oil and gold market.

Table 2 Log marginal likelihoods of GARCH and SV models for the crude oil and gold price. The numerical standard errors are in parentheses.

|          | Crude oil | Gold |
|----------|-----------|------|
| GARCH    | -1460.3   | -1213.3 |
|          | (0.02)    | (0.02) |
| SV       | -1433.6   | -1200.2 |
|          | (0.03)    | (0.02) |
| GARCH-2  | -1458.7   | -1213.6 |
|          | (0.04)    | -0.06 |
We perform standard unit root tests to determine whether the returns and volatility of oil and gold and U.S. partisan conflict index series are stationary and results are reported in Table 2. According to results in Table 2, the Augmented Dickey and Fuller (ADF, 1981) Phillips and Perron (PP, 1988) (PP) tests reject the null hypothesis of non-stationarity for all series. However, a major shortcoming with the standard unit root tests is that they do not allow for the possibility of structural breaks. Therefore, we follow Perron (1997) by allowing a break at an unknown location on both the trend and the intercept. We evaluate the test statistic focusing on the returns and volatility of oil and gold, and U.S. partisan conflict index. Table 2 reports the results of the Perron (1997) unit root test and estimated break date. The Perron unit root tests confirm these series are stationary, and there exists a break for oil returns,
gold returns and partisan conflict index at 2008:12, 1982:9 and 2009:12, respectively. Meanwhile, it detects that the oil volatility and gold volatility exist a break at 2008:10 and 1982:09, respectively. This finding of breakpoints in the returns and volatility of oil and gold and partisan conflict index indicates that the linear model based on mean estimation may not be suitable to depict the relationship between them.

Table 3 unit root test

|                | ADF     | PP      | Perron break test |
|----------------|---------|---------|-------------------|
|                | C       | C+T     | C                 | C+T    | C+T    | date    |
| Conflict       | -2.623* (3) | -3.096*** (3) | -5.357*** (6) | -6.637*** (8) | 6.229*** (3) | 2009m12 |
| Oil            | -12.045*** (1) | -12.054(1) | -10.869(17)      | -10.803*** (18) | -12.562*** (2) | 2008m12 |
| Gold           | -18.243*** (0) | -18.446*** (0) | -18.265*** (8)  | -18.402*** (7) | -19.261*** (0) | 1982m9  |
| Oil-VOL        | -4.006*** (1) | -4.487*** (1) | -2.942** (12)    | -3.311(12)     | -5.864*** (1) | 2008m10 |
| Gold-VOL       | -3.242*(1) | -3.152*(1) | -2.593*(14)      | -2.475(14)     | -4.900** (1) | 1982m9  |

Notes: C denotes constant, T denotes trend; ** and *** indicate significance at the 5% and 1% level, respectively. Oil and Gold represent the returns of oil and gold, respectively. Oil-VOL and Gold-VOL denote the price volatility of oil and gold based on the estimation of SV-MA model, respectively. The numbers in parentheses are the optimal lag order in the ADF and PP test based on the Schwarz Info criterion and Newey-west bandwidth.

5. Empirical results and discussions

5.1. Linear Granger causality test

Though our objective is to analyze the quantile causality running from the U.S. partisan conflict index to the returns and volatility of oil and gold prices, for the sake of completeness and comparability, we also conducted the standard linear Granger causality test (Granger, 1969) based on the VAR model. The lag parameters for VAR model are selected based on the Akaike information criterion (AIC). Table 4 presents the results for linear Granger causality test. As can be seen from Table 4, the null hypothesis of non-causality from U.S. partisan conflict index to the returns of oil and gold cannot be rejected at the 10% significance level. For the price volatility of gold, the null hypothesis of non-causality from the U.S. partisan conflict index to the volatility of gold can be rejected at the 5% significance level. However, for oil price volatility, the null hypothesis cannot be rejected. These results estimated in our paper may be due to the misspecification of the test model. It is well-known that the linear Granger causality test can miss the important nonlinear causal relationship (Balcilar et
Therefore, the insufficient or weak evidence for the causal relationship can be attributed to the low power of the linear Granger causality test if the time series analyzed are nonlinear or non-normal.

Table 4 Linear Granger causality test (U.S. Partisan Conflict and oil and gold price)

| Null hypothesis             | Lag | Chi-sq | P-value | Causality or not |
|-----------------------------|-----|--------|---------|------------------|
| **Panel 1:** oil and gold price changes |      |        |         |                  |
| *partisam* ↔ *oil*          | 8   | 9.003  | 0.342   | NO               |
| *oil* ↔ *partisam*          | 8   | 14.567*| 0.068   | Yes              |
| *partisam* ↔ *gold*         | 8   | 7.686  | 0.465   | NO               |
| *gold* ↔ *partisam*         | 8   | 10.738 | 0.217   | NO               |
| **Panel 2:** oil and gold price volatility |      |        |         |                  |
| *partisam* ↔ *oil*          | 8   | 9.052  | 0.338   | No               |
| *oil* ↔ *partisam*          | 8   | 3.544  | 0.896   | NO               |
| *partisam* ↔ *gold*         | 8   | 16.886** | 0.031 | Yes              |
| *gold* ↔ *partisam*         | 8   | 11.019 | 0.201   | No               |

Notes: *, **and ***indicate significance at the 10%, 5% and 1% level, respectively; the symbol ↔ represents the null hypothesis of Granger non-causality. The lag parameters are selected based on the Akaike information criterion (AIC). Yes in the last column indicates that the null hypothesis was rejected at least at the 10% significance level.

5.2. BDS test for the nonlinear feature

In order to motivate the use of the causality test in quantiles, in this section, we investigate the possibility of nonlinearity in the relationship between the U.S. partisan conflict index and returns and volatility of oil and gold prices. To this end, following Balcilar et al. (2017), we apply the BDS test (Broock et al., 1996) on the residuals of the returns and volatility of oil and gold price equation of the VAR(8) involving (relative) the U.S. partisan conflict, respectively. The BDS test is one of the most popular tests for nonlinearity. It is carried out by testing if increments to a data series are independent and identically distributed (i.i.d.). The test is asymptotically distributed as standard normal under the null hypothesis of i.i.d. increments. The basis of the BDS test is the concept of a correlation integral. A correlation integral is a measure of the frequency with which temporal patterns are repeated in the data.

The results of BDS test are reported in Table 5. As shown in the panel 1 of Table 5, for the returns and volatility series of oil and gold prices, the null hypothesis of i.i.d. residuals is strongly rejected at 1% level of significance across various dimensions (m). From the panel 2 and 3 of Table 5, we also see that for the residuals of the returns and volatility of oil and gold price equation of the VAR(8) involving (relative) the U.S. partisan conflict also pass the BDS test at the 1% significance level. It
indicates the relationship between the U.S. partisan conflict index and returns and volatility of oil and gold prices is nonlinearity and implies that the Granger causality tests based on a linear framework are likely to suffer from misspecification. In other words, the results of the linear test for Granger non-causality cannot be deemed robust and reliable.

Table 5 BDS tests

|        | m   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| Oil returns | 0.041*** | 0.065*** | 0.084*** | 0.095*** | 0.097*** |
| Gold returns | 0.014*** | 0.030*** | 0.038*** | 0.046*** | 0.050*** |
| Oil volatility | 0.185*** | 0.309*** | 0.390*** | 0.440*** | 0.469*** |
| Gold volatility | 0.196*** | 0.331*** | 0.422*** | 0.483*** | 0.522*** |

Panel 2: BDS test for the residuals of commodity price changes equation of the VAR model with Partisan Conflict

|        | m   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| Oil returns-VAR(8) | 0.022*** | 0.040*** | 0.052*** | 0.060*** | 0.065*** |
| Gold returns-VAR(8) | 0.015*** | 0.031*** | 0.040*** | 0.049*** | 0.053*** |

Panel 3: BDS test for the residuals of commodity price volatility equation of the VAR model with Partisan Conflict

|        | m   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| Oil volatility-VAR(8) | 0.035*** | 0.059*** | 0.074*** | 0.079*** | 0.078*** |
| Gold volatility-VAR(8) | 0.019*** | 0.035*** | 0.048*** | 0.056*** | 0.057*** |

Notes: The *** indicates significance at the 1% level. The parameter m is the embedding dimension. The lag parameters for VAR model are selected based on the Akaike information criterion (AIC). m stands for the embedded dimension.

5.3. Non-linear Granger causality tests

Given the strong evidence of nonlinearity obtained from the BDS tests, we further investigate whether there exists nonlinear Granger causality running from the U.S. partisan conflict index to the returns and volatility of commodities prices. To this end, we use the nonlinear Granger causality test of H&J test (Hiemstra and Jones, 1994) and D&P test (Diks and Panchenko, 2006). The results of H&J test and D&P nonlinear Granger causality test are presented in Table 6. We perform the tests for embedding dimension \( m = 1.5 \) and select the lags 1-6. As can be seen that the null hypothesis of no nonlinear Granger causality running from the U.S. partisan conflict index to the returns and volatility of oil and gold prices in the sample period cannot be rejected at the 10% significance level. For these findings of no causality, it is because the nonlinear Granger causality test approaches just rely on conditional-mean estimation, and fail to capture the entire conditional distribution of returns and
volatility of oil and gold prices. Given the nonexistence of any evidence on the nonlinear Granger causality, we next turn to causality-in-quantiles tests, which considers all quantiles of the distribution not only the center of the distribution. It can provide more detail information on the relationship between the U.S. partisan conflict and oil and gold price movements for investors.

Table 6 Non-linear Granger causality tests.

| $I_X = I_Y$ | Panel 1 Returns | Panel 2: Volatility |
|-------------|------------------|---------------------|
|             | H&J              | D&P                 | H&J                 | D&P                 |
|             | (P-value)        | (P-value)           | (P-value)           | (P-value)           |
|             | partisam$\leftrightarrow$ | partisam$\leftrightarrow$ |             |                     |
| 1           | 0.732 (0.231)    | 0.714 (0.237)       | 0.687 (0.245)       | 0.665 (0.252)       |
| 2           | 0.3179 (0.375)   | 0.233 (0.407)       | 0.443 (0.328)       | 0.329 (0.371)       |
| 3           | 0.468 (0.319)    | 0.405 (0.342)       | 0.693 (0.243)       | 0.601 (0.273)       |
| 4           | 1.388* (0.082)   | 1.149 (0.125)       | 0.763 (0.222)       | 0.768 (0.221)       |
| 5           | 1.531* (0.062)   | 1.321* (0.093)      | 0.684 (0.246)       | 0.641 (0.261)       |
| 6           | 1.361* (0.086)   | 1.145 (0.126)       | 0.345 (0.364)       | 0.393 (0.346)       |

Notes: *, ** and *** indicate rejection of the null hypothesis at the 10%, 5% and 1% level, respectively; $I_X = I_Y$ denotes the lag length. partisam$\leftrightarrow$ denotes the null hypothesis of no nonlinear Granger causality from partisan conflict index to oil prices.

5.4. Granger causality test in quantiles

In this section, we analyze the importance of U.S. partisan conflict index in predicting the returns and volatility of oil and gold price considering the quantiles conditional distribution of oil returns and volatility by employing a causality test in quantiles proposed by Troster (2016) (see results in Tables 7 and 8). Troster (2016) built a test statistic $S_T$ and proposed a subsampling procedure to calculate critical values for $S_T$. To apply the $S_T$ test, three different quantile auto-regressive (QAR) models are estimated for each dependent variable at lag length from one to three, respectively.
5.4.1. Causality from U.S. Partisan Conflict to returns

Table 7 presents the p-values for the test of the quantile-causality which running from the U.S. partisan conflict index to the returns of strategic commodities (crude oil and gold). Overall, it shows that the quantile-causality test for the quantile interval [0.1, 0.9] is significant at the 10% significance level, indicating that the U.S. partisan conflict has strong ability in predicting the returns of oil and gold prices. Moreover, it is mainly found that an outstanding pattern of Granger-causality from the U.S. partisan conflict index to the returns of oil and gold prices in the tails of the distribution of the strategic commodities prices movements.

More specifically, as for oil returns, the test results of causality-in-quantiles running from partisan conflict to oil returns are insignificant at the median (quantiles at 0.5), but become significant at the tail quantiles of the conditional distribution of oil returns. The insignificance of the test results at the median of the conditional distribution of oil returns is in line with the results of the conditional mean estimation analysis of Table 5 and Table 6 (the linear Granger causality test and nonlinear Granger causality test, respectively) which does not find any evidence that (relative) partisan conflict predict oil returns as well. U.S. EPU index and partisan conflict index are all important indicators to reflect the current uncertainty in the United States (Bilgin et al., 2018). Our finding is partly in line with Balciar et al. (2017) who find that U.S. EPU and equity market uncertainty have strong predictive power for oil returns over the entire distribution barring regions around the median. Likewise, Aloui et al. (2016), Shahzad et al. (2017) and Qadan and Nama (2018) confirm that there exist significant causal-flows from U.S. EPU to the oil returns over the entire sample period and for the majority of the quantile ranges as well. Furthermore, different from their studies, we find that the significance of the effect of U.S. partisan conflict on the conditional distribution of oil returns is particularly significant for the lower quantiles such as at around 0.1, 0.2, 0.3 and 0.4 quartiles. However, for oil returns at the higher quantiles such as at quantiles 0.6, 0.7, 0.8, it is found that the partisan conflict index cannot affect the oil returns, with the 0.9 quantile being an exception. This implies that the explanatory power of partisan conflict on the oil returns is heterogeneous in different market conditions. Specifically, when the crude oil market is in a bearish state (oil returns at the lower quantiles), the partisan conflict has a significant impact on the oil returns. However, under a bullish state (oil returns at the higher quantiles),
the impact of the partisan conflict on oil returns is limited. The possible reason behind the finding is that the partisan conflict in the United States has caused a panic to the uncertainty of future policy, thereby resulting in a decrease in oil demand. When crude oil is in a bear market, that is, the price of crude oil is very low, the reduction in oil demand caused by U.S. partisan conflict will be more likely to lead to the decrease of oil prices than that in a bullish market. This has explained why U.S. partisan conflicts more likely to have an impact on the oil price movements when the crude oil market is in a bear market.

Turn to gold returns, as can be seen from Table 7, the rejection of the null hypothesis of no causality running from partisan conflict to gold returns is concentrated more around the tail quantiles. Likewise, there is no evidence in favor of the predictable effect of partisan conflict on the gold returns at the median quantiles. The results confirm the finding of Balcilar (2016) and Jones and Sackley (2016) that there exists a causality running from U.S. EPU to gold returns. Li and Lucey (2017) find that EPU is a positive determinant of gold being an investment safe haven. Meanwhile, this finding also supports the conclusion of Bilgin et al. (2018) which is closet to our work they find that worsening U.S. partisan conflict index can contribute to increases in the price of gold. Not only that, for gold returns at lower quantiles, we only find the partisan conflict can affect the gold returns at 0.2 quantiles of the conditional distribution of gold returns, and for other lower quantiles, it is not valid. In comparison, for gold returns at higher quantiles, the null hypothesis of no causality can be rejected around the 0.6, 0.7, 0.8 and 0.9 quantiles. It indicates that the U.S. partisan conflicts are more likely to affect the higher quantiles of the conditional distribution of gold returns. In other words, partisan conflict matters only when the gold market is performing above its normal (average) mode, i.e., in bullish scenarios. This finding is different from the conclusions in the oil market. Media reports and investment recommendations often emphasize that gold acts as a classic safe-haven and hedging investment in times of economic and political uncertainty. Therefore, it is not surprising that when U.S partisan conflict intensifies, investors will choose gold to avoid risk, which has an impact on the gold market. Especially when the gold market is in a bull market, investors are more likely to choose gold to hedge their risk than that in a bear market, because they can gain profits in the bull market.

Table 7 Quantile causality test results (sub-sampling p-values) from U.S. Partisan Conflict to returns of oil and gold price
### 5.4.2. Causality from U.S. Partisan Conflict to volatility

The volatility of commodity prices is often regarded as an indicator for the calculation of hedging. Therefore, it is meaningful to study the determinants of commodity price volatility. In this section, we examine whether the U.S. partisan conflict index has predictive power for the volatility of oil and gold prices. Table 8 displays the results of causality in quantile test. As can be seen from Table 8, it is proven that the U.S. partisan conflict index affects the volatility of oil and gold prices over the entire conditional distribution, i.e., at various phases of the oil and gold market. This empirical evidence is consistent with Balcilar et al. (2017) who find that for oil volatility, the predictability of U.S. EPU and equity market uncertainty virtually covers the entire distribution.

**Table 8** Quantile causality test results (subsampling p-values) from U.S. Partisan Conflict to price volatility of oil and gold.

| Lag  | [0.1, 0.9] | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|------|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| **Oil** |            |     |     |     |     |     |     |     |     |     |
| 1    | 0.049*** 0.003*** 0.003*** 0.104 0.193 0.198 0.109 0.049** 0.029** 0.138 |     |     |     |     |     |     |     |     |     |
| 2    | 0.016*** 0.003*** 0.003*** 0.005*** 0.003*** 0.023*** 0.081* 0.018** 0.005*** 0.003*** |     |     |     |     |     |     |     |     |     |
| 3    | 0.008*** 0.003*** 0.003*** 0.008*** 0.003*** 0.003*** 0.052* 0.018** 0.008*** 0.003*** |     |     |     |     |     |     |     |     |     |
| **Gold** |            |     |     |     |     |     |     |     |     |     |
| 1    | 0.003*** 0.005*** 0.003*** 0.008*** 0.010*** 0.068* 0.102 0.003*** 0.003*** 0.010*** |     |     |     |     |     |     |     |     |     |
| 2    | 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.0161 0.003*** 0.003*** 0.003*** |     |     |     |     |     |     |     |     |     |
| 3    | 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** 0.003*** |     |     |     |     |     |     |     |     |     |

**Notes:** The symbol *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

### 5.5. Robustness analysis

In this section, we discuss the robustness of our results in this paper. One of our important conclusions is that the effect of U.S. partisan conflict on the returns and volatility of oil and gold clustered around the tail of the conditional distribution of returns. To this end, in the estimation process of quantile-causality test, we set more
numbers of quantiles with 0.05 step length. For lower quantiles, they are denoted by quantiles 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4; median quantiles including quantiles at 0.45, 0.5, higher quantiles contains the quantiles at 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95. Re-estimating the Granger quantiles causality test, results can be seen in Tables 9 and 10, the empirical results suggest that our main findings are not changed with the setting of more quantiles.

Table 9 Quantile causality test results (sub-sampling p-values) from U.S. Partisan Conflict to oil and gold price in more quantiles.

| Lag  | Oil returns |   |   |   | Gold returns |   |   |   |
|------|-------------|---|---|---|--------------|---|---|---|
| [0.05, 0.95] | 0.094 | 0.091 | 0.096 | 0.0038*** | 0.003*** | 0.005*** |
| 0.05 | 0.128 | 0.474 | 0.383 | 0.635 | 0.297 | 0.299 |
| 0.1 | 0.018 | 0.016 | 0.042 | 0.167 | 0.047 | 0.234 |
| 0.15 | 0.039 | 0.026 | 0.044 | 0.060* | 0.026** | 0.008*** |
| 0.2 | 0.047 | 0.016 | 0.057 | 0.013** | 0.008*** | 0.003*** |
| 0.25 | 0.078 | 0.055 | 0.065 | 0.031** | 0.339 | 0.112 |
| 0.3 | 0.078 | 0.068 | 0.073 | 0.154 | 0.130 | 0.284 |
| 0.35 | 0.083 | 0.070 | 0.078 | 0.685 | 0.638 | 0.797 |
| 0.4 | 0.091* | 0.081 | 0.089 | 0.685 | 0.547 | 0.508 |
| 0.45 | 0.128 | 0.276 | 0.398 | 0.401 | 0.292 | 0.273 |
| 0.5 | 0.852 | 0.763 | 0.938 | 0.286 | 0.266 | 0.396 |
| 0.55 | 0.135 | 0.078 | 0.089 | 0.148 | 0.021** | 0.047** |
| 0.6 | 0.122 | 0.102 | 0.107 | 0.003*** | 0.003*** | 0.003*** |
| 0.65 | 0.096* | 0.112 | 0.117 | 0.003*** | 0.010*** | 0.018** |
| 0.7 | 0.122 | 0.102 | 0.130 | 0.036** | 0.008*** | 0.0038*** |
| 0.75 | 0.125 | 0.133 | 0.138 | 0.003*** | 0.003*** | 0.003*** |
| 0.8 | 0.156 | 0.174 | 0.419 | 0.003*** | 0.003*** | 0.003*** |
| 0.85 | 0.089* | 0.091* | 0.091* | 0.003*** | 0.003*** | 0.003*** |
| 0.9 | 0.096* | 0.096* | 0.089* | 0.049** | 0.008*** | 0.016** |
| 0.95 | 0.167 | 0.289 | 0.102 | 0.049** | 0.044** | 0.057* |

Notes: see Table 7.

Table 10 Quantile causality test results (sub-sampling p-values) from U.S. Partisan Conflict to price volatility of oil and gold prices.

| Lag  | Oil volatility |   |   |   | Gold volatility |   |   |   |
|------|----------------|---|---|---|-----------------|---|---|---|
| 1    | 2              | 3 | 1  | 2  | 3              |

24
| Probability Level | Causality-in-Quantiles Test Results |
|-------------------|-----------------------------------|
| [0.05, 0.95]      | 0.047    0.016  0.008  0.003  0.003  0.003 |
| 0.05              | 0.003    0.008  0.010  0.003  0.049  0.039 |
| 0.1               | 0.003    0.003  0.003  0.005  0.003  0.003 |
| 0.15              | 0.003    0.034  0.026  0.003  0.003  0.003 |
| 0.2               | 0.003    0.003  0.003  0.003  0.003  0.003 |
| 0.25              | 0.031    0.005  0.003  0.010  0.003  0.003 |
| 0.3               | 0.104    0.005  0.008  0.008  0.003  0.003 |
| 0.35              | 0.096    0.018  0.005  0.003  0.003  0.003 |
| 0.4               | 0.193    0.003  0.003  0.010  0.003  0.003 |
| 0.45              | 0.284    0.003  0.003  0.013  0.003  0.003 |
| 0.5               | 0.198    0.023  0.003  0.068  0.003  0.003 |
| 0.55              | 0.096    0.070  0.065  0.164  0.003  0.003 |
| 0.6               | 0.109    0.081  0.052  0.102  0.161  0.091 |
| 0.65              | 0.060    0.036  0.036  0.003  0.078  0.073 |
| 0.7               | 0.049    0.018  0.018  0.003  0.003  0.003 |
| 0.75              | 0.031    0.010  0.010  0.003  0.003  0.003 |
| 0.8               | 0.029    0.005  0.008  0.003  0.003  0.003 |
| 0.85              | 0.044    0.003  0.003  0.003  0.003  0.003 |
| 0.9               | 0.138    0.003  0.003  0.010  0.003  0.003 |
| 0.95              | 0.516    0.016  0.016  0.010  0.003  0.003 |

Notes: Bold p-values denote rejection of the null hypothesis at the 10% significance level.

6. Conclusions

In recent years, U.S. politics have been characterized by a high degree of partisan conflict, which has led to increasing polarization and high policy uncertainty. Given the importance of US in the global commodity market, we employ the novel technique of causality-in-quantiles test to examine the ability of U.S. partisan conflict index in predicting the returns and volatility of oil and gold prices, using monthly data covering the period of January 1981 to October 2017. The main empirical findings of the current study can be summarized as follows.

First, there is strong evidence in favor of the significant predictable effect of U.S. partisan conflict index on the oil and gold returns at the tails of the conditional distribution of oil and gold returns, respectively. Furthermore, it is found that oil returns and gold returns have different responses to U.S. partisan conflict in different market condition. More specifically, for oil returns, the partisan conflict has a strong predictive power on the oil returns when the crude oil market is in a bearish state (oil
returns at the lower quantiles), however, under a bullish state (oil returns at the higher quantiles), the impact of the partisan conflict on oil returns is not significant. By contrast, for gold returns, partisan conflict matters only when the gold market is performing above its normal (average) mode, i.e., in bullish scenarios. It is found that for gold returns at lower quantiles, the partisan conflict index has limited predictive power on the gold returns, with the 0.2 quantiles being an exception. Second, it is proven that the U.S. partisan conflict index significantly affects the volatility of oil and gold prices over the entire conditional distribution, i.e., at various phases of the oil and gold market. Finally, a robustness exercise using more quantiles to represent the market states and the empirical results support the findings.

The results offer some meaningful implications to the investors and policymakers. For example, the study recommends that the U.S. partisan conflict index affect the lower quantiles of conditional distribution for oil returns, but it less likely to affect the higher quantiles of oil returns. It indicates that more attention should be drawn to track and monitor the U.S. partisan conflict risk when oil market is in the bearish state. However, for gold returns, partisan conflict matters for the gold returns only when the gold market is in a bullish scenario. It inspires gold investors that more prudent investment strategies are needed when gold market is in a bullish state. The volatility of oil and gold are affected by the partisan conflict in the United States. Therefore, the investors who choose the volatility of oil and gold as the monitoring index should pay close attention to the politics of the United States.

Acknowledgments
We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Nos. 71771082, 71371067, 71431008) and Hunan Provincial Natural Science Foundation of China (No. 2017JJ1012).

Reference
Afkhami, M., Cormack, L., Ghoddusi, H., 2017. Google search keywords that best predict energy price volatility. Energy Economics 67, 17-27.
Aloui, R., Gupta, R., & Miller, S. M. 2016. Uncertainty and crude oil returns. Energy Economics, 55 (2016), 92-100.

Antonakakis, N., Chatziantoniou, I., & Filis, G. 2014. Dynamic spillovers of oil price shocks and economic policy uncertainty. Energy Economics, 44(1), 433-447.

Aye, G.C., Chang, T., Gupta, R., 2016. Is gold an inflation-hedge? Evidence from an interrupted Markov-switching cointegration model. Resources Policy 48, 77-84.

Azzimonti, M. 2018. Partisan conflict and private investment. Journal of Monetary Economics 93,113-131.

Balcilar, M., Bonato, M., Demirer, R., Gupta, R., 2017. The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. Resources Policy 51, 77-84.

Balcilar, M., Gupta, R., & Pierdzioch, C. 2016. Does uncertainty move the gold price? New Evidence from a nonparametric causality-in-quantiles test. Resources Policy, 49(18), 74-80.

Balcilar, M., Bekiros, S., & Gupta, R. 2017. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empirical Economics, 53(3), 879-889.

Baur, D. G., & Mcdermott, T. K. 2010. Is gold a safe haven? International evidence. Journal of Banking & Finance, 34(8), 1886-1898.

Baur, D.G., Dimpfl, T., 2016. Googling gold and mining bad news. Resources Policy 50, 306-311.

Bekiros, S., Gupta, R., & Paccagnini, A. 2015. Oil price forecastability and economic uncertainty. Economics Letters, 132, 125-128.

Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. 1996. A test for independence based on the correlation dimension. Econometric Reviews, 15(3), 197-235.

Cai, J., Cheung, Y. L., & Wong, M. C. S. 2001. What moves the gold market?. Journal of Futures Markets, 21(3), 257-278.

Chan, J. C. C., & Grant, A. L. 2016. Modeling energy price dynamics: GARCH versus stochastic volatility. Energy Economics, 54, 182-189.

Chan, J. C. 2017. The stochastic volatility in mean model with time-varying parameters: An application to inflation modeling. Journal of Business & Economic Statistics, 35(1), 17-28.

Chan, J. C., & Eisenstat, E. 2015. Marginal likelihood estimation with the Cross-Entropy method. Econometric Reviews, 34(3), 256-285.

Chan, J. C., & Jeliazkov, I. 2009. Efficient simulation and integrated likelihood estimation in state space models. International Journal of Mathematical Modelling and Numerical Optimisation, 1(1-2), 101-120.

Chen, H., Liao, H., Tang, B. J., & Wei, Y. M. 2016. Impacts of OPEC’s political risk on the international crude oil prices: an empirical analysis based on the SVAR models. Energy Economics, 57(10), 42-49.

Chen, P. F., Lee, C. C., & Zeng, J. H. 2014. The relationship between spot and futures oil prices:
do structural breaks matter?. Energy Economics, 43(2), 206-217.

Coleman, L. 2012. Explaining crude oil prices using fundamental measures. Energy Policy, 40(1), 318-324.

Dickey, D.A., Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74 (366), 427-431

Diks, C., & Panchenko, V. 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control 30(9), 1647-1669.

Ewing, B. T., & Malik, F. 2016. Volatility spillovers between oil prices and the stock market under structural breaks. Global Finance Journal, 29, 12-23.

Fan, Y., & Xu, J. H. 2011. What has driven oil prices since 2000? A structural change perspective. Energy Economics, 33(6), 1082-1094.

Gallo, A., Mason, P., Shapiro, S., & Fabritius, M. 2010. What is behind the increase in oil prices? Analyzing oil consumption and supply relationship with oil price. Energy, 35(10), 4126-4141.

Gao, R., & Zhang, B. 2016. How does economic policy uncertainty drive gold–stock correlations? Evidence from the UK. Applied Economics, 48(33), 1-7.

Gil-Alana, L. A., Chang, S., Balcilar, M., Aye, G. C., & Gupta, R. 2015. Persistence of precious metal prices: a fractional integration approach with structural breaks. Resources Policy, 44(1 Pt 1), 57-64.

Granger, C. W. 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424-438.

Gupta, R., Pierdzioch, C., Selmi, R., & Wohar, M. E. 2018. Does partisan conflict predict a reduction in US stock market (realized) volatility? Evidence from a quantile-on-quantile regression model. The North American Journal of Economics and Finance, 43, 87-96.

Gupta, R., Mwamba, J. W. M., & Wohar, M. E. 2017. The role of partisan conflict in forecasting the US equity premium: A nonparametric approach. Finance Research Letters.

Hamilton, J.D., 2009. Causes and Consequences of the Oil Shock of 2007–08. National Bureau of Economic Research Working Paper.No.15002.Cambridge, MA.

Hammoudeh, S., & Yuan, Y. 2008. Metal volatility in presence of oil and interest rate shocks. Energy Economics, 30(2), 606-620.

Han, L.Y., Lv, Q.N., Yin, L.B., 2017. Can investor attention predict oil prices? Energy Economics 66, 547-558.

Hiemstra, C., & Jones, J. D. 1994. Testing for linear and nonlinear Granger causality in the stock price - volume relation. The Journal of Finance 49(5), 1639-1664.

Jeong, K., Härdle, W. K., and Song, S. 2012. A consistent nonparametric test for causality in quantile. Econometric Theory, 28(04), 861-887.

Jones, A. T., & Sackley, W. H. 2016. An uncertain suggestion for gold-pricing models: the effect of economic policy uncertainty on gold prices. Journal of Economics & Finance, 40(2),
Kang, W., & Ratti, R. A. 2013a. Structural oil price shocks and policy uncertainty. Economic Modelling, 35(5), 314-319.
Kang, W., & Ratti, R. A. 2013b. Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets Institutions & Money, 26(1), 305-318.
Kilian, L. 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-1069.
Kim, G., & Vera, D. 2018. Recent drivers of the real oil price: revisiting and extending Kilian’s (2009) findings. Energy Economics.
Li, S., & Lucey, B. M. 2017. Reassessing the role of precious metals as safe havens—What colour is your haven and why?. Journal of Commodity Markets, 7, 1-14.
Lombardi, M. J., & Van Robays, I. 2011. Do financial investors destabilize the oil price?.
Bilgin, M. H., Gozgor, G., Chi, K. M. L., & Xin, S. 2018. The effects of uncertainty measures on the price of gold. International Review of Financial Analysis.
Phillips, P. C., & Perron, P. 1988. Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.
Pershin, V., Molero, J. C., & de Gracia, F. P. 2016. Exploring the oil prices and exchange rates nexus in some African economies. Journal of Policy Modeling, 38(1), 166-180.
Perron, P. 1997. Further Evidence on Breaking Trend Functions in Macroeconomic Variables. Journal of Econometrics, Vol. 80, pp. 355–385.
Qadan, M., Nama, H., 2018. Investor sentiment and the price of oil. Energy Economics, 69, 42-58.
Raza, S. A., Shah, N., & Shahbaz, M. 2018. Does economic policy uncertainty influence gold prices? Evidence from a nonparametric causality-in-quantiles approach. Resources Policy.
Shahzad, S. J. H., Raza, N., Balcilar, M., Ali, S., & Shahbaz, M. 2017. Can economic policy uncertainty and investors sentiment predict commodities returns and volatility?. Resources Policy, 53, 208-218.
Sherman, E. J. 2009. A gold pricing model. Journal of Portfolio Management, 9(3), 68-70.
Troster, V. 2016. Testing for Granger-causality in quantiles. Econometric Reviews, 1-17.
Tully, E., & Lucey, B. M. 2007. A power GARCH examination of the gold market. Research in International Business & Finance, 21(2), 316-325.
Uddin, G. S., Bekiros, S., & Ahmed, A. 2018. The nexus between geopolitical uncertainty and crude oil markets: An entropy-based wavelet analysis. Physica A: Statistical Mechanics and its Applications, 495, 30-39.
Uludag, B. K., & Lkhamazhapov, Z. 2014. Long memory and structural breaks in the returns and volatility of gold: evidence from turkey. Applied Economics, 46(31), 3777-3787.
Wang, Q., & Sun, X. 2017. Crude oil price: demand, supply, economic activity, economic policy uncertainty and wars – from the perspective of structural equation modeling (SEM). Energy, 133, 483-490.
Yao, T., Zhang, Y. J., & Ma, C. Q. 2017. How does investor attention affect international crude oil prices?. Applied Energy, 205, 336-344.

Yin, L. 2015. Does oil price respond to macroeconomic uncertainty? New evidence. Empirical Economics, 1-18.