Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Infectious disease equity market volatility, geopolitical risk, speculation, and commodity returns: Comparative analysis of five epidemic outbreaks

Shaobo Long a,b,*, Jiaqi Guo c

a Research Center for Public Economy & Public Policy, Chongqing University, China
b School of Public Policy and Administration, Chongqing University, 174 Shazheng Street, Shapingba District, Chongqing 400044, China
c Department of Economics, The University of Manchester, Oxford Rd, Manchester M139FL, United Kingdom

ARTICLE INFO

JEL classification:
C32
F30
G15
O16

Keywords:
Infectious Disease Pandemic
COVID-19
Commodity Returns
Geopolitical Risk
Speculation

ABSTRACT

This paper uses a time-varying Granger causality test and time-varying parameter vector autoregression with stochastic volatility model to analyze the effects of infectious disease equity market volatility (ID-EMV), geopolitical risk (GPR), and speculation on commodity returns. The time-varying effects of ID-EMV, GPR, and speculation on commodity returns are investigated and compared in five epidemics during 1998–2021: Bird Flu in 1998, SARS in 2003, Swine Flu in 2009, MERS and Ebola in 2014, and COVID-19 in 2019. A further analysis is performed for five commodity subcategories of textiles, industry, metals, livestock, and food. Results show that time-varying effects are significant, and most responses to ID-EMV are positive, to GPR are changing from negative to positive, and to speculation are negative. Notably, ID-EMV in the ongoing COVID-19 pandemic is the worst hit to commodity returns in more than two decades.

1. Introduction

From the beginning of the new century, extreme events have occurred frequently, and health and geopolitical risks (GPRs) have significantly increased, thereby adding uncertainties to the global economy and financial markets. Currently, the COVID-19 pandemic has become a source of global systemic risk from 2020. Almost all countries have been hit by declining output and stock prices, which have affected international commodity markets. The sharp response of stock and commodity markets to COVID-19 cannot be explained simply by its lethality but rather by government restrictions on mobility and business activities and voluntary social distancing (Baker et al., 2020). Therefore, the uncertainty caused by epidemics has become a crucial factor in the fluctuation of international commodity prices.

Moreover, with the expanding impact of the pandemic, political instability and GPR have further caused investors to change their investment strategies in the commodity market. GPR entails risks associated with war, acts of terrorism, and tensions among states or regions affecting the normal peace process of international relations (Caldara and Iacoviello, 2021). GPR has non-negligible effects on both the supply of commodities and economic activities, and it is a factor affecting the fluctuation of the commodity market. The understanding of information transmission from GPR to the financial market is only emerging (Liu et al., 2021). Moreover, the financialization of primary commodities and speculative activities in commodity futures markets has increased rapidly (Lawson et al.,...
2021). Some market participants, analysts, and regulators believe that speculation significantly affects commodity price movements (Etienne et al., 2018). Therefore, investors and authorities are attentive toward the impacts of epidemic uncertainty, GPR, and speculation on commodity prices. For investors, understanding the impacts of the three factors contributes to making more reasonable investment and hedging decisions; for the authorities, formulating relevant policies is conducive to reduce commodity market volatility and strengthen market stability.

However, because of the difficulty of measuring epidemics and geopolitical uncertainties, few studies have provided evidence and reliable conclusions on the effects of epidemics and GPRs on commodities, and fewer have included speculation. Moreover, no relevant literature focuses on their time-varying and nonlinear relationship during epidemics. The relationships between commodities and financial variables are more complex and nonlinear in reality (Bekiros et al., 2020; Chowdhury et al., 2021), which require improved evaluation by nonlinear models.

Thus, this article examines whether ID-EMV, GPRs, and speculation have nonlinear impacts on commodities over time, particularly during the previous five epidemic outbreaks and whether there are any implications and solutions to these impacts. To better characterize the nonlinear relationship over time, we use the newly developed time-varying Granger causality test (Shi et al., 2018; Shi et al., 2020) and the time-varying parameter vector autoregression with stochastic volatility (TVP-VAR-SV) model to analyze their time-varying effects from the perspective of aggregate and subcategories commodity, respectively.

The primary contributions of this paper lie in the following aspects. First, this paper aims to integrate ID-EMV, GPR, and speculation into commodity markets to study their impacts on commodity returns during the five most recent outbreaks: Bird Flu (HSN1) in 1998, SARS in 2003, Swine Flu (H1N1) in 2009, MERS and Ebola in 2014, and COVID-19 in 2019. It attempts to find new evidence for the debate on speculation in previous studies as well. Second, uniquely, this paper uses a nonlinear and dynamic model to compare the time-varying effects of ID-EMV, GPR, and speculation on commodity returns in the five epidemics. Finally, various responses of five commodity categories’ returns are compared to provide a comprehensive understanding of the heterogeneous responses to shocks from two types of uncertainties and speculation.

The remaining parts of this paper are as follows: Section 2 presents the literature review; Section 3 introduces the method of a time-varying causality test and TVP-VAR-SV model; Section 4 explains the variables and data; Section 5 reports the estimated results and conducts a time-varying impulse response analysis; and the final Section 6 is the conclusion.

2. Literature review

With the global spread of COVID-19 and the implementation of lockdowns, health risks have become more closely associated with international financial markets, and uncertainties surrounding infectious diseases are drawing wide attention. Studies on COVID-19 primarily examined the hedging capacity of assets to optimize the asset portfolio for managing the impact of infectious diseases. Numerous studies on stock markets, such as Salisu and Vo (2020) and Salisu et al. (2020), showed that a strong correlation exists between the current pandemic and financial assets. Caggiano et al. (2020) argued that the COVID-19 lockdown triggered the worst economic downturn from the Great Depression. Bouri et al. (2020) believed that the financial market experienced a substantial and unprecedented peak of uncertainty. Baker et al. (2020) highlighted that the COVID-19 pandemic had a stronger negative impact on the stock market than any previous infectious disease outbreak, and the developed ID-EMV was widely used in empirical studies as a proxy for epidemic-related uncertainty, such as Salisu and Sikiru (2020), Salisu and Adediran (2020), Salisu et al. (2020), and Adediran et al. (2021a, 2021b). Although different studies have not reached consistent conclusions, they reported the importance of commodities. Liu et al. (2022) used the thermal optimal path (TOP) method to study the dynamics leader-lag relationship of jumps among Chinese stock index and futures market, and found that the relationship changed significantly before and after the outbreak of COVID-19.

GPR is another crucial factor influencing stock and commodity markets, thereby providing significant incremental explanatory power beyond fundamental variables of supply and demand, realized volatility, financial stress, and economic policy uncertainty (Liu et al., 2021). Brandt and Gao (2019) highlighted that both investor sentiment and trading decisions would be substantially influenced by GPRs. Asai et al. (2020) further believed that geopolitical events provide opportunities for crucial shifts in government policies, which had a broad impact on investor sentiment in financial and commodity markets. Cheng and Chiu (2018) found that GPR is integral in explaining business cycle fluctuations in emerging countries. Caldara and Iacoviello (2018) stated that GPRs reduce actual activity and stock returns. Gkillas et al. (2018), Bouri et al. (2018), and Balcilar et al. (2018) found that GPR affects the stock market’s volatility. Aysan et al. (2019), Colon et al. (2021), and Gkillas et al. (2019) investigated the impact of GPR on cryptocurrencies and gold. Liu et al. (2021) found that GPR had a significant positive impact on energy fluctuations in the long term. Nogueira-Santaella (2016), Omar et al. (2017), and Bouoiyour et al. (2019) studied the impact of GPR on crude oil, and Antonakakis et al. (2017) validated the predictive ability of GPRs in crude oil and its negative effect on oil price returns and price volatility. Jia et al. (2021) used the US Partisan Conflict Index (PCI) to find that arbitrage currencies are sensitive to US policy risks, and that partisan conflict reduces the risk of policy changes. Selmi et al. (2022) used BlackRock Geopolitical Risk Indicator (BGRI) to conduct empirical research on gold as safe havens for assets and find that gold has a positive response to GPRs, and Ding et al. (2022) found that gold has weak hedging ability and time-lag effect on GPRs by using the International Country Risk Guide (ICRG) political risk index.
Regarding commodity financialization, Baffes and Haniotis (2010) argued that index fund activity (one type of speculative activity among the many that the literature refers to) was crucial during the 2008 commodity prices spike. Ekeland et al. (2014) defined financialization as a process wherein the presence of speculators becomes more crucial in futures markets. Büyüksahin and Robe (2014) further provided evidence of the growing importance of different types of financial traders in numerous commodity futures markets. This transformation started in 2003–2004 and was associated with a gradual shift toward electronic commodity trading and increased commodity index trading (Ekeland et al., 2014). Because commodity index traders are considered the primary channel through which commodity markets become more financialized, most studies have focused on it, whereas Lawson et al. (2021) considered various speculative measures that reflect different underlying assumptions regarding the role of speculation in commodity price dynamics. Tang and Xiong (2012) found that large index investments started to flow into the commodity market after 2004, thereby leading to the commodity market integrating with other financial markets. Furthermore, Huang et al. (2020) argued that the portfolio rebalancing of index investors leads to volatility spillovers into commodity markets. Bosch and Smimou (2022) found that returns in commodity futures markets can be largely attributed to position changes of hedgers and well-known speculators, while small speculators and swap dealers are critical to some weak commodity markets and metal markets, respectively.

Presently, the impact of speculative activities on commodity markets is unclear, and the relevant debate can be summarized as efficient market and speculative bubble hypotheses. Supporters believed that speculation is a useful component of financial markets and has a net stabilizing effect on prices, whereas opponents believed that non-commercial traders are destabilizing commodity prices. Related empirical studies selected speculative indicators based on different basic assumptions, primarily including net long commodity index traders’ positions (NLCT), non-commercial net long positions, speculative T index (WT) of Working (1960), and excess speculative volume (ESV) of Tadesse et al. (2014). These four indicators reflect researchers’ different interpretations and definitions of speculation. Irwin and Sanders (2012) proposed the “Masters hypothesis,” thereby arguing that pure long investment activities are in essence synthetic long positions affecting commodity prices through futures trading in the real market. Therefore, these measures are primarily used to examine traditional speculation or non-commercial transaction activity. However, these indicators have been criticized because non-commercial positions fail to distinguish between speculative and fundamental influences. Working (1960) believed that the degree of speculation in futures trading was meaningful only when combined with the degree of hedging activities. Peck (1980) further pointed out that Working’s T index reflected the extent to which the level of speculation exceeded the minimum necessary to absorb long and short hedging. Therefore, Working’s T index is primarily used to investigate the excessive speculation relative to hedging activities and has been widely used in empirical studies.

The impact of speculation on commodities has been fraught with controversy primarily because of the different definitions of speculation and the selection of key variables for commodities. Etienne et al. (2018) compared these four speculative measures and found that the impact of speculative trading on corn prices depended on the measures used: non-commercial net position or Tadesse’s ESV index would significantly push up prices, whereas excessive speculation measured by Working’s T would have zero or negative impact. Lawson et al. (2021) extend the research of Etienne et al. (2015) and found that the impact of speculation on different commodities depends on how speculation was defined. Although Gilbert (2010) and Bass (2011) et al. argued that speculation drives up commodities prices, Boyd et al. (2016) and Kim (2015) believed that speculators can provide liquidity to stabilize the commodity market and even suppress prices. Boyd et al. (2018) rechecked the role of speculation in commodity markets and found scarce evidence of instability, whereas McPhail et al. (2012) and Etienne et al. (2015) concluded that speculative trading had a net stabilizing effect on prices. Will et al. (2015) further found no evidence that speculation leads to price increase. Haase et al. (2016) reviewed the results of 100 empirical studies and found that the studies for and against speculation were roughly the same, with approximately 20% finding a strengthening effect and more than 50% finding a weakening effect on commodity returns.

Because more advanced econometric approaches are widely used, more studies discuss the nonlinear characteristics and nature of commodity markets. Huang et al. (2009), Rubaszek and Uddin (2020), and Rubaszek et al. (2020) found that the threshold model can better understand the dynamic relationship between spot and futures prices of energy commodities. Mamatzakis and Remoundos (2011), Beckmann et al. (2014), Joëts et al. (2017), de Albuquerqueemello et al. (2018), and Chowdhury et al. (2021) used the threshold vector error-correction (TVECM) model, smooth transition regression (STR) model, structural threshold vector autoregressive (TVAR) model, self exciting threshold auto-regressive (SETAR) model, and nonlinear autoregressive distributed Lag (NARDL) model, respectively, to study the nonlinear dynamics of commodity prices. With the progress of econometric technology, Uddin et al. (2019) used hybrid wavelet approaches to improve the predictability of crude oil markets, and Bekiros et al. (2020) applied a wavelet multiscale analysis on returns and volatilities of Brent and West Texas Intermediate crude oil indices to forecast in the crude oil market. Yahya et al. (2020) found that the conditional dependencies between commodity assets are time-varying and asymmetric with the potential for tail dependence by using time-varying copulas. Sun et al. (2021) employed bootstrap full-sample and sub-sample rolling window Granger causality tests for empirical research on the agricultural commodity market. Lyu et al. (2021) argued that the macroeconomic structure and oil market system are dynamic, which has been validated (Baumeister and Peersman, 2013; Riggi and Venditti, 2015), and Salisu et al. (2017) and Chowdhury et al. (2021) found prominent nonlinear behavior in agricultural commodity markets.

In general, although infectious disease and GPRs are receiving substantial attention, relatively little research has been conducted on their impact on commodity markets before building the ID-EMV and GPR index because these risks are difficult to measure. Moreover,
because of a lack of consistent definition and measurement of speculation, no consensus has been reached on the response of commodity returns to speculation. Therefore, employing a nonlinear dynamic model to investigate and compare the time-varying returns of aggregate commodity and categories to ID-EMV, GPR, and speculation in five epidemics in recent years is essential. In contrast to previous studies, this is an early exploration of integrating ID-EMV, GPR, and speculation into commodity markets to study their impact on commodity returns.

3. Methodology

3.1. Time-varying Granger causality test

We use a new time-varying Granger causality test by Shi et al. (2018, 2020) to evaluate the existence of the nonlinear causality of ID-EMV, GPR, and speculation on commodity returns. This new method can track the changes in the causal relationships over time, and it considers the stylized facts that are observed in the financial market data, such as heteroskedasticity, deterministic trend, and nonlinearity. It can examine the change in any causal relation and detects the exact dates of the origination and collapse of the episode of causality (Maghyereh et al., 2022).

Let the k-vector time series $y_t$ generated by $y_t = \alpha_0 + \alpha_t t + u_t$, with $u_t = \beta_1 u_{t-1} + \ldots + \beta_p u_{t-p} + \epsilon_t$ following the VAR(p) process. Suppose $y_t$ are the functions of $\alpha_i$ and $\beta_j$ with $i = 0, 1$ and $j = 1, \ldots, p$, we have the following:

$$y_t = \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \epsilon_t$$  \hspace{1cm} (1)

According to Hammoudeh et al. (2020), the Granger causality test for a possible integrated variable $y_t$ can be conducted using a lag-augmented VAR (LA-VAR) $Y = \pi' + X\Theta' + B\theta' + \epsilon$, which is as follows:

$$\begin{pmatrix} y_1 \\ y_r \\ y_{T-n} \end{pmatrix} = \begin{pmatrix} \tau_1 \\ \tau_r \\ \tau_{T-n} \end{pmatrix} \Gamma + \begin{pmatrix} x_1 \\ x_r \\ y_{T-n} \end{pmatrix} \Theta_p \beta_{p+1} + \begin{pmatrix} \beta_1 \\ \beta_r \\ \beta_{T-n} \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_r \\ \epsilon_{T-n} \end{pmatrix}$$  \hspace{1cm} (2)

Where $x_t = (y_{t-1}, \ldots, y_{t-p})'$, $b_t = (y_{t-p-1}, \ldots, y_{t-p-d})'$ and $\tau_t = (1, t)_{2 \times 1}$ with the maximum order $d$ of integration for $y_t$.

Shi et al. (2018, 2020) introduced a time-varying causality test based on supremum Wald statistical sequences. Let $\hat{\Theta} = \text{vec}(\hat{\Theta})$ represents the row vectorization with the OLS estimator $\hat{\Theta} = X'QX(X'QX)^{-1}$, $R$ and $\hat{\Omega} = T^{-1}\hat{\epsilon}\hat{\epsilon}'$ are $(m \times n^2p)$ matrix where $m$ is the number of restrictions. The Wald test of the restrictions imposed by $R\hat{\theta} = 0$ is as follows:

$$w = [R\hat{\Theta}]' [R(\hat{\Omega} \otimes (X'QX)^{-1})R']^{-1} [R\hat{\Theta}]$$  \hspace{1cm} (3)

The Wald statistic over $[f_1, f_2]$ with a sample size fraction of $f_0 = f_2 - f_1 \geq f_0$ is denoted by $W_{f_0}(f_1)$, and thus, the supremum Wald statistic for the recursive expanding procedure is as follows:

$$SW_{f_0}(f_1) = \sup_{f_1 \in [f_0, f_2]} W_{f_0}(f_1)$$  \hspace{1cm} (4)

where $\Lambda_0 = \{f_1, f_2 : 0 < f_0 + f_2 \leq f_1 \leq 1, \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for a minimal sample size $f_0 \in (0, 1)$ in the regressions. Shi et al. (2018) argued that the forward expanding and rolling window processes are special cases of recursive expanding processes. Let $\hat{f}_e$ and $\hat{f}_r$ represent the estimated first chronological observations whose test statistics exceed or fall below the critical values for the origination and termination points in the causal relationship, the dating rules for the forwarding, rolling, and recursive expanding procedures are as follows:

$$\hat{f}_e = \inf_{f \in [f_0, 1]} \{ f : W_f(0) > cv \}, \text{ and } \hat{f}_r = \inf_{f \in [f_0, 1]} \{ f : W_f(0) < cv \}$$  \hspace{1cm} (5)

$$\hat{f}_e = \inf_{f \in [f_0, 1]} \{ f : W_f(f - f_0) > cv \}, \text{ and } \hat{f}_r = \inf_{f \in [f_0, 1]} \{ f : W_f(f - f_0) < cv \}$$  \hspace{1cm} (6)

$$\hat{f}_e = \inf_{f \in [f_0, 1]} \{ f : SW_f(f_0) > scv \}, \text{ and } \hat{f}_r = \inf_{f \in [f_0, 1]} \{ f : SW_f(f_0) < scv \}$$  \hspace{1cm} (7)

where $cv$ and $scv$ are the corresponding critical values of the $W_f$ and $SW_f$ statistics.
3.2. TVP-VAR-SV model

A traditional VAR model assumes that the variances of parameters and perturbation terms are fixed, and thus, it cannot describe the time-varying relationship among variables. Accordingly, Canova and Ito (1991) included time-varying parameters to study the US exchange rate, Uhlig (2005) then included random volatility for empirical study, and Primiceri (2005) and Nakajima (2011) included time-varying parameters and error covariance and proposed the TVP-VAR-SV. Compared with a constant parameter VAR model, the TVP-VAR-SV model need not divide data into sub-samples to validate the change in the model structure (Nakajima et al., 2011). Therefore, based on the complete sample, it can avoid the risk of information loss and the possibility of getting wrong results depending on the arbitrary choice of the sub-samples intervals. By incorporating stochastic volatility, time-varying variances capture the change in the impact and nature of the shocks, thereby enabling the modeling of the apparent decline in volatility (Jebabli et al., 2014).

Assume that the structural VAR model is \( \Delta y_t = \Pi \Delta y_{t-1} + \cdots + \Pi F y_{t-4} + u_t \), where \( y_t \) is the \((k \times 1)\) vectors of observable variables, \( A, F_1, \ldots, F_5 \) are the \((k \times k)\) coefficient matrices, the lower triangular matrix \( A \) identifies the simultaneous relationship of the specified structural impact through recursion, and the random disturbance term \( u_t \sim N(0, \Sigma^2) \) is the \((k \times 1)\) structural impact:

\[
A = \begin{pmatrix}
1 & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
\vdots & \ddots & \ddots & \vdots \\
a_{k1} & \cdots & a_{k,k-1} & 1
\end{pmatrix}, \quad \Sigma = \begin{pmatrix}
\sigma_1 & 0 & \cdots & 0 \\
0 & \sigma_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \sigma_k
\end{pmatrix}
\] (8)

The simplified form of the structural VAR model is \( y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + A^{-1} \Sigma \epsilon_t \), where \( \epsilon_t \sim N(0, I_k) \). Stack up the row elements of \( B_t = A^{-1} F_t \) to form \((k^2 \times 1)\) vector. The Kronecker product is used to define \( X_t = I_k \otimes (y'_{t-1}, \ldots, y'_{t-4}) \), and the discussion on it is as follows:

\[
y_i = X_t \beta_t + A^{-1} \Sigma \epsilon_t, \quad t = s + 1, \ldots, n
\] (9)

where the parameter to be estimated are \( \beta, A, \Sigma \). A structural VAR model is obtained when \( \beta, A \) are fixed parameters, and a TVP-VAR model is obtained by changing these into time-varying parameters, that is, introducing the time-varying parameter \( \Sigma \).

Let the column vectors \( a_t = (a_{t1}, a_{t2}, a_{t3}, \ldots, a_{tk-1}) \)' and \( h_t = (h_{t1}, h_{t2}, \ldots, h_{tk}) \)' be the accumulation vectors of the elements \( a \) and \( h \) = \( 2 \sigma_k^2 \) in \( A_k \), where \( j = 1, \ldots, k \). Assuming that the TVP-VAR-SV model obeys the following random walk process, we yield the following:

\[
\begin{align*}
\beta_{t+1} &= \beta_t + u_{\beta_t} \\
\alpha_{t+1} &= \alpha_t + u_{\alpha_t} \\
h_{t+1} &= h_t + u_{h_t}
\end{align*}
\]

(10)

where \( \beta_{t+1} \sim N(u_{\beta_t}, \Sigma_{\beta}) \) represents the change series of coefficient, \( \alpha_{t+1} \sim N(u_{\alpha_t}, \Sigma_{\alpha}) \) represents the change series of structural information, and \( h_{t+1} \sim N(u_{h_t}, \Sigma_{h}) \) represents the change series of volatility.

The parameter to be estimated is \( \beta, \alpha, h, \Sigma_{\beta}, \Sigma_{\alpha}, \Sigma_{h} \), whereby assuming that the dynamic parameter obeys the random walk process. Set the covariance matrix \( \Sigma_{\beta}, \Sigma_{\alpha}, \Sigma_{h} \) of a parameter disturbance term as a diagonal matrix, and the model result is not sensitive to the setting of the diagonal matrix. The recursive recognition of the model requires a lower triangular matrix \( A_k \), which can make the estimation simpler and effective. Bayesian estimation requires the careful selection of prior values. This paper assumes that there is no information about the prior, and sets reasonable monotone prior values artificially. The Markov chain Monte Carlo (MCMC) methods with Bayesian inference can solve the problem of parameter oversimplification and sample autocorrelation.

4. Data and variables

The TVP-VAR-SV model used in the study includes four variables: ID-EMV, GPR, speculation, and commodity return. To obtain stationary series, all variables are in a logarithmic form, and the first-order difference is performed. Monthly data from January 1998 to June 2021 are used, which include the five outbreaks of infectious disease epidemics, namely, Bird Flu (HSN1), SARS, Swine Flu (H1N1), MERS and Ebola, and COVID-19.

This paper refers to the ID-EMV by Baker et al. (2020) as an uncertainty measure of infectious diseases, which reflects the volatility of infectious diseases on the equity market by tracking approximately 3000 American newspapers in specified terms. ID-EMV specifies four sets of terms (including E, M, V, and ID) and counts the corresponding newspapers, then scales them according to all the articles of the day, and finally uses the overall EMV index to match the VIX level for reflecting the ratio of ID-EMV articles to the total number of EMV articles. The daily data of ID-EMV are converted into monthly data. The data can be downloaded from http://www.https://www.
We select the index of GPRs developed by Caldara and Iacoviello (2018) as a measure of geopolitical uncertainty, which tracks geopolitical tensions in 11 leading international newspapers. GPR identifies six groups of words related to GPRs by calculating the number of associated articles in each newspaper per month (accounting for the total number of news articles) and then normalizing the average value across 2000–2009 to 100. Caldara and Iacoviello (2021) claimed that higher values of the GPR index mean higher current intensity of negative events, probability of negative events in the future, and expected intensity of future negative events. This index represents the GPRs and has not yet been applied empirically on a large scale because it is relatively new. The GPR data can be downloaded from: https://www.matteoiacoviello.com/gpr.htm.

For speculation, Sanders et al. (2010) suggested Working’s (1960) T index to quantify the relative involvement of financial investors, which compares the positions of speculators to hedgers’ demands. This indicator has also been widely used in empirical studies, such as Büyüksahin and Robe (2011), Büyüksahin and Robe (2014), Alquist and Gervais (2013), and Bruno et al. (2017). The calculation of Working’s T is as follows:

\[
T_{i,t} = \begin{cases} 
1 + \frac{SS_{i,t}}{HL_{i,t} + HS_{i,t}}, & HS_{i,t} \geq HL_{i,t} \\
1 + \frac{SL_{i,t}}{HL_{i,t} + HS_{i,t}}, & HS_{i,t} < HL_{i,t}
\end{cases}
\]

\[
WT_t = \sum_{i=1}^{N_i} w_i T_{i,t}
\]

where \(SS_{i,t}\) and \(SL_{i,t}\) are the non-commercial short and long position of commodity futures market \(i\) at time \(t\), respectively. \(HS_{i,t}\) and \(HL_{i,t}\) are the non-commercial high and low position of commodity futures market \(i\) at time \(t\), respectively.

---

1 GPR index searches for articles containing: explicit mentions of geopolitical risk, alongside mentions of military-related tensions involving large regions of the world and a US involvement; nuclear tensions; war and terrorist threats; actual adverse geopolitical events which can be reasonably expected to lead to increases in geopolitical uncertainty; and other tensions.
are the commercial short and long positions, respectively. Let \( w_{ij} \) be the weight of the corresponding commodity in the commodity index, and the speculation of the aggregate commodity market containing \( N \) commodities can be described by the weighted average \( W_T \).

Originating in the Large Trader Reporting System of the Commodity Futures Trading Commission, this paper develops a database to calculate this speculation index regarding the Reuters/Jefferies Commodity Research Bureau Index (RJ/CRB), which records weekly trader positions in 17 US commodity futures markets during 1998–2021 and converts them into monthly data. In the category model, they are further classified into five groups according to the CRB spot index to investigate the situation of different commodity categories.

For commodities, the first-order difference of logarithmic, the RJ/CRB index, is a natural choice as a broad-based indicator of price fluctuations, which are widely concerned and applied in the global commodity market. Therefore, numerous scholars use this index to conduct empirical studies. Fig. 1 shows the trends of the aforementioned variables.

Table 1 presents the summarized information of statistical description and stationary test, where \( \Delta \ln ID-EMV \), \( \Delta \ln GPR \), and \( \Delta \ln WT \) show positive skewness; the CRB index shows negative skewness, and all variables have positive kurtosis with values greater than 3, which indicate the shape of the peaks are sharp, and the distribution peak is steep. Compared with the mean value, the standard errors of \( \Delta \ln ID-EMV \), \( \Delta \ln GPR \), \( \Delta \ln WT \), and \( \Delta \ln CRB \) are large, thereby indicating that the four variables have changed sharply during the sample. Jarque–Bera statistics show that all variables are not normally distributed except \( \Delta \ln WT \). To prevent spurious regression caused by non-stationary data, we test the stationarity of each variable. Both Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) statistics show that all variables are stationary at a 1% significance level.

### 5. Empirical results

#### 5.1. Time-varying Granger causality test

To investigate the existence of the nonlinear causality of ID-EMV, GPR, and speculation on commodity returns over time, we implement Shi et al.'s (2018; 2020) time-varying Granger causality test. The simulation results of Shi et al. (2020) show that compared with a forward expanding algorithm, the recursive expanding algorithm is the most reliable, followed by the rolling window algorithm. Therefore, we primarily display and analyze the results of the recursive expanding and rolling window algorithms.

This approach adopts robust econometric methods for integration and cointegration properties, and data need not be filtered by detrending or differencing (Shi et al., 2018; Hammoudeh et al. 2020). Following Shi et al. (2018), the logarithm of the sequences is used to test.

Fig. 2 shows the time-varying causal relationship between ID-EMV, GPR, speculation, and commodity returns, respectively, which plots the Wald statistic sequences and their corresponding bootstrapped 5% and 10% critical values for rolling and recursive expanding procedures. The two procedures identify that causality running from ID-EMV, GPR; speculation to commodity returns is substantially significant most of time and has time-varying effects across the sample range. Moreover, the recursive expanding algorithm validated
causal events better than the rolling window algorithm. In summary, there is causality between ID-EMV, GPR, and speculation and commodity returns.

5.2. TVP-VAR-SV model estimation

Further, we use the TVP-VAR-SV model. All variables $\Delta \ln ID$, $\Delta \ln EMV$, $\Delta \ln GPR$, $\Delta \ln WT$, and $\Delta \ln CRB$ in the models are stationary, and the optimal lag order is selected as one period according to the SIC criterion. Referring to Nakajima (2011), a flat prior distribution without information is set for the initial values of parameters. Assume that the elements of covariance matrix $\Sigma_\beta$, $\Sigma_\alpha$, and $\Sigma_h$ obey prior distribution $(\Sigma_\beta)^{-1/2} \sim \text{Gamma}(40, 0.02)$, $(\Sigma_\alpha)^{-1/2} \sim \text{Gamma}(4, 0.02)$, and $(\Sigma_h)^{-1/2} \sim \text{Gamma}(4, 0.02)$. If the mean is initially $\mu_\beta = \mu_\alpha = \mu_h = 0$ and the covariance matrix is $\Sigma_{\beta_0} = \Sigma_{\alpha_0} = \Sigma_{h_0} = 10 \times I$, then the initial states are $\beta_0 \sim N(\mu_\beta \Sigma_{\beta_0})$, $\alpha_0 \sim N(\mu_\alpha \Sigma_{\alpha_0})$, and $h_0 \sim N(\mu_h \Sigma_{h_0})$.

Table 2
Estimation Results of the TVP-VAR-SV Model.

| Parameter | Mean | St.dev | 95%U  | 95%L  | Geweke | Inef. |
|-----------|------|--------|-------|-------|--------|------|
| sb1       | 0.0038| 0.0010 | 0.0024| 0.0063| 0.311  | 69.72|
| sb2       | 0.0038| 0.0010 | 0.0024| 0.0063| 0.201  | 64.61|
| sa1       | 0.0058| 0.0019 | 0.0034| 0.0105| 0.357  | 79.42|
| sa2       | 0.0035| 0.0006 | 0.0026| 0.0046| 0.189  | 31.22|
| sb1       | 0.0062| 0.0026 | 0.0035| 0.0127| 0.304  | 140.44|
| sb2       | 0.0060| 0.0020 | 0.0035| 0.0113| 0.521  | 125.10|
$h_0 \sim N(\mu_{h_0}, \Sigma_{h_0})$. Take 22,000 MCMC samples and discard first 10% of pre-simulated samples in a burn-in period for 20,000 effective samples to ensure that sample points do not depend on initial selection.

Table 2 presents the estimation results. Convergence diagnostics tests by Geweke (1992) indicate that the null hypothesis of convergence to a posterior distribution cannot be rejected at the significance level of 5%. Therefore, the burn-in interval is sufficient for Markov chain convergence. The maximum invalidity factor of 125.1 indicates that at least 160 unrelated samples can be obtained with 20,000 samples. The estimation results show that the model sampling is valid and can be inferred posteriori.

### 5.3. Impulse response of aggregate commodity returns to ID-EMV, GPR, and speculation

Fig. 3 shows the three-dimensional impulse response of commodity returns to ID-EMV, GPR, and speculation during 1998–2021, wherein the X, Y, and Z axes are the duration, occurrence time, and impulse response value of commodity returns, respectively. Fig. 3 shows that the impact of the three shocks on commodity returns is indeed time-varying during different periods. During the aforementioned five outbreaks, the impact of ID-EMV shocks on commodity returns is primarily negative and has become increasingly negative in recent outbreaks, particularly during the COVID-19 pandemic. The impact of GPR shock on commodity returns shows a trend from negative to positive from 2007. However, the impacts of speculation (WT) shocks on commodity returns are all negative, and the time-varying effect is not evident.

We further select the time-varying impulse response of commodity returns to ID-EMV, GPR, and speculation (WT) with different periods ahead and the key time points during the previous five infectious disease epidemics for a comparative analysis. The upper half of Fig. 4 shows the trajectories of impulse response of commodity returns to shocks of ID-EMV, GPR, and speculation in 1, 3, and 6 months ahead. The trajectory of impulse responses of commodity returns to ID-EMV, GPR, and speculation in 1-month fluctuations are
most violent, 3-month fluctuations tend to be stable, and 6-month fluctuations converge to zero. Therefore, the impacts of the three shocks on commodity return are primarily concentrated in the short term, particularly in 1-month fluctuations. The lower half of Fig. 4 represents the time-varying responses to three types of shocks at different time points, which are selected by the peak of ID-EMV during the five infectious diseases epidemics. On the five-time points, ID-EMV, GPR, and speculation have evident time-varying effects on commodity returns.

ID-EMV measures the impact of infectious diseases on equity market volatility and risk. Fig. 4 shows that except for a small number of brief positive impacts in 2000, 2004, and 2012, the other shocks on commodity returns are all negative in most periods during the sample, particularly the most serious negative impacts in 2009 and 2020. The positive impact of ID-EMV on commodity returns primarily reflects the investment substitution effect between commodities and equity markets during the epidemic, and the commodity market can play the role of “safe haven” when the volatility and risk of the stock market rise in 1998 and 2003. Although the negative impact of ID-EMV on commodity returns primarily reflects the systemic risk caused by the serious epidemic to the entire financial market mainly in 2009 and 2020. The effects of Swine Flu in 2009 superimposed on the international financial crisis have brought substantial risks to the stock market and the complete financial market including the commodity markets. The outbreak of COVID-19 in 2020 and the economic recession brought about by restrictions on commercial activity and social distancing engender enormous uncertainties and risks in the global economy and financial markets, which had seriously affected the commodity market. Fig. 4 shows that except for Bird Flu and SARS, which had small positive impacts, all the other ID-EMV shocks of Swine Flu, MERS and Ebola, and COVID-19 negatively affected commodity returns, thereby indicating a trend of increasing negative impact of ID-EMV shocks on commodity returns with time. This finding shows that the recent infectious disease epidemics have added uncertainty to the stock and commodity markets together, and the commodity and equity markets have become more interconnected when experiencing the financial risks brought by the epidemics. Adekoya and Oliyide (2021) further found that ID-EMV had a significant causal effect on the connectivity of the complete market and believed that the pandemic was the primary reason for spreading risks in various commodities and financial markets. The commodity market cannot serve as a safe haven for epidemic risk because the return of commodity is negative when experiencing uncertainty of infectious disease epidemics.

The global geopolitical tensions from GPR further has a crucial impact on commodity prices. Consistent with Su et al. (2019), the occurrence of unexpected geopolitical events can significantly affect commodity production and aggregate demand, thereby leading to large volatility in commodity prices and significant impact on commodity returns. Fig. 4 shows that the impact of GPR shocks on commodity returns is primarily negative until 2007 and turn positive after. The negative impact on commodity returns primarily reflects that GPRs reduce more demand than supply for commodities before 2007. In particular, the investment sentiments depression in industries dependent on commodities, and economic downturn reduce the demand for commodities because of events, such as 9/11, London bombmings, and Iran nuclear tensions. After 2007, the positive impact of GPR on commodity returns primarily reflects the adverse impact of war and trade barriers on the supply side of commodities, such as the decline in commodity supply caused by events, such as the Arab Spring, Syrian War, Russia Annexes tensions, US-Iran tensions, Sino–US trade conflicts. Fig. 4 shows that except for during Bird Flu and SARS, the other shocks of GPR all had positive impacts on commodity returns, which shows that GPRs are increasingly affecting the supply side more than the demand side of commodities. It is also interesting to note that the ID-EMV and GPR shocks on commodity returns are in opposite directions and show inverse effects, particularly during the five epidemics, possibly
because GPRs divert attention from governments’ inadequate responses to COVID-19 (Wang et al., 2021).

WT measures speculative activities in the commodity market, and it has a crucial impact on commodity returns under the increasing financialization of commodities. Fig. 4 shows the effects of speculative activities on commodity returns are all negative, and this negative impact has gradually increased from 2007 and maintained a relatively stable situation. The speculation index WT indicates that when the short position held by hedging players is large in the market, the numerator term is non-commercial short, and the speculation index essentially refers to a speculative short. By observing the detailed data of positions held in the sample, short positions are the majority most of the time in the commodity market. We expect increased buying pressure to lead to higher prices, whereas increased selling pressure leads to lower prices. Therefore, the negative impact here can be understood as a speculative short impact that restrains commodity returns. Consistent with Lawson et al. (2021), the increase in WT is from an increase in speculative short positions rather than long positions, and we intuitively expect an increase in short positions to cause prices to decline relative to total positions. Etienne et al. (2018) further found that Working’s T (WT) was negatively correlated with other speculation measures, such as non-commercial net position and ESV index, which supported this intuition. Fig. 4 shows that during Bird Flu, SARS, and MERS and Ebola, the effects of speculation on commodity returns are similar and relatively small, whereas during Swine Flu and COVID-19, its impacts on commodity returns are similar and relatively large. Thus, in the epidemic period of high uncertainty and market risk, the short positions are more serious, which puts a downward pressure on commodities returns.

Fig. 5. Impulse Response of Commodity Categories Returns for Different Horizons.
5.4. Impulse response of commodity categories returns to ID-EMV, GPR, and speculation

With the heterogeneity of commodity markets in different industries for financial speculation, storage, convenience of supply, and dependence on weather conditions (Lyu et al., 2021), we divide commodities in CRB index into five categories for comparative analysis (textiles, industry, metals, livestock, and food). The relevant settings of the empirical models are consistent with the aforementioned aggregate commodity. For different types of commodity return, we select the corresponding CRB spot index and calculate the corresponding WT accordingly (Fig. 1). The estimation results of five commodity categories show that all models can perform a posteriori inference well.

Figs. 5 and 6 summarizes the specific time-varying impulse response, which show that shocks of ID-EMV, GPR, and speculation on commodity returns in various categories are consistent with the aggregate commodity in Section 5.3. The responses of commodity returns to shocks from ID-EMV, GPR, and speculation fluctuate most violently in a 1-month period and gradually converge to zero within half a year.

The impacts of ID-EMV shock on commodity returns of various categories are consistent with the aggregate commodity, with large negative fluctuations occurring around 2009. During COVID-19, differentiation responses of various commodity categories returns to ID-EMV shock are evident; textiles and industry are positive, whereas metals, livestock, and food are negative. In particularly, the trends of returns of textiles and industry to ID-EMV shocks are similar with negative fluctuations before 2014 and then become positive, whereas the trends of returns of metal, livestock, and food are similar with almost completely negative response to ID-EMV.
shock in the complete sample. During Swine Flu and COVID-19, the negative effects of ID-EMV shock on returns of metal, livestock, and food are the largest. The difference is textiles and industry, which show a large positive return after 2014 when encountering ID-EMV shock, thereby indicating that returns of these two commodities have changed from being adversely infected by epidemic risk to having the ability to resist. Notably, Sikiru and Salisu (2021) found that metals such as gold may behave differently from other metals and that their prices are positively correlated with the uncertainty index. Although the returns of other commodities show the most significant negative trend in the final two decades, particularly around 2020, thereby indicating that risks associated with epidemics have always led to a decline in returns. This finding complements Zhang and Broadstock (2020), thereby indicating a higher degree of connectivity between the commodity market and other markets.

The impacts of GPR on various commodities returns differ substantially from the aggregate commodity. Conflicts and tensions among major powers, including potential risks of financial instability, all lead to significant changes in the impact of uncertainty shocks on commodity markets (Ding et al., 2021). Because of the complexity of political conflicts and policy shifts and the characteristics and heterogeneity of different commodities, the impacts of a GPR shock are intuitively diverse. Similar to the aggregate commodity, the effects of a GPR shock on return of textile changed from a negative to a positive in 2007 but then reconverged to a negative influence in 2016. Returns of both industry and metals to the GPR shock are almost negative during the complete sample. However, when experiencing a GPR shock, the negative effect on metal return shows a gradually increasing trend overall. Returns of livestock and food response to GPR move in the same direction from negative to positive in 2007 and back to negative around 2015. According to Liu et al. (2019), GPRs may lead to serious differences in expectations of producers, consumers, and speculators, thereby affecting their decisions. Therefore, we believe that alongside supply and demand factors, the different expectations of commodity market participants significantly impact the diversity of GPR shocks.

The impacts of WT shock on various commodities returns are similar to that of the aggregate commodity, which show a negative influence. Compared with other shocks, speculation has the least impact, which may be because of the impact of international trade shocks from other countries weakening the speculative effect in commodity markets (Lawson et al., 2021). Livestock and food products associated with agricultural products have been least hit probably because buffer stocks and government interventions have helped insulate them from external shocks, such as financial markets; their production is geographically dispersed. Lawson et al. (2021) noted that precautionary buffer stocks and government intervention are likely to be larger for rice and wheat than other commodities, and wheat and rice production are more geographically dispersed. During the sample period, the influence of speculation on returns of textiles, industry, and metals show a gradual strengthening trend; return of livestock is very stable, and the return of food gradually strengthened and then weakened from 2010. Lawson et al. (2021) argued that when commercial traders frequently alternate their net positions, the impact of speculation on commodities may be weakened because of commercial traders’ agility. Therefore, we believe that the increasing impact of speculation on commodities is due to the shift of commercial traders from a regular long/short rotation to a more consistent pattern (short-dominated), which may reflect long-term commodity fundamentals.

Fig. 6 shows that the responses of various commodities return to ID-EMV and GPR shocks during the five epidemics are different, with very significant time-varying effects, whereas speculation shocks were not. In particular, during Bird Flu, ID-EMV shocks harmed returns of livestock and food, which may be due to the reduction of the supply of livestock caused by avian influenza. The GPR shock negatively impacted returns of all commodities except industry. The speculation (WT) further harmed returns of all five commodity categories. During SARS, ID-EMV shocks negatively impacted returns of industry, livestock, and food and positively impacted returns of textiles and metals. The GPR shock harmed returns of textiles, livestock, and food but has positively impacted returns of industry and metals. The impact of speculation (WT) is identical as that of Bird Flu, which also negatively impacted returns of all commodities. During Swine Flu, ID-EMV harmed returns of textiles and food, whereas the effect on returns of industrial, livestock, and metals were positive but then became negative. GPR shocks had a positive impact on returns of all commodities except metals. This finding shows that during this epidemic period, the impact of GPR on the reduction of metal demand was greater than that on metal supply. The impact of speculation (WT) was the same as that mentioned previously, and metal and food fluctuated more sharply in the 3rd period. During MERS and Ebola, the impact of ID-EMV on returns of commodities was similar to Swine Flu. The GPR shock had a negative impact on returns of almost all commodities except livestock, which was first positive but then became negative. Speculation (WT) impact on returns of commodities was consistent with SARS and Bird Flu. During COVID-19, the impacts of ID-EMV shocks on returns of commodities were strongest since 1998, with negative impacts on returns on textiles and industry and positive impacts on returns of metals, livestock, and food. GPR shocks had a negative impact on returns of industry and metal, whereas returns of textile, livestock, and food were positive but then showed negative characteristics after suffering ID-EMV shocks. The respond of returns of commodities to speculation (WT) were consistent with Swine Flu.

Comparing returns of commodity categories during the five epidemics, finding solid safe-haven assets is difficult, which is broadly consistent with the findings for commodities in general. Because of the evident time-varying effect, the change of each commodity return in different periods is diversified. When focused on COVID-19, Sharif et al. (2020) believed that this unprecedented rise in GPR is the result of the combined impact of emerging infectious diseases and the recent free fall in oil prices. When extreme events related to GPRs occur, investors’ panic will lead to abnormal market fluctuations and eventually affect the returns and fluctuations of the commodity market (Tiwari et al., 2021). We can find that the crisis and uncertainties are systemic, with health and GPRs both at their highest in nearly two decades (ID-EMV peaked at 1556.68 in March 2020 and GPR index reached its second highest 380 in January 2020). During this period, industry and food played the role of hedge assets in dealing with ID-EMV and GPR shocks, respectively, and textile dealt well with the challenges of these two shocks, whereas metals and livestock were negatively impacted.
6. Conclusion

The significant increase in health and GPRs in recent years and the rapid increase in speculation in international commodity markets have drawn attention to the effects of infectious disease risk, GPR, and speculation on commodity returns. However, few studies have provided evidence and solid conclusions on their impact on commodities. This paper uses a time-varying Granger causality test and a TVP-VAR-SV model to examine the impact of ID-EMV, GPR, and speculation shocks on commodity returns in five epidemics over 1998–2021 (Bird Flu, SARS, Swine Flu, MERS and Ebola, and COVID-19). We primarily focus on the time-varying characteristics of commodity returns and further conducting a detailed comparative analysis of the differentiated responses of commodity categories' returns.

The results show that the time-varying effects of shocks on commodity returns are evident, and ID-EMV, GPR, and speculation have different impacts on various commodities categories' returns during different epidemics. In general, ID-EMV and GPR shocks have a greater impact, whereas speculative shocks have the least impact. During the sample period, the majority of effects of ID-EMV shocks on categories returns are negative, thereby indicating that its negative impact of systemic risks is greater than the hedging effect of commodities. Therefore, commodities cannot be used as safe-haven assets when experiencing epidemic risks. The effects of GPR shocks on commodity return change from negative to positive, thereby indicating that its impact on reducing the supply of commodities is smaller than the depression of investment demand in the early stage, and the situation reverses later on. Speculation has negative impacts on commodity returns in the whole sample, thereby indicating that it is primarily in a short position, speculators are short on commodities, which has a downward effect on commodity prices and returns. We further note that the ID-EMV and GPR shocks have contradictory effects on commodity returns during the pandemics possibly because GPRs have diverted attention from governments' poor pandemic responses. In particular, the diversification of ID-EMV and GPR shocks during the five epidemics made it difficult to identify solid safe-haven assets due to the heterogeneity of different commodity categories in storage, availability, and dependence on weather conditions, including the complexity of political conflicts and policy shifts. During the five outbreaks, the biggest impact on commodity returns is COVID-19, followed by Swine Flu.

These results can provide valuable guidance for investors to hold assets during periods of high market uncertainty caused by infectious disease epidemics or GPR and have implications for policymakers on how to respond to pandemics and stabilize commodity markets. Academics, policymakers, and practitioners should further consider these findings. COVID-19 has profoundly impacted the global economy and financial markets. Governments should improve emergency responses to infectious disease events, implement lockdown and isolation policies in affected areas more rapidly, and quickly stabilize market sentiments to mitigate systemic risks. Commodities in general are not safe-haven assets from pandemic and GPRs. However, because of the heterogeneity of the commodity market, different categories of commodity returns show different time-varying characteristics. Therefore, investors should rationally treat the original investment portfolio strategy and select an appropriate asset portfolio to hedge risks brought by crises. Concerning speculation, no evidence indicated that the financialization of commodity markets pushes up prices into bubbles. By contrast, the “excess speculation” measured by Working’s T index reduces commodity returns, thereby suggesting that policymakers should be cautious about speculation.

CRediT authorship contribution statement

Shaobo Long: Conceptualization, Methodology, Formal analysis, Writing – review & editing. Jiaqi Guo: Data curation, Software, Writing – original draft.

Conflict of interest statement

No potential conflict of interest was reported by the authors.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central Universities [Grant number 2019CDSKXYGG0042].

Submission declaration

The author would like to declare on behalf of all co-authors that this work is original research that has not been published previously, and is not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed. And its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language including electronically without the written consent of the copyright-holder.

References

Adediran, I.A., Salawudeen, A., Sabzwari, S.N.A., 2021a. Islamic stock markets and COVID-19-induced shocks: simulations with global VAR approach. Int. J. Islamic Middle Eastern Financ. Manag. 15 (2), 287–309.
Abedirana, I.A., Yinua, O.D., Lakhanhi, K.H., 2021b. Where lies the silver lining when uncertainty hang dark clouds over the global financial markets? Res. Policy 70, 101932.

Adesola, O., Aiyedokun, O.B., 2021. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Res. Policy 70, 101898.

de Albuquerque, V.P., de Medeiros, R.K., da Nóbrega, C., Maia, S.F., 2018. Forecasting crude oil price: does it exist an optimal econometric model? Energy 155, 578–591.

Aquilani, R., Gervais, O., 2013. The role of financial speculation in driving the price of crude oil. Energy J. 34 (3), 35–54.

Antonakakis, N., Gupta, R., Kollas, C., Papadamo, S., 2017. Geopolitical risks and the oil-stock nexus over 1899–2016. Financ. Res. Lett. 23, 165–173.

Asal, M., Gupta, R., McAllem, M., 2020. Forecasting volatility and co-volatility of crude oil and gold futures: efforts of leverage, jumps, spillovers, and geopolitical risks. Int. J. Forecast. 36 (3), 933–948.

Ayus, A., Demir, E., Gogoz, G., Lai, C.-K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. Res. Int. Bus. Financ. 47, 511–518.

Baies, J., Hanitotiis, T., 2010. Placing the 2006/08 commodity price boom into perspective. World Bank Policy Res. Work. Paper (5971).

Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020. Covid-Induced Economic Uncertainty. National Bureau of Economic Research.

Baloglu, M., Bonato, M., Demirer, B., Gupta, R., 2018. Geopolitical risks and stock market dynamics of the BRICS. Econ. Syst. 42 (2), 295–306.

Bas, H.H., 2011. The relevance of speculation. Rural 21 (05), 17–21.

Baumeister, C., Peersman, G., 2013. The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. J. Appl. Econ. 28 (7), 1087–1109.

Beckmann, J., Beltke, A., Czudaj, R., 2014. Regime-dependent adjustment in energy spot and futures markets. Econ. Model. 40, 400–409.

Bekhradnia, J., Selimi, R., Hamdoum, S., Wohar, M.E., 2019. What are the categories of geopolitical risks that could drive oil prices higher? Acts or threats? Energy Econ. 84, 104523.

Bouri, E., Das, M., Gupta, R., Roubaud, D., 2018. Spillovers between Bitcoin and other assets during bull and bear markets. Appl. Econ. 50 (55), 5935–5949.

Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L., Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. Quart. Rev. Econ. Financ. 77, 156–164.

Boyd, N.E., Büyüksahin, B., Haigh, M.S., Harris, J.H., 2016. The prevalence, sources, and effects of herding. J. Futures Mark. 36 (7), 671–694.

Boyd, N., Harris, J.H., Li, B., 2018. An update on speculation and financialization in commodity markets. J. Commodity Market. 10, 91–104.

Brandt, M.A.W., Gao, L., 2019. Macro fundamentals or geopolitical events? A textual analysis of news events for crude oil. J. Emp. Financ. 51, 64–94.

Bruno, V.G., Büyüksahin, B., Robe, M.A., 2017. The financialization of food. Am. J. Agric. Econ. 99 (1), 243–264.

Büyüksahin, B., Robe, M.A., 2011. Does paper oil matter? Energy markets’ financialization and equity-commodity co-movements. Soc. Sci. Res. Netw. NY USA.

Büyüksahin, B., Robe, M.A., 2014. Speculators, commodities and cross-market linkages. J. Int. Money Financ. 42, 38–70.

Caggiano, G., Castelnuovo, E., Kimia, R., 2020. The global effects of Covid-19-induced uncertainty. Econ. Lett. 194, 109392.

Calder, A., Iacoviello, M., 2018. Measuring geopolitical risk. FRB Int. Financ. Discuss. Paper (1222).

Calder, A., & Iacoviello, M. (2021). Measuring geopolitical risk. Board of Governors of the Federal Reserve Board Working Paper, November 2021.

Canova, F., Ito, T., 1991. The time-series properties of the risk premium in the Yen/us dollar exchange market. J. Appl. Econ. 6 (2), 125–142.

Cheng, C.H.J., Chiu, C.W.J., 2018. How important are global geopolitical risks to emerging countries? Int. Econ. 156, 305–325.

Chopra, K.A., Gupta, A.M., Uddin, A., Haque, M.M., 2021. Asymmetric effect of energy price on commodity price: new evidence from NARDL and time frequency analysis. Energy 233, 120934.

Colon, F., Kim, C., Kim, H., Kim, W., 2021. The effect of political and economic uncertainty on the cryptocurrency market. Financ. Res. Lett. 39, 101621.

Ding, Q., Huang, J., Zhang, H., 2021. The time-varying effects of financial and geopolitical uncertainties on commodity market dynamics: a TVP-SVAR-SV analysis. Resour. Policy 72, 102079.

Ding, Q., Huang, J., Hao, W., Zhang, H., 2022. Does political risk matter for gold market fluctuations? A structural VAR analysis. Res. Int. Bus. Financ. 60, 101618.

Ekeland, I., Lautier, D., & Villeneuve, B. (2014). Speculation in commodity futures markets: A simple equilibrium model. SSRN ID, 2323560.

Etienne, X.L., Irwin, S.H., Garcia, P., 2015. Price explosiveness, speculation, and grain futures prices. Am. J. Agric. Econ. 97 (1), 65–87.

Etienne, X.L., Irwin, S.H., Garcia, P., 2018. Speculation and corn prices. Appl. Econ. 50 (44), 4724–4744.

Geweke, J., 1992. Evaluating the accuracy of sampling-based approaches to the calculations of posterior moments. Bayesian Anal. 4, 614–649.

Gilbert, C.L., 2010. How to understand high food prices. J. Agric. Econ. 61 (2), 398–425.

Gillias, K., Gupta, R., Wohar, M.E., 2018. Volatility jumps: the role of geopolitical risks. Financ. Res. Lett. 27, 247–258.

Gillias, K., Tsganakos, A., Vortelinos, D.I., 2019. Integration and risk contagion in financial crises: evidence from international stock markets. J. Bus. Res. 104, 350–365.

Haase, M., Zimmermann, Y.S., Zimmermann, H., 2016. The impact of speculation on commodity futures markets—a review of the findings of 100 empirical studies. J. Commodity Mark. 3 (1), 1–15.

Hammond, A., Mokni, V., Razafindrabe, T., 2017. Does the volatility of commodity prices reflect macroeconomic uncertainty? Energy Econ. 68, 313–326.

Kim, A., 2015. Does futures speculation destabilise commodity markets? J. Futures Mark. 35 (8), 696–714.

Lawson, J., Alam, R., Etienne, X., 2021. Speculation and food-grain prices. Appl. Econ. 53 (20), 2305–2321.

Liu, J., Ma, F., Tang, Y., 2019. Geopolitical risk and oil volatility: A new insight. Energy Econ. 84, 104548.

Liu, W., Gui, Y., Qiao, G., 2022. Dynamics lead-lag relationship of jumps among Chinese stock index and futures market during the Covid-19 epidemic. Res. Int. Bus. Financ. 61, 101669.

Liu, Y., Han, L., Xu, Y., 2021. The impact of geopolitical uncertainty on energy volatility. Int. Rev. Financial Anal. 75, 101743.

Lyu, Y., Yi, H., Hu, Y., Yang, M., 2021. Economic uncertainty shocks and China’s commodity futures returns: a time-varying perspective. Resour. Policy 70, 101979.

Maghyereh, A., Abdoh, H., Awartani, B., 2022. Have returns and volatilities for financial assets responded to implied volatility during the COVID-19 pandemic? Journal of Commodity Markets 26, 101934.

Mamatkar, E., Resmondos, P., 2011. Testing for adjustment costs and regime shifts in Brent crude futures market. Econ. Model. 28 (3), 1000–1008.

McPhail, L.L., Du, X., Muhammad, A., 2012. Disentangling corn price volatility: the role of global demand, speculation, and energy. J. Agric. Appl. Econ. 44 (3), 401–410.

Nakajima, J., 2011. Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. Monetary Econ. Stud. 29, 107–142.
Nakajima, J., Kasuya, M., Watanabe, T., 2011. Bayesian analysis of time-varying parameter vector autoregressive model for the Japanese economy and monetary policy. J. Jpn. Int. Econ. 25 (3), 225–245.

Noguera-Santaella, J., 2016. Geopolitics and the oil price. Econ. Model. 52, 301–309.

Omar, A.M., Wisniewski, T.P., Nolte, S., 2017. Diversifying away the risk of war and cross-border political crisis. Energy Econ. 64, 494–510.

Peck, A.E., 1980. The role of economic analysis in futures market regulation. Am. J. Agric. Econ. 62 (5), 1037–1043.

Primiceri, G.E., 2005. Time varying structural vector autoregressions and monetary policy. Rev. Econ. Stud. 72 (3), 821–852.

Riggi, M., Venditti, F., 2015. The time varying effect of oil price shocks on euro-area exports. J. Econ. Dyn. Control 59, 75–94.

Rubaszek, M., Uddin, G.S., 2020. The role of underground storage in the dynamics of the US natural gas market: a threshold model analysis. Energy Econ. 87, 104713.

Rubaszek, M., Karolak, Z., Kwas, M., Uddin, G.S., 2020. The role of the threshold effect for the dynamics of futures and spot prices of energy commodities. Stud. Nonlinear Dyn. Econ. 24, 5.

Salisu, A., Adediran, I., 2020. Uncertainty due to infectious diseases and energy market volatility. Energy Res. Lett. 1 (2), 14185.

Salisu, A.A., Sikiru, A.A., 2020. Pandemics and the Asia-Pacific Islamic stocks. Asian Econ. Lett. 1 (1), 17413.

Salisu, A.A., Vo, X.V., 2020. Predicting stock returns in the presence of COVID-19 pandemic: the role of health news. Int. Rev. Financ. Anal. 71, 101546.

Salisu, A.A., Isah, K.O., Gywole, O.J., Akanni, L.O., 2017. Modelling oil price-inflation nexus: the role of asymmetries. Energy 125, 97–106.

Salisu, A.A., Akanni, L., Raheem, L., 2020. The COVID-19 global fear index and the predictability of commodity price returns. J. Behav. Exp. Financ. 27, 100383.

Sanders, D.R., Irwin, S.H., Merrin, R.P., 2010. The adequacy of speculation in agricultural futures markets: too much of a good thing? Appl. Econ. Perspect. Policy 32 (1), 77–94.

Selmi, R., Bouoiyour, J., Wohar, M.E., 2022. “Digital Gold” and geopolitics. Res. Int. Bus. Financ. 59, 101512.

Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal. 70, 101496.

Shi, S., Phillips, P.C., Hurn, S., 2018. Change detection and the causal impact of the yield curve. J. Time Series Anal. 39 (6), 966–987.

Shi, S., Hurn, S., Phillips, P.C., 2020. Causal change detection in possibly integrated systems: Revisiting the money-income relationship. J. Financ. Econ. 18 (1), 158–180.

Sikiru, A.A., Salisu, A.A., 2021. Assessing the hedging potential of gold and other precious metals against uncertainty due to epidemics and pandemics. Qual. Quantity 1–16.

Su, C.W., Khan, K., Tao, R., Nicoleta-Claudia, M., 2019. Does geopolitical risk strengthen or depress oil prices and financial liquidity? Evidence from Saudi Arabia. Energy 187, 116003.

Sun, T.T., Su, C.W., Mirza, N., Umar, M., 2021. How does trade policy uncertainty affect agriculture commodity prices? Pac.-Basin Financ. J. 66, 101514.

Tadesse, G., Algieri, B., Kalkuhl, M., Braun, J.V., 2014. Drivers and triggers of international food price spikes and volatility. Food Policy 47, 117–128.

Tang, K., Xiong, W., 2012. Index investment and the financialization of commodities. Financ. Anal. J. 68 (6), 54–74.

Tiwari, A.K., Roachie, M.K., Suleman, M.T., Gupta, R., 2021. Structure dependence between oil and agricultural commodities returns: The role of geopolitical risks. Energy 219, 119584.

Uddin, G.S., Gençay, R., Bekiros, S., Sahamkhadam, M., 2019. Enhancing the predictability of crude oil markets with hybrid wavelet approaches. Econ. Lett. 182, 50–54.

Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. J. Monetary Econ. 52 (2), 381–419.

Wang, Q., Bai, M., Huang, M., 2021. Empirical examination on the drivers of the US equity returns in the during the COVID-19 crisis. Front. Public Health 9, 1–7.

Will, M.G., Prehn, S., Pies, I., Glauben, T., 2015. Is financial speculation with agricultural commodities harmful or helpful?: A literature review of empirical research. J. Altern. Invest. 18 (3), 84–102.

Working, H., 1960. Speculation on hedging markets. Food Res. Inst. Stud. 1 (2), 185–220.

Yahya, M., Ghosh, S., Kanjilal, K., Dutta, A., Uddin, G.S., 2020. Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes. Energy 202 (1), 1–14.

Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. Int. Rev. Financ. Anal. 68, 101239.