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Public attention, oil and gold markets during the COVID-19: Evidence from time-frequency analysis

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doi.org/10.1016/j.resourpol.2022.102868

1. Introduction

Since the outbreak of COVID-19 in early 2020, it has spread to almost all countries in the world by April 2022, infecting 492 million people and resulting in 6 million deaths, according to the World Health Organization’s (WHO) dashboard. The COVID-19 pandemic’s impact extends beyond infection and deaths. Furthermore, it has a huge economic impact, affecting production and consumption, trade patterns and economic activities, as well as destabilizing the global economy (e.g., Baker et al., 2020; Xu et al., 2021; Ambros et al., 2020; Havrlant et al., 2020; Akeel and Khoj, 2020). This unprecedented global health catastrophe initiates a period of a financial crisis that penetrates the entire financial system, including commodity markets. (Goodell and Huynh, 2020; Atri et al., 2021).

The crude oil and gold markets, as the two main representatives of the large commodity markets, have witnessed big swings since the COVID-19 outbreak, attracting the attention of all countries in the world. Since the COVID-19 pandemic was declared by the WHO in early 2020, West Texas Intermediate (WTI) crude oil prices have fallen from around $60 to below $30 in early March 2020 and then slipped to -$37 per barrel in April 2020, the lowest level in 18 years and the first time in history. 1 Relatively, gold prices decreased slightly when COVID-19 broke out but then began to recover from February 2020. Gold gained strongly against all major currencies, reaching $2063.19 per ounce in August 2020, its highest level in nearly a decade. This could be because gold is a unique long-run inflation hedging instrument. These fluctuations in crude oil and gold prices may be due to serious economic stagnation and strong hedging demand triggered by investor panic caused by the COVID-19 pandemic.

A large amount of evidence has shown the crude oil and gold markets have obvious financial characteristics and there is a close interaction between them (Zhang and Wei, 2010; Tiwari and Sahadudheen, 2015; Yang et al., 2020; among others), particularly during economic turbulence (Nissanke, 2012; Oztek and Ocal, 2017; Junttila et al., 2018; Tanin et al., 2022). This could be because they have some common influencing elements. For example, the US dollar exchange rate will affect the prices of crude oil and gold. It impacts crude oil prices since oil is traded in US dollars and is increasingly used as a financial asset. The US dollar’s rise may cause nominal crude oil prices to fall in some market conditions (Jawadi et al., 2016; Mensi et al., 2017). When the US dollar declines...
versus other currencies, the prices of gold rise due to increased demand, which eliminates arbitrage opportunities (Reboredo, 2013; Dai et al., 2020). Further, gold and crude oil prices tend to interact through inflation and inflation expectations. Rising crude oil prices tend to push up global inflation expectations, and increased demand for emergency hedging will lead to rising gold prices (Erb and Harvey, 2013; Salisu et al., 2017). Through cross-market pricing transmission, a rise in gold prices yields a lagged decrease in bond prices, which in turn is followed by an increase in the oil price level, and finally pushes up inflation (Narayan et al., 2017).

Apart from macroeconomic fundamentals, supply and demand, the impact of sentiment on crude oil and gold markets has also garnered increased scholarly interest (Deeney et al., 2015; Maslyuk-Escobedo et al., 2016; Qadan and Nama, 2018; Li et al., 2019; Chen et al., 2022; Jain and Biswal, 2019; Hu et al., 2020; Balcilar et al., 2017; Luo et al., 2022). Four types of sentiments are taken into account when analyzing the relationship between crude oil and gold markets, including consumer sentiment, market sentiment, news-based sentiment, and investor sentiment. However, most of the previous sentiment indicators measured sentiment towards the financial market and rarely considered public attention about major public health emergencies (Atiri et al., 2021). During the COVID-19 pandemic, a large number of infections and deaths inevitably caused public attention, which may play an important role in crude oil and gold markets. First, public attention has a dual role. On the one hand, the information and discussion about COVID-19 spread rapidly on the Internet causing great panic among the public. On the other hand, the change in public opinions may imply public participation which is crucial for the prevention of coronavirus disease (Han et al., 2020). In this way, public attention may also be crucial in preventing coronavirus disease (Gao et al., 2020; Zhao et al., 2020), helping to further alleviate public panic and improve public expectations for the future. Second, from the perspective of behavioral finance, investor behavior and psychological factors, such as panic, have been proved to affect crude oil and gold markets during the COVID-19 pandemic (Mensi et al., 2020; Algamdi et al., 2021; Ali et al., 2020; Niu et al., 2021; Atiri et al., 2021; Zhang et al., 2022). The severity of the COVID-19 pandemic has aroused public attention to COVID-19 related information, which may cause panic among investors. Panic will distract investors from speculative investment and affect market trading (Tetlock, 2007; Kaplanski and Levy, 2010; Su et al., 2017). If they have incomplete information about the COVID-19 pandemic, they tend to infer from the change in the public attention to COVID-19. When the public attention suddenly increases, investors may panic, probably inferring that the pandemic is worse than previously anticipated. Then investors tend to sell out of fear, resulting in a temporary drop in market prices. On the contrary, a decrease in public attention may indicate the pandemic is under control, investor panic could be relieved, and the market prices tend not to show extreme movements. These considerations motivate us to investigate the relationship between public attention, crude oil and gold markets.

At present, most relevant studies are based on the time domain (Algamdi et al., 2021; Ali et al., 2020; Mensi et al., 2020; Atiri et al., 2021; Niu et al., 2021; Zhang et al., 2022), and the relationship between sentiment, crude oil and gold markets over time and frequency has rarely been examined. However, investors’ responses to different economic and financial events are usually various. More precisely, investors participate in the financial markets over a range of time horizons, densities by frequencies ranging from seconds to years, based on their varying beliefs, preferences, and objectives, as well as their varying levels of information integration and risk tolerance. As a result, economic and financial shocks can spread across markets, resulting in a range of frequency responses (Khan et al., 2020). In crude oil and gold markets, the investment horizon will also vary due to different investment strategies. For example, in the crude oil and gold futures markets, hedgers only try to reduce risks in the spot market, while speculators are more concerned with short-term gains (Chen et al., 2022). The effects of public attention on crude oil and gold prices may vary according to investment strategies and horizons, especially during the COVID-19 pandemic, which motivates us to employ time-frequency analysis. Besides, time-frequency dependence has been demonstrated to exist between crude oil and gold markets (Hu et al., 2020; Hung and Vo, 2021; Li et al., 2021; Ding et al., 2021), between investor attention and crude oil markets (Abdelhedi and Boujeabene-Abben, 2020; Chen et al., 2022), as well as between investor attention and gold markets (Su and Li, 2020; Zhang et al., 2022), but limited research on the public attention, crude oil and gold markets during the COVID-19 pandemic (Zhang et al., 2022; Tuna and Tuna, 2022). Therefore, our research adopts the wavelet analysis and time-frequency domain causality method to investigate the possible nonlinear relationship between public attention to the COVID-19 pandemic, oil and gold markets across time and frequency.

There are several reasons for focusing on the G7 countries. Firstly, according to the World Bank 2020 GDP ranking, the G7, i.e., the US, Canada, the UK, Germany, France, Italy and Japan, are the seven most advanced economies in the world. They are all among the top 10 in the world, comprising 10% of the world population and 45% of world GDP. Generally, the US is the focus of most research, while other developed nations are followed individually or through well-known groups such as the G7. However, their economic systems exhibit remarkable differences in terms of policy interventions, economic reforms and financial regulation activities, which makes the study of their heterogenous relationship between COVID-19, oil and gold markets extremely informative. Secondly, according to the BP Statistical Review of World Energy in 2020, the US has always been the world’s largest oil consumer, with total oil consumption of 19.4 million barrels per day in 2019; Japan is a large oil consumer in the Asia Pacific region, which is the largest oil consumption region, accounting for 36.8% of the global oil consumption; Europe is the third-largest oil consumption region in the world, with Germany, France, the UK and Italy ranking top four in Europe. Thirdly, the gold markets of developed countries (the US, the UK, Japan, etc.) have developed into mature financial markets with large transaction scales. For example, the New York Mercantile Exchange (COMEX) is one of the world’s largest gold futures trading centers. The London Bullion Market is the top one of the four major gold markets in the world, with a history of 300 years, and the largest spot gold market in the world. The Tokyo Commodity Exchange (TOCOM) is the second-largest gold market. The Tokyo Gold Exchange keeps pace with the other four major international gold markets, making the Japanese gold market become the main force driving the fluctuation of the Asian gold plate. Fourthly, in the early COVID-19 pandemic, the US, Japan, Germany, the UK, France, and Italy were all in the top ten most affected by the disease. Therefore, it is necessary to investigate the relationship between public attention to COVID-19, crude oil and gold markets for the G7 economies.

The contribution of our study is as follows. First, although numerous studies have been conducted on the relationship between sentiment, crude oil, and the gold market, the majority of sentiment measurements are based on investor sentiment for the financial markets and do not take into account the increased public attention to major public health emergencies. This paper aims to explore the multivariate relationship between public attention to the COVID-19 pandemic, crude oil and gold markets, so as to enrich the limited study on the association between commodity markets and public attention to major public health emergencies. Second, we use time-frequency analysis, including wavelet analysis and time-frequency domain causality, to evaluate the relationship between public attention to the COVID-19 pandemic, crude oil,
and gold markets over time and different investment horizons. However, previous research has paid little attention to the fact that the impact of public attention on crude oil and gold markets differs depending on investment strategies and investment horizons. Additionally, we analyze the possible heterogeneity in the effect of public attention on the crude oil and gold markets for the G7 countries. Due to the pandemic’s varying transmission time and severity in the G7, public perceptions and potential impact are also heterogeneous. An in-depth understanding of the relationship between public attention to the COVID-19 pandemic, crude oil and gold markets in the G7 is of utmost importance to investors, regulators, and policymakers to mitigate the risks posed by major public health emergencies.

The article is organized as follows: After reviewing the works of literature, data and the empirical methodology are described, leading to discussions of the empirical results and the conclusions.

2. Literature reviews

Numerous studies have established that the crude oil and gold markets exhibit clear financial features and that they are inextricably linked (see, for example, Zhang and Wei, 2015; Tiwari and Sahadudheen, 2015; Yang et al., 2020), particularly during times of economic upheaval (Nissank, 2012; Oztekm and Ocal, 2017; Junitila et al., 2018; Tanin et al., 2022), such as the economic turmoil caused by COVID-19 pandemic. For example, Dutta et al. (2020), Gharib et al. (2021) and Salisu et al. (2021) demonstrate gold has hedging effectiveness against risks related to crude oil, notably during the pandemic period. Mensi et al. (2020) show that gold price returns affect the S&P500 index returns, which contribute negatively to oil price returns, particularly during the COVID-19 outbreak. Gharib et al. (2021) reveal that bubbles in the oil and gold markets had a bidirectional contagion effect during the COVID-19 pandemic. Huang and Wu (2021) find that spillover from the oil market to the gold market occurs more frequently during pandemics. Farid et al. (2021) observe a rise in volatility correlations across multiple asset classes, including oil, gold, silver, and natural gas, during the COVID-19 outbreak. Hung and Vo (2021) illustrate that there are substantial dependent patterns in terms of information spillovers between the S&P 500, crude oil, and gold markets, with return transmissions becoming more apparent during the COVID-19 crisis. Due to the “financialization” of the commodity market, crude oil and gold are favored not just by institutional investors, but also by individual investors seeking diversification. The public fear sparked by COVID-19 is expected to force investors to rebalance their portfolios, sell crude oil in response to the economic recession and purchase gold in significant quantities to hedge against hazards. Finally, it will affect crude oil and gold prices.

Speculation has been demonstrated in the increasingly financialized commodity markets, and behavioral factors have been shown to affect both the crude oil and gold markets (Li et al., 2015; Akinsomi et al., 2016; Acharjya and Natarajan, 2019; Li et al., 2019; Vasileiou, 2021; etc.). For the crude oil market, Borovkova (2011) provides the first overview of the relationship between news sentiment and energy markets, concluding that oil futures prices respond strongly and positively to news sentiment. Maslyuk-EScobedo et al. (2016) establish a substantial association between crude oil and consumer sentiment in the US. Deevey et al. (2015) suggest a financial proxies-based sentiment for West Texas Intermediate oil (WTI) and Brent crude oil futures and showed that sentiment influences crude oil futures prices. Qadan and Nama (2018) argue that investor sentiment, captured by nine different proxies, significantly affects oil prices. Li et al. (2019) and Chen et al. (2022) select the Google search volume index as the proxy variable of investor attention and found investor attention has an apparent asymmetric impact on crude oil prices and returns, especially under extreme bearish market conditions.

In the case of the gold market, Smales (2014) utilizes commodity-specific news sentiment data and discovers that negative news sentiment results in a greater contemporaneous response in gold futures returns. Jain and Biswal (2019) employ Google Search Trends for gold as investor attention and report a bi-directional causality between investor attention and gold returns. Hu et al. (2020) demonstrate how macro factors affect commodities markets volatility, revealing that crude oil and gold are more sensitive to market sentiment. While Bystrom (2020) and Bonato et al. (2021) study the link between happiness and gold markets. Luo et al. (2022) demonstrate the predictive value of investor sentiment-related elements in enhancing the prediction accuracy of commodity volatility dynamics. Balcilar et al. (2017) find investors’ extreme fear contributes to positive volatility jumps in gold returns. Furthermore, Ji and Guo, 2015 discover the changes of public concern on the Internet can well depict the changes of commodity market prices, including crude oil, heating oil, gold, and corn. Bampinas et al. (2019) find information flows from internet-search reduce the proportion of the significant volatility asymmetry produced by negative shocks in both crude oil and gold markets. Farid et al. (2021) prove that contagion effects driven by the market sentiment of fear quickly transmitted across US financial markets, including oil, gold, silver and natural gas markets, and volatility connectedness among different asset classes spiked during the COVID-19 outbreak. As can be seen, sentiment factors have an important effect on the oil and gold markets, particularly during periods of significant market volatility.

Four types of sentiments are taken into account when analyzing the relationship between crude oil and gold markets, including consumer sentiment, market sentiment, news-based sentiment, and investor sentiment. The Consumer Confidence Index (CCI) and the University of Michigan’s Index of Consumer Sentiment are frequently used to gauge consumer sentiment (Maslyuk-EScobedo et al., 2016), but can not fully present investor sentiment. Market sentiment is typically quantified using the CBOE volatility index (VIX), the oil volatility index (OVX), the speculative and hedge ratios for gold and WTI (Hu et al., 2020; Luo et al., 2022), and the index constructed by principal component analysis based on several market-based variables (Deeney et al., 2015; Baker and Wurgler, 2006, 2007). However, investor sentiment relates not only to market-wide sentiment but also to individual sentiment. The news-based sentiment is another popular measure in many works of literature. For example, Borovkova (2011) provides the first overview of the relationship between news sentiment measured by Thomson Reuters News Analytics and energy. Smales (2014) utilizes commodity-specific news sentiment data to examine the relationship between news sentiment and gold futures returns. Atri et al. (2021) use the percentage of all news sources associated with COVID-19 as the COVID-19 media coverage indicator (CMC) and analyze the impact of COVID-19 media coverage on the dynamics of oil and gold prices. However, the news-induced sentiment is limited to a single sentiment about news and events, investor sentiment is most likely to reflect the “pure” sentiment in the entire market, which is exogenous to economic fundamentals and less likely to be driven by confounding factors. Therefore, some studies prefer to employ investor sentiment usually proxied by some internet-related variables, such as the Google search volume index (Li et al., 2019; Jain and Biswal, 2019; Chen et al., 2022) and the Twitter-based sentiment index (Bystrom, 2020). The majority of investor sentiment measurements are based on investor attention to the financial markets and do not take into account the increased public attention to major public health emergencies.

During the COVID-19 pandemic, a large number of infections and deaths inevitably caused public attention, which may play a predominant role in crude oil and gold markets. Mensi et al. (2020) examine the impacts of COVID-19 on the multifractality of gold and oil prices and conclude that the efficiency of gold and oil markets is sensitive to scales, market trends, and the pandemic outbreak, highlighting the investor sentiment effect. Algami et al. (2021) study the substantial impact of COVID-19 death cases on oil prices, finding that the mortality of COVID-19 has an obvious negative impact on the dynamics of oil prices. Ali et al. (2020) investigates the impact of COVID-19 deaths on oil and...
gold markets and find the relatively safer commodities have suffered as the pandemic moves into the US. Tuna and Tuna (2022) also show there is a temporary causality between gold and oil prices and the number of COVID-19 cases in the short term. Niu et al. (2021) find coronavirus news (in China and globally) contains incremental information to predict the volatility of China’s crude oil. Atri et al. (2021) use the percentage of all news sources associated with COVID-19 as the COVID-19 media coverage indicator (CMC), and determine that COVID-19 media coverage has positive effects on the dynamics of oil and gold prices. Zhang et al. (2022) focus on information spillover from epidemic-related news to the crude oil, gold, and Bitcoin markets. Previous research on the influence of COVID-19 panic on crude oil and gold markets has relied on either deaths or media coverage as proxies for public attention but has mostly ignored Internet-based opinion, which may be more appropriate to represent individual sentiment towards the COVID-19 pandemic than deaths and media coverage. Therefore, it motivates us to investigate the relationship between Internet-based public attention to the COVID-19 pandemic, crude oil and gold markets.

From the perspective of methodology, most relevant studies are based on the time domain (Algamdi et al., 2021; Ali et al., 2020; Mensi et al., 2020; Atri et al., 2021; Niu et al., 2021; Zhang et al., 2022), but the time-frequency domain relationship between sentiment, crude oil and gold markets has rarely been examined. However, some studies, such as Zhang and Li (2019), Ye et al. (2020) and Wang et al. (2021) have proved that the patterns of co-movement between investor sentiment and crude oil prices alter not only with time, but also with frequency. Zhang et al. (2022) find that during the COVID-19 pandemic, the return and volatility spillovers from epidemic-related news to the crude oil and gold markets are different in both time and frequency. Maghrebeh and Abdoh (2020) argue that the inter-dependence between sentiment and commodity, including crude oil and gold, differs according to time and frequency. Besides, time-frequency dependence has been demonstrated to exist between crude oil and gold markets (Hu et al., 2020; Hung and Vo, 2021; Li et al., 2021; Ding et al., 2021), between investor attention and crude oil markets (Abdelhedhi and Boujebene-Abbes, 2020; Chen et al., 2022), as well as between investor attention and gold markets (Su and Li, 2020; Zhang et al., 2022). However, limited research is on the public attention, crude oil and gold markets during the COVID-19 pandemic (Tuna and Tuna, 2022; Zhang et al., 2022). To fill this gap, our research adopts the wavelet analysis and time-frequency domain causality method to investigate the potential nonlinear relationship of public attention to the COVID-19 pandemic, oil and gold markets across different time and frequencies.

3. Data

We use WTI crude oil futures prices downloaded from the EIA website and gold futures prices coming from https://www.gold.org/. All the data are daily closing prices, with a sample period from December 1, 2019, to March 25, 2022. This sample period is chosen since COVID-19 infection cases were originally reported in December 2019 by Wuhan, China. Since then, the COVID-19 spread has begun to garner public notice. Following Ye et al. (2020) and Chen et al. (2022), the public attention to the COVID-19 is proxied by the results of principal component analysis (PCA) based on the daily google search volume index (GSVI) from https://trends.google.com/trends. The GSVI represents the frequency of searches compared to all conceivable queries and is scaled from 0 to 100.

Different from previous studies based on the COVID-19 news and death toll, the use of the GSVI is motivated by the following factors. First, Google is the most popular search engine. It helps people collect direct online information, which is more comprehensive than other indirect proxies, including news, headlines and psychological barriers (Barber et al., 2008; Aggarwal and Luxoy, 2007; Han et al. 2017; Li et al., 2019). Second, web-search volumes related to the COVID-19 pandemic have been proved to be an effective proxy of public attention and to have a significant impact on financial markets during the COVID-19 pandemic (Costola et al., 2021). Although the public has paid attention to the COVID-19 news such as the number of deaths and the relevant government policies, they tend to gain more timely and comprehensive information from Google apart from official media. The search boom could be indicative of the pandemic’s severity or widespread panic. That is, the public may panic as a result of the significantly increased search volume, which implies that the pandemic is worse than previously believed. As a favorable proxy for public attention, GSVI may provide investors with current information that is publicly available (Afkhami et al., 2017; Han et al., 2017). Additionally, GSVI can be downloaded for specific geographic regions or on a global basis, which could be utilized as proxy indicators for national public attention and examine their impact on the crude oil and gold markets during the COVID-19 pandemic.

In line with Ahundjanov et al. (2020), we collect google search queries containing “COVID-19”, “COVID 19”, “COVID19”, “COVID” and “coronavirus” for all the G7 countries. Given that some countries’ native languages are not English, we add some phrases in their mother tongue in addition to the English phrases above. The google search queries with phrases “COVID”, “coronavirus France”, “COVID19”, “COVID France” and “COVID attestation” are supplemented for France. The google search queries containing the keywords “corona zahlen”, “corona regeln”, “corona aktuell”, “corona Bayern” and “news corona” are added for Germany. The google search queries with “coronavirus italia”, “Italia corona virus”, “sintomi corona virus”, “corona virus oggi” and “news corona” are collected for Italy. For Japan, the google search queries containing the keywords “新型 コロナ”, “新型 コロナ ウイルス”, “新型 コロナ 感染”, “新型 コロナ ウイルス 感染” and “コロナ 感染 症” are gathered. Further, principal component analysis is applied to recombine the original GSIVs into a group of new comprehensive GSVI, which can retain the information of the original GSIVs as much as possible. We select the main components whose cumulative contribution rate is more than 85% as the proxy to the public attention in each G7 country.  

Fig. 1 displays the time series of GSVI, crude oil and gold prices in G7 countries. Between December 2019 and February 2020, the beginning of the COVID-19 outbreak, each G7 country has a low GSVI. However, following March 11, 2020, the COVID-19 search fever peaked multiple times and has remained elevated, which may be related to the COVID-19 being declared a global pandemic by WHO on March 11, 2020. At the same time, oil and gold prices showed a sharp downward trend, which may reflect that China was experiencing an outbreak and other countries began to have confirmed cases. It appears as though public awareness of the pandemic is inversely related to market trends. From an aggregate perspective, the WTI oil price has been declining since January 2020, even falling to a historic low of $-37.63, and then gradually recovered. There are two possible explanations. Initially, governments implemented a strategy of lockdown and tourism restrictions in response to the COVID-19 spread, leading to a major reduction in oil demand. Second, on April 13, 2020, the oil-producing countries agreed to reduce oil production; at the same time, concerns over excess oil storage grew dramatically. With the end of the first wave of the pandemic and increased public awareness of COVID-19, the economy and production have steadily recovered, as have oil prices. As a traditional safe-haven

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4 New-based attention is limited to a single sentiment about news and events, while the Internet-based attention like Twitter could be considered more appropriate when more expertise is necessary (Shen et al., 2019).  
5 Meanwhile, following the Kaiser-Harris criterion, we select the components with eigenvalues greater than 1 as the main components whose cumulative contribution rate is about 80%; we also use the weighted average of GSIVs with equal weight as the proxy to the public attention in each G7 country. The corresponding empirical results are very similar. The detailed results are not reported in the paper due to space limitations but are available from the authors upon request. We thank the reviewer for the comments.
asset, gold appears to be trending in the other direction, rising to a peak in August 2020, and then gradually falling back and fluctuating slightly. Table 1 illustrates the descriptive statistics of GSVI, crude oil and gold prices. The skewness, kurtosis and JB statistics show the distributions of crude oil and gold prices are asymmetric and abnormal with fat tails. The GSVI in the US reports the largest standard deviation, followed by the GSVI in Canada and the UK, and GSVI in France has the smallest fluctuation. Table 2 shows the correlation coefficients. The correlations between gold prices and GSVI in most G7 countries are almost positive, which may indicate the nature of gold as a safe-haven asset. While the correlations between GSVI and oil prices are negative, implying during the COVID-19 pandemic, an increase in the public attention may be a signal that the pandemic is escalating, prompting the government to impose lockdown measures, resulting in economic recession and lower

![Fig. 1. The time series of GSVI, crude oil and gold prices.](image)

### Table 1
Descriptive statistics of GSVI, crude oil and gold prices.

| Variables | Mean  | Std. Dev. | Median | Min.  | Max.  | Skewness | Kurtosis | JB Stat. |
|-----------|-------|-----------|--------|-------|-------|----------|----------|----------|
| US GSVI   | 46.441| 26.605    | 48.683 | 0.000 | 100.815| -0.292   | 2.147    | 25.870***|
| CAN GSVI  | 42.921| 24.335    | 46.328 | 0.000 | 95.475 | -0.302   | 2.267    | 23.861***|
| UK GSVI   | 45.744| 24.331    | 48.943 | 0.000 | 101.832| -0.468   | 2.419    | 29.399***|
| FRA GSVI  | 14.173| 9.268     | 13.351 | 0.000 | 53.573 | 1.041    | 4.971    | 199.040***|
| GER GSVI  | 37.390| 17.485    | 40.105 | 0.000 | 76.269 | -0.582   | 2.717    | 34.759***|
| ITA GSVI  | 21.946| 11.393    | 23.070 | 0.000 | 47.063 | -0.450   | 2.409    | 28.071***|
| JAP GSVI  | 26.339| 12.998    | 25.961 | 0.000 | 75.190 | 0.201    | 3.251    | 5.440*   |
| WTI       | 57.915| 20.646    | 59.470 | -37.630| 123.700| 0.104    | 3.581    | 9.215***|
| GOLD      | 1804.097| 116.974   | 1804.700| 1494.600| 2115.200| -0.420   | 3.239    | 18.473***|

Notes: JB Stat. represents the statistic of the Jarque-Bera test for normality. * and *** denotes statistical significance at the 10% and 1% levels, respectively.
oils and gold consumption. There seems a potential nonlinear relationship exists between public attention to the COVID-19 pandemic, WTI oil and gold markets. Table 3 reports the unit root test results for the variables, including the ADF, ADF-GLS and KPSS tests. The results show the stationarity of the first difference of all the variables, suggesting the WTI oil and gold returns are stationary.

4. Methods

4.1. Principal component analysis

Since COVID-related Google search phrases varied by G7 country, selecting one as a proxy for public attention is tricky. As a result, a comprehensive variable can be taken to retain as much information as possible from the original variables. In this study, we utilize PCA to recombine the original variables into a group of new proxy. PCA could recombine the original variables into a group of new comprehensive variable unrelated to each other, from which a fewer steps of the PCA method are as follows.

Firstly, suppose that \( g_i \) is the \( i \)-th Google search phrases we have selected. Then we calculate the covariance matrix between variables and the eigenvalues of \( \sum \). We select principal components whose cumulative contribution rate is relatively high; that is, the selected principal components can explain most of the information and each principal component is a linear combination of the original variables, as shown below:

\[
P C_j = \sum_{i=1}^{n} d_{i} g_i, \quad i = 1, ..., n.
\]

where \( PC_j \) represents the \( j \)-th principal component selected and \( n \) represents the total number of Google search phrases selected for each G7 country.

Finally, public attention is constructed by weighting the contribution rate of each principal component eigenvalue. To unify the original form of the Google search index, this paper normalizes public attention and multiplies it by 100, and the formula is as follows:

\[
GSVI_j^t = \frac{\sum_{j=1}^{n} d_j^t \times PC_j^t}{\sum_{j=1}^{n} d_j^t} 
\]

\[
GSVI_j = \frac{\max GS VI_j - GS VI_j}{\max GS VI_j - GS VI_j} \times 100 
\]

where \( d_j^t \) is the \( j \)-th selected eigenvalue. \( GS VI_i \) is the GSVI’s last proxy at time \( t \), as well as the proxy of public attention for each G7 country.

4.2. Continuous wavelet transform and wavelet coherence

The wavelet approach analyzes a signal in both time and frequency simultaneously. It is useful to study the interactions between time series on a scale-by-scale basis (Shahzad et al., 2020). Analytically, the wavelet transform decomposes a signal in terms of elementary functions called daughter wavelets, denoted by \( \psi_s^t(t) \), which are derived from a time-localized mother wavelet \( \psi(t) \) by translation and dilation in the following way:

\[
\psi_s^t(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t - t}{s}\right)
\]

where \( t \) stands for the location parameter, \( s \) represents the scale parameter and \( \frac{1}{\sqrt{s}} \) is a normalization factor to ensure that wavelet transforms are comparable across scales and time series. The continuous wavelet transform (CWT) of a time series or signal \( x(t) \) with respect to \( \psi(t) \) operates over every possible scale and position in time and is given by the following convolution:

\[
W_s(t) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) \psi_s^t(t) dt
\]

where * refers to the complex conjugate. The most commonly used mother wavelet in the CWT is the Morlet wavelet, defined as:

\[
\psi(t) = e^{-t^2/2} \cos(\sqrt{\pi}t)
\]

Table 2

The correlation coefficient matrix between the variables.

|          | US GSVI | CAN GSVI | UK GSVI | FRA GSVI | GER GSVI | ITA GSVI | JAP GSVI | WTI | GOLD |
|----------|---------|----------|---------|----------|----------|----------|----------|-----|------|
| US GSVI  | 1       | 0.876    | 0.829   | 0.729    | 0.795    | 0.704    | 0.667    | -0.415 | 0.218 |
| CAN GSVI | 0.876   | 1        | 0.837   | 0.673    | 0.810    | 0.723    | 0.601    | -0.378 | 0.235 |
| UK GSVI  | 0.829   | 0.837    | 1       | 0.643    | 0.806    | 0.734    | 0.615    | -0.268 | 0.214 |
| FRA GSVI | 0.729   | 0.673    | 0.643   | 1        | 0.647    | 0.595    | 0.419    | -0.560 | -0.047 |
| GER GSVI | 0.795   | 0.810    | 0.806   | 0.647    | 1        | 0.786    | 0.491    | -0.244 | 0.273 |
| ITA GSVI | 0.704   | 0.723    | 0.734   | 0.595    | 0.786    | 1        | 0.548    | -0.329 | 0.237 |
| JAP GSVI | 0.667   | 0.601    | 0.615   | 0.419    | 0.674    | 1        | 0.548    | -0.165 | 0.307 |
| WTI      | -0.415  | -0.378   | 0.214   | -0.047   | 0.273    | 0.237    | 0.307    | 0.111  | 1    |
| GOLD     | 0.218   | 0.235    | 0.214   | -0.047   | 0.273    | 0.237    | 0.307    | 0.111  | 1    |

Table 3

The unit root test results for the variables.

|          | US GSVI | CAN GSVI | UK GSVI | FRA GSVI | GER GSVI | ITA GSVI | JAP GSVI | WTI | GOLD |
|----------|---------|----------|---------|----------|----------|----------|----------|-----|------|
| ADF Test |         |          |         |          |          |          |          |     |      |
| Level    | 1.493   | -1.428   | 1.169   | 1.986**  | -1.160   | -1.196   | -1.399   | 1.002| 0.925|
| 1st diff. | -9.739***| -6.835***| -9.572***| 28.995***| -7.933***| -18.709***| -12.224***| -23.108***| -23.943***|
| ADF-GLS Test |         |          |         |          |          |          |          |     |      |
| Level    | -1.589  | -1.522   | -1.254  | 2.109**  | -1.257   | -1.284   | -1.418   | -1.569| -0.168|
| 1st diff. | -25.527***| -28.422***| -23.136***| -24.087***| -33.864***| -21.422***| -17.575***| -23.373***| -1.976**|
| KPSS Test |         |          |         |          |          |          |          |     |      |
| Level    | 0.334***| 0.359*** | 0.392***| 0.409*** | 0.496***  | 0.444***  | 0.511***  | 2.142***| 0.809***|
| 1st diff. | 0.118   | 0.109    | 0.136   | 0.055    | 0.169    | 0.147    | 0.148    | 0.079 | 0.149|

Notes: The null hypothesis is that the series has a unit root test in the ADF and ADF-GLS tests, whereas the null hypothesis is that the series is stationary in the KPSS test. *** and ** denote significance at the 1%, 5% and 10% levels, respectively.
where $\omega_0$ is the central frequency of the wavelet, which controls the number of oscillations within the Gaussian envelope. Following Torrence and Compo (1998), $\omega_0 = 6$ is selected because it provides an optimal balance between resolution in time and frequency.

Wavelet coherence (WTC) is used to explore the possible relationship between two processes in the time-frequency domain. Following Grinsted et al. (2004) and Ng and Chan (2012), WTC can be defined as:

$$R^2(\tau, s) = \frac{|\mathcal{W}(y, \tau) \cdot \mathcal{W}(x, s)|^2}{|\mathcal{W}(y, \tau)| \cdot |\mathcal{W}(x, s)|}$$

(7)

where the $\mathcal{W}$ operator is the continuous wavelet transform (CWT) when it has one argument and the cross-wavelet transform when it has two, $\tau = 5s^{-1}$, in which $5$ is the smoothing operator. The statistical significance level of WTC is determined by Monte Carlo methods.

Then, WTC can find the common change area of two time series in time-frequency domain and identify the possible relationship between the two time series (Grinsted et al., 2004). WTC between $y$ and $x_1$, $y$ and $x_2$, as well as $x_1$ and $x_2$ is written as:

$$R(y, x_1) = \frac{|\mathcal{W}(y, \tau) \cdot \mathcal{W}(x_1, s)|}{|\mathcal{W}(y, \tau)| \cdot |\mathcal{W}(x_1, s)|}$$

$$R(y, x_2) = \frac{|\mathcal{W}(y, \tau) \cdot \mathcal{W}(x_2, s)|}{|\mathcal{W}(y, \tau)| \cdot |\mathcal{W}(x_2, s)|}$$

$$R(x_1, x_2) = \frac{|\mathcal{W}(x_1, s) \cdot \mathcal{W}(x_2, s)|}{|\mathcal{W}(x_1, s)| \cdot |\mathcal{W}(x_2, s)|}$$

(8)

### 4.3. The partial and multiple wavelet coherence

Partial wavelet coherence (PWC) is a technique similar to the partial correlation that helps to find the resulting WTC between two time series $y$ and $x_1$ after eliminating the influence of the time series $x_2$. Mihanović et al. (2009) extended the concept of wavelet coherence and suggest that the PWC squared (after controlling the effect of $x_2$) can be defined by an equation similar to the partial correlation squared, as:

$$RP^2(\tau, s, x_2) = \frac{|R(y, x_1, x_2) - R(y, x_2) \cdot R(x_1, x_2)|^2}{1 - R(y, x_2)^2 \cdot |1 - R(x_1, x_2)|^2}$$

(9)

Like the simple WTC, the value of PWC ranges from 0 to 1.

Besides, the multiple wavelet coherence (MWC) can be used to explore the resulting coherence which gives the resulting wavelet coherence squared that computes the proportion wavelet power of dependent time series $y$ that is explainable by the two independents $x_1$ and $x_2$ at a given time and frequencies. Using the WTC between $y$ and $x_1$, $y$ and $x_2$, as well as $x_1$ and $x_2$ calculated in (2), the MWC squared can be defined as:

$$RM^2(\tau, s, x_2, x_1) = \frac{R^2(y, x_1, x_2) + R^2(y, x_2) - 2Re[R(y, x_1) \cdot R(y, x_2) \cdot R(x_1, x_2)]}{1 - R^2(x_1, x_2)}$$

(10)

The MATLAB software package provided by Ng and Chan (2012) is used to compute PWC and MWC.

### 4.4. Time-frequency domain causality

The time-frequency domain causality method proposed by Olayeni (2016) measures the causality in CWT and quantifies the Granger causal linkages between two time series in the time-frequency domain, which is an extension of the wavelet-based correlation (Ruo, 2013). That is denoted by $\rho_{XY}(\tau, s)$, is given by:

$$\rho_{XY}(\tau, s) = \frac{\xi \{s^{-1} |R(\mathcal{W}(\tau, s))|\} \cdot s^{-1} \sqrt{|W_X(s, \tau)|}}{\xi \{s^{-1} \sqrt{|W_X(s, \tau)|}\} \cdot s^{-1} \sqrt{|W_Y(s, \tau)|}}$$

(11)

where $\mathcal{W}$ is the real part of the cross-wavelet spectrum and $\xi$ denotes a smoothing operator in both time and frequency. Eq. (11) quantifies the degree of co-movement of two time series both over time and at the frequency level within a unified framework. As a correlation coefficient, $\rho_{XY}(\tau, s)$ ranges between $-1$ and $+1$. Based on it, the causality in CWT can be employed to examine the causal links evolve over time and across frequencies simultaneously. The following CWT-causality metric is used to determine if predictive information flows from $x$ to $y$:

$$G_{X \rightarrow Y}(s) = \frac{\xi \{s^{-1} |R(\mathcal{W}(\tau, s))| I_{X \rightarrow Y}(\tau, s)|\}}{\xi \{s^{-1} \sqrt{|W_X(s, \tau)|}\} \cdot s^{-1} \sqrt{|W_Y(s, \tau)|}}$$

(12)

where $I_{X \rightarrow Y}(\tau, s)$ represents the indicator function defined as follows:

$$I_{X \rightarrow Y}(\tau, s) = \begin{cases} 1, & \text{if } \rho_{XY}(\tau, s) \in (0, \pi/2) \cup (-\pi, -\pi/2) \\ 0, & \text{otherwise} \end{cases}$$

(13)

in case we are interested in the negative (or out-of-phase) causal relationship, or

$$I_{X \rightarrow Y}(\tau, s) = \begin{cases} 1, & \text{if } \rho_{XY}(\tau, s) \in (0, \pi/2) \\ 0, & \text{otherwise} \end{cases}$$

(14)

in case we are interested in the positive (or in-phase) causal relationship.

The MATLAB software package supported by Olayeni (2016) is applied to test the CWT-causal relationship between two time series, including positive (in-phase) and negative (out-of-phase) causal effects.

### 5. Empirical results and discussions

#### 5.1. The partial and multiple wavelet coherence

Fig. 2 presents the partial wavelet coherence (PWC) results, which are computed to gauge the partial impact between GSVI, WTI oil and gold returns for G7 countries, respectively. Fig. 3 displays the multiple wavelet coherence (MWC) results, which are computed to measure the combined impact of two variables on the third one. The color code indicates the height of the level curves which runs from 0 to 1 and indicates the strength of the relationship. The vertical axis reports the frequency reported in days while the horizontal axis reports the time. The thick black contour represents the 5% significant level based on the Monte Carlo simulation against red noise. Compared with Fig. 3, the association between WTI oil and gold returns seems relatively weak in Fig. 2, since only several large red and significant islands are identified from December 2019 to March 2020 and from November 2021 to April 2022, which corresponds to the COVID-19 broke out and declared as a pandemic and Omicron is classified as a variant of concern by the WHO.
Fig. 2. Partial wavelet coherence
Notes: Partial wavelet coherence computed to gauge the partial impact between GSVI, WTI oil and gold. The black contour designates the 5% significance level estimated from Monte Carlo simulations. The region with large (small) coherency is described in red (blue) color.
Fig. 3. Multiple wavelet coherence
Notes: The black contour designates the 5% significance level estimated from Monte Carlo simulations. The region with large (small) coherency is described in red (blue) color.
respectively. It probably implies the interdependence between WTI oil and gold returns becomes stronger during these two periods.

Fig. 2 also displays relatively limited and small red areas when the effect of WTI oil or gold returns is controlled. However, Fig. 3 presents a different situation. The MWC results of GSVI and WTI oil on gold returns in almost G7 countries show some clear and substantial red areas marked with a black line at the 32–64 day frequency from December 2019 to March 2020, reflecting the significant combined effect of GSVI and oil on gold markets. It seems that the gold market has been disproportionately affected by the COVID-19 outbreak, especially in Japan. Considering the combined impact of WTI oil and gold returns on GSVI, the MWC results are more significant during the periods from December 2019 to March 2020 and from November 2021 to April 2022, while a long and flat red region at the bottom is throughout the whole period in almost G7 countries, implying the impact of WTI oil and gold returns on GSVI lasts at the 32–64 day frequency. Referring to the combined effect of GSVI and gold on the WTI oil returns, European countries depict a large and deep red island at the 32–64 day frequency during April and June 2021, when most European countries started easing coronavirus health restrictions in April and May. However, the highly transmissible variant Delta has brought a new round of epidemic in Europe in the following two months. Besides, large quantities of small red circles with black outlines are present at the 0–8 day frequency during the whole period in all plots, suggesting that GSVI, WTI oil and gold markets have been interacting with each other not only at high frequency but also at low frequency during the COVID-19 pandemic. This kind of temporary causality is also proved by Tuna and Tuna (2022).

5.2. Time-frequency domain causality analysis

In this section, we employ causality in continuous wavelet transforms to examine how causal relations have evolved over time and frequency. Figs. 4–6 present the results of the time-frequency causality between WTI oil and gold returns, between GSVI and WTI oil returns, as well as between GSVI and gold returns, respectively. Since our focus is not only on whether one variable leads another but also on the direction of the relation, we report the in-phase (positive) causal effects and the out-of-phase (negative) causal effects respectively.

From the perspective of the oil-gold nexus, a positive causality from WTI oil to gold returns is demonstrated in early 2020 at the 2–8 day frequency, while a positive causality from gold to WTI oil returns is presented in November 2021 at the 16–32 day frequency. The former corresponds to the outbreak of COVID-19, whereas the latter corresponds to the spread of Omicron, which is classified as a variant of concern by the WHO. This may mean that WTI oil lead gold returns when COVID-19 broke out, and vice versa when Omicron spread. Although the positive causality plot from gold to WTI oil returns shows a long and flat red island at the 128-day frequency, the negative causality plot shows a greater red region. There appears to be some complexity in the relationship between gold and WTI oil returns, particularly in the first half of 2020. Given the findings of these two graphs, it seems likely that gold returns lead oil returns in a negative direction on a bimonthly basis. These results are unsurprising. When the COVID-19 broke out, investors may sell their financial assets out of panic, resulting in a dramatic decline in crude oil prices. Gold prices also declined concurrently, since the global stock market fell sharply in the short term, and even the US stock market tripped the circuit breaker five times in a month, leading many investors lost confidence in the stock market, preferring instead to hold the US dollar. When capital flows in the market dwindle, investors will inevitably be prompted to sell large quantities of gold to obtain cash, putting downward pressure on the price of gold. However, when the Federal Reserve releases the unlimited quantitative easing decision, it will encourage investors to gradually reinvest their cash in the market. When the market has an adequate supply of funds, gold prices will naturally grow steadily as an ideal hedging product. As countries implemented closure measures, demand for crude oil fell precipitously, and the link between oil and gold markets shifted in the reverse direction.

Concerning the GSVI-oil nexus, there is positive unidirectional causality from crude oil returns to public attention for the US and Canada at the 64–128 day frequency in early 2020, due to the COVID-19 outbreak. The possible reason is that during the early stages of the COVID-19 outbreak, the public in the US and Canada may be relatively optimistic and pay less attention to the pandemic. With the drop in oil prices, the public attention to COVID-19 has not increased. This could be due to the public’s limited attention span. During the outbreak’s early stages, the continuous sharp drops of US stocks and the decline of oil futures prices drew the majority of the American public’s attention, while concern about the COVID-19 spread waned. Meanwhile, there is a strong negative causality from the US public attention to crude oil returns at the 64–128 day frequency between July 2021 and March 2022, corresponding to the fact that the Delta variant becomes the dominant variant in the US and initiates a third wave of infections during the summer of 2021. Following that is the Omicron spread. Increased public attention in the US indicates an escalation of the pandemic, which could trigger market fear, resulting in a decline in crude oil returns. These findings are consistent with those of Farid et al. (2021), who demonstrate that contagion effects fueled by fear swiftly spread across WTI oil and gold markets. However, for Canada, crude oil returns have a negative causal influence on public attention between July 2021 and January 2022 at a 64–128 day frequency. The outcome may be Canada is one of the world’s greatest oil exporters; in the post-pandemic period, an increase in crude oil returns might bolster the Canadian people’s confidence, thereby diminishing public attention to the pandemic. For the UK, a bidirectional causal effect between crude oil return and public attention from August 2020 to February 2021, may be related to the repeated rebound of the pandemic and the frequent changes in policy responses to COVID-19, including the Eat Out To Help Out scheme in August, the three-tier system of COVID restrictions, the UK becoming the first country in the world to approve a coronavirus vaccination in December, and a new national lockdown in January 2021, among others.

For France, Germany, and Italy, negative causality from public attention to crude oil returns between late 2021 and early 2022, showing that since the WHO classified Omicron as a variant of concern on 26 November 2021, increased public concern about the new virus in Europe has once again resulted in a significant decline in oil prices. There is a positive causal association between Italy’s GSVI and crude oil returns with a 16–32 day frequency in late 2020. While Italy is still suffering from the second wave of the pandemic, it received emergency approval from the European Union in August for 6 billion euros in donor funds to assist Italy in assisting small and medium-sized enterprises affected by the pandemic in order for these enterprises to exit the crisis and reclaim market competitiveness as quickly as possible. It is possible that this signal, which is closely tied to the pandemic, has piqued public interest and enhanced future expectations, which benefits the price of crude oil. For Japan, there is causality from public attention to crude oil at the 8–64 day frequency in early 2020. This may be because Japan and China are geographically adjacent and have a strong economic relationship. The outbreak of COVID-19 in China drew the Japanese public’s attention to the virus and resulted in divergent expectations for the future market, leading to oil price fluctuations. Besides, different from other G7 countries, a positive causality is found from WTI oil returns to GSVI at 32–64 day frequency recently. Since a major oil importer, public concern about the pandemic has intensified again in Japan, as recent increases in oil prices and the fact that China is once again affected by the COVID-19 have reawakened the Japanese public’s concern about the pandemic.

Regarding the GSVI-gold nexus, in early 2020, the US and Canada...
notice a bidirectional negative causality between gold and public attention at the 16–64 day frequency. It once again verifies the previous analysis results in the oil-gold nexus. The collapse of global stock markets may cause US investors to lose confidence in the stock market and choose to invest in the US dollar. The reduction of market capital flow will force investors to sell a large amount of gold to get cash, thus reducing the price of gold. For the UK, gold has a negative causal influence on public attention at the 16–64 day frequency in late 2020, matching the second wave of COVID-19. The Prime Minister holds a hastily arranged press conference on October 31 to announce a four-week lockdown in England. On November 11 the UK becomes the first country in Europe to pass 50,000 COVID-19 deaths after a further 22,950 cases and 595 deaths are recorded. As the aggravation of COVID-19 in the UK, the increase in gold prices tends to heighten market fear and the public attention to the pandemic. While there is rather substantial unidirectional causality from public attention to the gold market at the 32–64 day frequency in the early stages of COVID-19 for France, Germany, and Italy. In Germany, there is also a positive causal relationship between public attention to the gold market at the 32–64 day frequency in late 2020 and early 2021, which corresponds to the Federal and state authorities agreeing to a partial lockout in October and then a hard lockdown in December. This has resulted in another increase in the price of gold as a result of public worry over the outbreak. While in Italy, there is a negative causality between GSVI and gold returns at a 64–128 day frequency between December 2020 and June 2021, which is likely related to the agreement reached by EU leaders in December 2020 on the implementation of the recovery plan, which is an economic recovery plan worth more than 1.8 trillion euros in total. Although Europe is witnessing the second wave of the pandemic, the Italian public appears hopeful about future economic prospects, lowering demand for gold as a safe haven and leading to a decline in gold prices. For Japan, there is only positive causality from public attention to the gold market in the second half of 2021. It is fair to assume that during this time period, the Delta variation swept throughout Japan, reviving the epidemic. Japan is increasingly buying gold rather than oil for hedging purposes, increasing the price of gold. For the UK, a bidirectional causal relationship between crude oil return and public attention at the 8–16 day frequency from August 2020 to February 2021 may be related to the repeated rebound of the pandemic and the frequent shifts in policy responses to COVID-19. Among these, the lockdown policy in November has the greatest impact and results in positive causality from public attention to the gold market in late 2020 and early 2021 at the 32–64 day frequency. For France, Germany, and Italy, the public attention to the COVID-19 pandemic has a detrimental effect on gold returns in early 2020 and on crude oil returns in late 2021 and early 2022. This correlates to the WHO classifying Omicron as a variant of concern on 26 November 2021, implying that European public attention caused by the COVID-19 outbreak has a strong impact on gold returns, while public attention generated by the Omicron spread has a significant impact on crude oil returns. The Italian public appears to be the most sensitive to the EU’s economic support plan, which includes the EU’s commitment of 6 billion euros in donor funding in August 2020 and the agreement to implement the recovery plan in December 2020. Japan’s public attention has a significant impact on WTI oil returns in early 2020 and on gold returns in late 2021. It seems that the Japanese public is more concerned about the pandemic situation in China, particularly the outbreak of COVID-19 in 2020 and the recent re-emergence of the pandemic in China.

5.3. Robustness analysis

5.3.1. Robustness analysis based on Panic Index

This section examines the robustness of the results. We use the Panic Index (PI) during the COVID-19 pandemic as the proxy of public attention, and select the data from January 2, 2020 to March 25, 2022. The PI variable is computed as the daily count of distinct stories that co-mention panic keywords and coronavirus, divided by the total daily count of distinct stories, and it measures the panic by measuring the level of news that refers to panic or hysteria and coronavirus. The index value is scaled from 0 to 100, where 0 (100) indicates the lowest (highest) level of news talking about panic and COVID-19. PI may reflect media attention to the COVID-19 pandemic, while GSVI may represent Internet-based individual attention to the pandemic. They all could serve as indicators of public attention.

Figs. 7 and 8 present the partial wavelet coherence (PWC) and multiple wavelet coherence (MWC) results, which are computed to gauge the partial and combined impact between PI, WTI oil and gold returns for G7 countries, respectively. In comparison to Fig. 8, the link between WTI oil and gold returns appears to remain relatively moderate after removing the influence of PI in Fig. 7, with some negligible differences in Germany and Japan. Only several large red and significant islands are found during the COVID-19 outbreak and Omicron

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7 The Panic Index data of the COVID-19 is obtained from https://www.ravenpack.com, and the period is selected by data availability.
Fig. 5. In-phase and out-of-phase plots of causality between GSVI and WTI oil
Notes: The white (red) contour indicates a 5% (10%) significance level. The significance levels are based on 3000 draws from Monte Carlo simulations estimated on an ARMA (1,1) null of no statistical significance. The green line is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. Positive causality denotes in-phase (positive) causal effects from one variable to another one, while negative causality represents out-of-phase (negative) causal effects from one variable to another one.
Fig. 6. In-phase and out-of-phase plots of causality between GSVI and gold

Notes: The white (red) contour indicates a 5% (10%) significance level. The significance levels are based on 3000 draws from Monte Carlo simulations estimated on an ARMA (1,1) null of no statistical significance. The green line is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. Positive causality denotes in-phase (positive) causal effects from one variable to another one, while negative causality represents out-of-phase (negative) causal effects from one variable to another one.
Fig. 7. Partial wavelet coherence
Notes: Partial wavelet coherence computed to gauge the partial impact between Pl, crude oil and gold. The black contour designates the 5% significance level estimated from Monte Carlo simulations. The region with large (small) coherency is described in red (blue) colors.
Fig. 8. Multiple wavelet coherence
Notes: The black contour designates the 5% significance level estimated from Monte Carlo simulations. The region with large (small) coherency is described in red (blue) color.
occurrence. When the effect of gold returns is controlled, the PWC results in Fig. 8 appear to be more significant than those based on GSVI, showing that the PI has a stronger impact on the WTI oil than GSVI. Notably, the MWC results of PI and gold on WTI oil returns are more significant than the GSVI’s results, whereas the MWC results of PI and WTI oil on gold returns are less significant than those based on GSVI. It may imply while WTI oil returns are more sensitive to PI, gold returns are more responsive to GSVI.

Figs. 9 and 10 report the time-frequency domain causality results between PI, WTI oil and gold returns. These results are very similar to those based on GSVI, except for some minor differences in the causality of PI-oil returns and PI-gold returns nexus. On the one hand, we observe a relatively stronger causality running from WTI oil returns to PI at the 64–128 day frequency in early 2020 in almost all G7 countries, implying that during the outbreak of COVID-19, WTI oil returns have a greater impact on PI rather than on GSVI. This may be because, in the early days of the pandemic, the public in G7 countries was more focused on the collapse of the global financial market, instead of the COVID-19. From mid-2021 until March 2022, a negative causality runs from PI to WTI oil returns at the 8–128 day frequency, which is similar to that based on GSVI but more significant. It may suggest that PI has a stronger impact on WTI oil markets than GSVI. Furthermore, the effect of GSVI appears to occur at a lower frequency in most cases. On the other hand, the results show that gold returns have a relatively strong negative causal effect on PI for the US, Canada and UK in the first half of 2020, a relationship similar to that observed for GSVI and gold returns. While for the other G7 countries, the causality from gold returns to PI seems to be less significant. Additionally, except for Japan, the negative Granger causality from PI to gold returns is relatively strong at the 16–64 day frequency in early 2020. While the positive causality from PI to gold returns is significant only for the US, Canada and Italy at the 2–16 day frequency in the first half of 2021, it appears to be less significant than the results of GSVI. Several of these findings contradict those of Atri et al. (2021), who find that media attention has a detrimental influence on oil prices but a beneficial effect on gold prices. This could be because they did not consider the frequency domain relationship and only used a short sample period from January 23, 2020 to June 23, 2020. In conclusion, the results of both PI and GSVI show that public attention has a serious impact on the crude oil and gold markets.

5.3.2. Robustness analysis on subsamples

Since oil and gold markets have always been concerned by the public, the relationship we observe between public attention, oil and gold markets may not be caused by the pandemic but is inherent. To account for this impact, we separate the data into two sub-samples before and after the lockdown2 to verify the strengthening of the relationship between the public attention, WTI oil and gold markets during a pandemic. According to the time-frequency domain causality results,6 we can detect a clear difference between the case before and after countries’ lockdown. Firstly, for WTI oil and gold, it is clear that there is a causality relationship from gold returns to oil returns in December 2020 and the second half of 2021, which again partially verifies the prior empirical analysis’s conclusion. Secondly, while the causality between oil returns and public attention nearly entirely matches the prior findings, certain negative causality from public attention to oil returns in late 2021 and early 2022 is weaker than the equivalent previously. Finally, the causal relationship between gold returns and public attention essentially follows the major empirical findings, with the exception that the positive causality from Japanese public attention to gold returns has been strengthened between the lockdown and October 2020. This could be because, as a result of the countries’ lockdown, public attention to the COVID-19 pandemic in Japan has increased, and the public has a tendency to acquire gold as a safe haven, resulting in gold price increases. In G7 countries, the causal relationship between oil/gold returns and public attention to COVID-19 is heterogeneous, varying over time and different frequencies.

6. Conclusions

This paper uses time-frequency analysis, including wavelet analysis and time-frequency domain causality, to evaluate the relationship between public attention to the COVID-19 pandemic, crude oil, and gold markets over time and different frequencies. Empirical findings show that WTI oil returns lead gold returns when COVID-19 broke out, and vice versa when Omicron spread. It appears heterogeneity for the G7 countries in the relationship between public attention to the COVID-19 and WTI oil/gold markets. European public attention caused by the COVID-19 outbreak has a strong impact on gold returns at the 32–64 day frequency, while public attention generated by the Omicron spread has a significant effect on crude oil returns at the 4–128 day frequency. During the COVID-19 outbreak, the public in the US and Canada is more concerned about the global stock and WTI oil markets slump but lack of concern for the COVID-19 pandemic. The Italian public seems to be the most sensitive to the economic support plan implemented by the EU, including the European Union for 6 billion euros of donor funds in August 2020 and the agreement on the implementation of the recovery plan in December 2020.

These findings may help policymakers, investors, and decision-makers who are interested in the WTI oil and gold markets in the G7 countries. First, the findings indicate that the public tends to use gold as a safe haven during the COVID-19 pandemic. The results also indicate the fact that the impacts of public attention to the COVID-19 on the crude oil and gold markets gradually varies, because different countries have different cultures and government’s response policies to the COVID-19. For policymakers, the temporary impact of public attention to the COVID-19 pandemic on financial markets may suggest the instability of the public sentiment, while the evidence of a longer-time effect may suggest the necessity of the economic support plan or recovery plan. A better understanding of how government behavior is associated with public attention may guide policies related to the resurgence of COVID-19 currently observed in many countries (Zhang et al., 2022). It suggests that the government should pay more attention to the public reaction, take necessary measures in time and announce larger stimulus packages to boost investor confidence and stabilize the market development. For investors and market participants, public attention can help them make trading and risk management strategies at various investment horizons. Specifically, the heterogeneity of the public attention-oil/gold nexus in G7 also suggests that it may be of great value to diversify the portfolios across different markets and different investment horizons. In addition, we find that although European countries took timely measures to prevent the COVID-19 pandemic, the interaction among public attention to the COVID-19 pandemic, oil and gold markets has not weakened. Therefore, during the outbreak of world health emergencies, no country can escape. All countries should join hands to cope with the pandemic and tide over the difficulties.

Author statement

We certify that all authors have seen and approved the final version of the manuscript being submitted. They warrant that the article is the
Fig. 9. In-phase and out-of-phase plots of causality between PI and WTI oil

Notes: The white (red) contour indicates a 5% (10%) significance level. The significance levels are based on 3000 draws from Monte Carlo simulations estimated on an ARMA (1,1) null of no statistical significance. The green line is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. Positive causality denotes in-phase (positive) causal effects from one variable to another one, while negative causality represents out-of-phase (negative) causal effects from one variable to another one.
Fig. 10. In-phase and out-of-phase plots of causality between PI and gold
Notes: The white (red) contour indicates a 5% (10%) significance level. The significance levels are based on 3000 draws from Monte Carlo simulations estimated on an ARMA (1,1) null of no statistical significance. The green line is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. Positive causality denotes in-phase (positive) causal effects from one variable to another one, while negative causality represents out-of-phase (negative) causal effects from one variable to another one.
authors’ original work, hasn’t received prior publication and isn’t under consideration for publication elsewhere.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the National Social Science Foundation of China under No. 18BTJ032.

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