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The impact of COVID-19 news, panic and media coverage on the oil and gold prices: An ARDL approach

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ABSTRACT

This study investigates whether COVID-19 news, panic and media coverage affect oil and gold prices. Using the ARDL approach over the period January 23, 2020 to June 23, 2020, we find that COVID-19 deaths and panic have negative effects on crude oil price. However, the propaganda created by the media in the long term has a negative impact on oil price. The empirical results show that the COVID-19 new infections, deaths and media coverage have positive effects on the gold price. Our findings prove that oil price is sensitive to bad news unlike gold price. According to our study, gold, which is a hedge against economic and geopolitical crises, is additionally a safe haven during COVID-19 health crisis. Overall, our results also demonstrate that the economic and financial uncertainty affect oil and gold prices negatively during the COVID-19 pandemic. We conclude that the impact of the COVID-19 new infections on oil and gold prices is depending on whether the disease is an epidemic or a pandemic.

1. Introduction

Since its start in early 2020, the COVID-19 health crisis is causing disaster and tragedy around the world, infecting 14,876,330 people and triggering 613,722 deaths. The new Coronavirus has quickly spread and attacked 215 countries (China, Italy, Iran, Spain, France, the United Kingdom, the United Stated, etc.). On the 11th of March, World Health Organization declared this contagious infectious disease as a pandemic. As a result, many countries implemented different policies aided to limit the spread of the disease. Among the protective measures, we mention the social distancing, the workplace closings, the suspension of air travel and transport and the applying of partial or full lockdown.

Considering the lockdown and the uncertainty around this respiratory infection, the COVID-19 disease influences investor sentiment and generating additionally terrible psychological effects (fear, panic and hysteria). The world has gone through a period of high fear (like war, climatic phenomena, etc.). The RavenPack website reports that the level of news chatter that refers to Coronavirus panic or hysteria peaked on 30th March. The data exposed, on this date, indicates the following values for the COVID-19 panic index: in the world (9.24), USA (11.33), Italy (13.39), Brazil (36.57), Iran (36.87), etc.

The impact of COVID-19 pandemic is not limited only to infections, deaths and psychological threat, but this pandemic has a dramatic economic effect. This unprecedented international health crisis is generating an economic damage, a financial instability and a worldwide peril. A financial distress period begins with COVID-19 and pervades the entire financial sector, including banks, stock markets and insurance (Goodell and Huynh, 2020).

Since the COVID-19 outbreak, financial markets have become declining and extremely volatile and have been followed by the deterioration of energy and metal prices. This infection has also triggered an exceptional collapse in commodity markets, which are moving up and down with the pandemic news and has crippled the economy. To deal with the COVID-19 pandemic, borders have been closed and cities have been placed under quarantine, which has reduced trade in goods and commodities between countries and slows activity. In this situation, the
supply of resources generally exceeded the demand, which led to a drop in commodity prices. Energy resources linked to transport, particularly oil, are the most rapidly affected by this health crisis. The protective measures, such as the travel restrictions and the suspension of transport activities (stopping cars, boats and planes) have caused the disruption of supply chains and the unprecedented fall in oil demand.

In particular, the oil price experienced the most serious decline at the worst time of 2020. Protective measures, taken to limit the new Coronavirus, negatively affected oil demand, but that was not the only cause. Along with COVID-19 impacts, other international features are also causing the oil price collapse as the disagreements among oil-producing countries (Ali et al., 2020). The oil export ban in the presence of abundant oil-production (OPEC meeting oil, are the most rapidly affected by this health crisis. The protective measures, such as the travel restrictions and the suspension of transport supply chains and the unprecedented fall in oil demand.

On the other hand, to enforce physical distancing in workplaces, industries have been closed and industrial activity is halted. The result of these emergency measures was the decline not only in the energy demand, but also in the metals demand. The metals prices, which are closely linked to global economic activity, fell in early 2020 because of the disruption of supply and logistics chains and the limitation of exports.

These conditions have sown more and more panic among investors regarding the rise in commodity prices during this global health crisis. Alternatively, despite the COVID-19 cases increased, the gold price was climbing sharply. Subsequently, exasperated investors under stress, seeking to escape to a safe haven asset during market turmoil, took refuge in precious metals like gold. As a result, the gold trade has increased along with worries about the health crisis.

The new Coronavirus has gained great media devotion since January 2020. The media play an important role in the dissemination of information instantaneously and sheds light on the spread of the pandemic, its hostile damages, its economic and financial impacts and public panic (Mairal, 2011). The directors of the World Health Organization (WHO) organized 75 briefings 1 with the media to explain the situation and present their reports, in the form of transcripts, videos and audio recordings, etc. all of which are available online. Since the announcement of the first cases in Wuhan-China, media (television, radio, newspapers, billboards, social media, etc.) have played a protective role and have been used to transmit preventive health messages, which has an impact on people’s behavior and investor sentiment (Tetlock, 2007). By staying at home during the COVID-19 pandemic, many people rely on media and technology to keep up to date and stay connected. Yiping and Cui (2012) indicated that media aid to reduce the spread of diseases and the transmission rate. According to previous studies (Edington and Lee, 1994), financial markets are responding to the most important news in the media.

In this framework, our aim is to explore how the COVID-19 health crisis affects oil and gold prices. Furthermore, this study provides evidence of the effect of the number of COVID-19 new confirmed cases and deaths, the panic of COVID-19 and the COVID-19 media coverage on oil and gold prices during the global health crisis.

This paper expands the literature over three dimensions. Primarily, it investigates whether contagious infectious diseases affect commodities markets. Rare are the studies dealing with the consequences of health crises in financial markets given the singularity of these events. There are only two studies to mention in this regard. Chen et al. (2007) and Ichev and Marinic (2018) studied, respectively, the impact of SARS disease and Ebola Virus on stock markets. We are contributing to these studies by examining the fallout from a health crisis also triggering an economic crisis more devastating than the disease itself on commodities markets. The COVID19 health crisis looks as a special case of a dual health and economic crisis that generated much more uncertainty than the stock market crash of 1987 and far exceeded that observed during the banking and financial crisis of 2008. Secondly, it also enriches the first studies dealing with the impact of the COVID-19 health crisis on financial markets. Some investigations have been limited to examining the association between COVID-19 pandemic and stock market return and volatility (Al-Awadi et al., 2020; Zhang et al., 2020). While we are concerned with studying the response of commodity market to the COVID19 health crisis. Last of all, this study is the first, to our knowledge, to explore how the COVID-19 panic sentiment and media coverage are affecting oil and gold prices. Pioneering studies addressed only the effect of the number of COVID-19 new cases (Albulescu, 2020) on the crude oil price and the impact of deaths on oil and gold return (Ali et al., 2020). While our contribution consists in studying the impact of the health crisis in terms of number (new cases of infections and deaths at global level), in terms of sentiment (panic) and in terms of media coverage on the oil and gold prices.

This paper examines how oil and gold prices react to four different coronavirus evidences: COVID-19 confirmed new infection cases, Coronavirus deaths, Coronavirus panic index and COVID-19 media coverage, from January to June 2020. We use a dynamic model such as the ARDL approach, which considers the temporal dynamics (the delay time (lag)) in the explanation of our variables to improve the predictions and the effectiveness of our results. For the reason that COVID-19 media coverage and the feeling of panic can have an impact not only on the same day, but they will certainly have repercussions delayed for a few days after receiving and processing new information about the disease. Thus, the choice of the ARDL approach is explained by the objective of analyzing how COVID-19 news (new cases and deaths), the media coverage and the panic index affect oil and gold prices in the short-term and long-term by considering the lag.

Some interesting results can be seeming from this study. The COVID-19 pandemic has a negative effect on the oil market. Deaths and panic, caused by COVID-19 disease, are the cause of the short-term oil prices drop. On the other hand, our results point to the fact that gold is less sensitive to “bad news” and tends to react unlike oil. In fact, gold price responds positively to deaths in short-term and to new infections in long-term. Secondly, the short run ARDL model revealed that the COVID-19 media coverage have a positive impact on the dynamics of the oil and gold market. Thirdly, the impact of COVID-19 new confirmed cases on oil and gold prices differs depending on the phase of the COVID-19 disease (epidemic or pandemic).

Our article is organized as follows. Section 2 focuses on literature and theoretical background. Section 3 presents respectively data and methods. Section 4 reports and discussions the empirical findings and finally Section 5 offers the conclusion.

2. Literature and theoretical background

To find out what factors determine the commodity prices and specials with regard to oil and gold, previous investigations generally point to macroeconomic fundamentals and policies such as: Benhmad (2012) (exchange rate of the dollar), Klett et al. (2005) (macroeconomic shocks), Radetzki (2006) (production capacities), Pascaud and Zambrakas (2010) (geopolitical considerations), etc. These surveys generally omit to verify the effect of health and scientific factors, behavioral issues (Qadan and Nama 2018) and media in explaining the volatility of oil and gold prices.

The existing literature is limited to few studies verified the epidemic’s effect on financial markets. The study of Chen et al. (2007)
that stocks less covered by the media have more returns. Moreover, evolution of stock prices, Fang et al. (2014) demonstrated that stock depends on information in the media, which consequently affects stock (Engelberg and Parsons, 2011; Klibanoff and al., 1998; Mairal, 2011; expected that there was a link between the media and the stock market influence markets. A review of the literature shows a set of surveys sus demonstrate that market returns responded to the Severe Acute Respiratory Syndrome (SARS) disease. During the period from 2003 to 2014, Donadelli et al. (2017) verified the impact of the appearance of dangerous diseases on the mood of investors. The researchers found a positive and significant effect of disease news on pharmaceutical firms’s stock returns. Likewise, Ichev and Marinic (2018) examined the impact of information related to Ebola Virus Disease (EVD) (2014–2016) on the financial markets, taking into account the epidemic media coverage, the panic triggered by the disease and investors’ risk aversion. Using an event study, they found that the stocks of companies, which are geographically close to the birthplace of the epidemic, are the most volatile.

Given the spread and severity of the new coronavirus as well as its harmful economic effects, some researchers have focused lately on the impact of the COVID-19 impact on the stock market returns (Al-Awadhi et al., 2020). On the other side, the new coronavirus is rocking the commodity markets. That is why a very small body of research is beginning to investigate the real impact of the COVID-19 health crisis on commodity markets. To the best of our knowledge, there is one recent published empirical paper by Musa et al. (2020), which focuses on examining the impact of cases of coronavirus infected cases on the crude oil price and the food price index using an ARDL model from January 20 to March 31, 2020. The results indicate that the COVID-19 pandemic has a negative impact on the oil price and a positive influence on the food price index in the long-term. However, in the short term, the relationship between COVID-19 disease and the oil price and the food price index is significantly negative. The aim of the recent working paper of Albulescu (2020) is analyzing the impact of new coronavirus cases reported in and outside China on oil price. On the other hand, the new investigation by Johan (2020) aims to determine the economic factors that explain an investor preference for investing in gold during the recession triggered by the COVID-19 pandemic. The results indicate that inflation and income growth explain the preference for gold investments over the interest rate, which is not significant. On the basis of GARCH exponential models, the research of Ali et al. (2020) is to study the reaction of nine financial markets to the first countries affected by COVID-19 in terms of performance and volatility when COVID-19 spread from China to Europe and then to the United States. The authors have added corporate bonds index, US treasury bonds core index, Bitcoin, Oil and Gold. The results signal that global markets decrease as the pandemic spread. Whereas, gold returns was negative but less volatile when the COVID-19 disease beat the United States. Others have found that the growth of coronavirus cases increases the volatility of gold returns using GARCH and GJR-GARCH models (Yousef and Shehadeh, 2020).

The media play a major role in informing the community. In fact, information moves at high speed through various communication channels and the Internet. News and opinions from the media can influence markets. A review of the literature shows a set of surveys suspected that there was a link between the media and the stock market (Engelberg and Parsons, 2011; Klibanoff and al., 1998; Mairal, 2011; Paul, 2007). These studies illustrated that investors are paying more attention to stock equity that the media offer more importance and coverage. The researchers confirmed that the reaction of investors depends on information in the media, which consequently affects stock prices. Besides, by studying the nexus between the trade media and the evolution of stock prices, Fang et al. (2014) demonstrated that stock returns, volatility and trading volume decrease on days of newspaper strikes. In the same spirit, Fang and Peress (2009) provided evidence that stocks less covered by the media have more returns. Moreover, Cakan et al. (2015) analyzed the impact of US macroeconomic news related to inflation and the unemployment rate on the volatility of 12 emerging stock markets. The results indicated that volatility increases following bad news dramatically, unlike good news.

On the other hand, fewer studies have tested the relationship between macroeconomic news and commodity prices. Similar to the results reported by Frankel and Hardouvelis (1985), Hess et al. (2008), Kilian and Vega (2008) confirmed that macroeconomic news has significant impacts on commodity prices in the United States. According to Frankel (2008), press announcements regarding interest rates and the U. S. dollar exchange rate affect commodity prices. Using a GARCH model, Roache and Rossi (2009) mentioned that most commodities are influenced by new macroeconomic surprises, with the exception of gold, which remains sensitive only to uncertainty and bad news.

During health crises, media play an important role in transmitting news, statistics and protective measures. Information about the spread of epidemics and contagious diseases influence financial markets. As an example, Blendon et al. (2004) examined the SARS media coverage. In addition, Huberman and Regev (2001) absorbed the interaction between financial markets and media coverage of cancer research. The authors found that the share prices of biopharmaceutical companies were reacting positively to the occurrence of an enthusiastic article about a research finding in the Sunday New York Times, despite being announced five months earlier. Despite the role played by the media throughout the COVID-19 pandemic, we found that only one study by Haroon and Rizvi (2020) that suggests that the panic generated by the COVID-19 press media contributes increase the volatility of stock markets.

The new emerging research field, which is behavioral finance, explains the market behavior by human psychology. Researchers are interested in studying the impact of behavioral and psychological factors following some events on the economy and financial markets. Few studies explained the disparity of commodities prices by emotional factors. Maslyuk-Escobedo et al. (2017) documented that the deviation of energy prices depends on the market sentiment fluctuation. In particular, a notable number of studies consider that the deviation of the crude oil price is linked to investor sentiment changes (Qadan and Nama, 2018). According to Deeney et al. (2015), Du et al. (2016) and Du and Zhao (2017), investor sentiment is considered as an explanatory factor for the oil price. We also mention that Li et al. (2017) confirm that the investor sentiment is used to anticipate the oil price. In addition, Ji et al. (2019), Yang et al. (2019) reported a finding that the investor sentiment affects oil price returns.

Recently, the new coronavirus triggered investor panic. Some studies have investigated the strict effect of investor panic on stock prices during the COVID-19 health crisis. Yang et al. (2020) affirm that the panic index can be employed to forecast the stock market crash. Another study indicates that confirmed cases of COVID-19, uncertainty and investor panic sentiment have negative effects on the abnormal returns of stock indices in Asian countries (Liu et al., 2020). Ali et al. (2020) find that panic and market deteriorating increased dramatically in two times. The first phase is when the Coronavirus was confirmed as a pandemic and the second time is when the disease invaded all geographic areas and continents. More recently, Salisu et al. (2020) calculated a COVID-19 Global Fear Index (GFI) relying on two factors: reported cases and deaths. They examined the predictive power of this index in determining the price returns of metals (like gold) and agricultural commodities. The results indicate a positive relationship between the fear index and commodity price returns. To the best of our thought, there is not yet any empirical paper, which directly links COVID-19 panic index with oil and gold prices.

The dual economic and health crisis linked to the COVID-19 pandemic has increased the extent and persistence of economic policy uncertainty (EPU). However, the latter has a major influence on
ARDL analysis, found that gold is useful as a portfolio hedge against financial and economic crises. For example, Shakil et al. (2018) through quite limited and refers to the role of gold as a hedging asset during financial instability is the cause of the fluctuation of energy and metal implications of the financial market volatility on commodity market. Kang et al. (2017) indicated that economic policy uncertainty for United States (EPU) data is obtained from the Federal Reserve Economic Data website (Saker et al., 2016). To our knowledge, the WHO reports communicate data on COVID-19 after having been announced by the press in countries at the end of the previous day. It seems obvious that the impact of the economic policy uncertainty and media reports on oil and gold prices does not appear directly on the same day but with a slight delay. Therefore, we take into account: the impact of the new infections and deaths data declared at (t – 1), the impact of the EPU index and the media coverage index data declared at (t – 1) and the VIX and panic index declared at (t) on the price of gold and oil reported in date (t).

We discuss the descriptive statistics of the study variables in the following. Table 1-A presents the descriptive statistics of the retained series. We note that new cases have a very high volatility (ST.Dev = 49037.39). During the period of COVID-19 pandemic, oil experienced the perfect storm and attained the lowest value (−36.98%). While the gold is traded between 1,477.3$ and 1772.1$. The gold price has jumped very strongly despite uncertainty, panic and investor fears following the COVID-19 pandemic that is considered one of the major crises that rocked the world. The gold price hits record high during COVID-19 crisis and registers a 19.95% increase since COVID-19 was declared a global pandemic. The panic index (CPIX) reaches a high value indicating that 9.24% of international news deals with the subject of panic and hysteria caused by COVID-19 crisis. We report that 83, 93% of media coverage worldwide specifically concerns the topic of COVID-19 pandemic.

Table 1-B shows that the correlation between variables related to COVID-19 pandemic (COVID-19 new cases, COVID-19 deaths, COVID-19 panic index and COVID-19 media coverage index) is strong and positive. On the other hand, we note the presence of a negative correlation between the oil price and all the other variables of the study. On the contrary, the gold price is correlated positively with the COVID-19 new cases (0.739025), COVID-19 deaths (0.779186) and the COVID-19 media coverage index (0.697625), with the exception of COVID-19 panic index (0.484046).

The results indicate a strong and positive correlation between the economic policy uncertainty and the COVID-19 pandemic (COVID-19 new cases (0.895117), COVID-19 deaths (0.905367), COVID-19 panic index (0.876560) and COVID-19 media coverage index (0.902087). We also mention that the financial volatility index as well as the gold price are correlated positively to the economic policy uncertainty. However, the correlation between the economic policy uncertainty and oil price is negative. We explain these results by the fact that economic uncertainty and financial volatility increased as a result of the COVID-19 pandemic, while reduced the price of gold and oil price reacted inversely.

Table 2 indicates that the ADF test in the first difference, gives statistical t values much higher in absolute value at different critical thresholds (1%, 5% and 10%) for all the variables. Therefore, our

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4 https://research.stlouisfed.org/fred2/series/DCOILWTICO/downloaddata.
5 https://www.investing.com/commodities/gold.
6 World Health Organization https://www.who.int/emergencies/diseases/novel-coronavirus2019/situation-reports.
7 https://ourworldindata.org/coronavirus-source-data.
8 http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historicaldata.
9 https://fred.stlouisfed.org/series/USEPUINDEXD.
variables are integrated of order (1) or I (1).

3.2. Methodology

We adopt the ARDL analysis to explore how daily oil and gold prices are responding to media coverage, new cases, deaths and panic generated by the COVID-19 by controlling the impact of the financial volatility and the economic policy uncertainty. This approach allows us to determine the effects of COVID-19 on the two commodity prices in the short and long term by referring to the studies by Musa et al. (2020) and Shakil et al. (2018).

The ARDL model proposed by Pesaran et al. (2001) uses a linear transformation to integrate short-term adjustments into the long-term equilibrium, using an Error Correction Model (ERM). We present the four oil price models and then the gold price models, as follows:

Oil- Models

\[
\text{Model 1 - O} \quad \Delta \text{Oil}_t = c + \delta_{\text{Oil}} \Delta \text{Oil}_{t-1} + \delta_{\text{CNC}} \text{CNC}_t + \delta_{\text{VIX}} \text{VIX}_t + \delta_{\text{EPU}} \text{EPU}_t + \sum_{i=1}^{p} \alpha_i \Delta \text{Oil}_{t-i} + \sum_{i=1}^{p} \beta_i \Delta \text{CNC}_{t-i} \\
+ \sum_{i=1}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \delta_i \Delta \text{EPU}_{t-i} + \theta \text{ECT}_{t-i} + \epsilon_t
\]  

\[
\text{Model 2 - O} \quad \Delta \text{Oil}_t = c + \delta_{\text{Oil}} \Delta \text{Oil}_{t-1} + \delta_{\text{CND}} \text{CND}_t + \delta_{\text{VIX}} \text{VIX}_t + \delta_{\text{EPU}} \text{EPU}_t + \sum_{i=1}^{p} \alpha_i \Delta \text{Oil}_{t-i} + \sum_{i=1}^{p} \beta_i \Delta \text{CND}_{t-i} \\
+ \sum_{i=1}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \delta_i \Delta \text{EPU}_{t-i} + \theta \text{ECT}_{t-i} + \epsilon_t
\]  

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Table 1
Summary statistics.

| Variable | Min | Max | Mean | Std. Dev. |
|----------|-----|-----|------|-----------|
| CNC CND | 177251 | 3212.306 | 33.9141 | 1659.634 |
| Oil Gold | 266 | 9 | 1477.3 | 19.85 |
| CMC EPU | 10520 | 3212.306 | 686.2435 | 83.93 |
| CPIX VIX | 55.51 | 2642.687 | 73.20359 | 861.1 |

Table 2
Unit root test.

| Level | ADF statistics | Result | First difference | ADF statistics | Result |
|-------|----------------|--------|------------------|----------------|--------|
| CNC CND | 4.414500 | Non stationary | –12.38729 | stationary |
| Oil Gold | –0.683805 | Non stationary | –11.26927 | stationary |
| CND CNC | –2.190725 | Non stationary | –17.78620 | stationary |
| CPIX EPU | –0.174976 | Non stationary | –14.91258 | stationary |
| CMC VIX | –2.390661 | Non stationary | –10.08544 | stationary |
| EPU CMC | –1.703287 | Non stationary | –12.45927 | stationary |
| VIX CPIX | –1.277464 | Non stationary | –9.29415 | stationary |
| EPU CMC | –2.469903 | Non stationary | –17.58451 | stationary |

CNC: COVID-19 new cases, CND: COVID-19 deaths, CPIX: COVID-19 panic index, CMC: COVID-19 media coverage index, VIX: financial volatility index, EPU: Economic Policy Uncertainty index.
Model 3 – O
\[
\Delta \text{Oil}_t = c + \delta_{\text{Oil}} \text{Oil}_{t-1} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Oil}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{VIX}_{t-i}
\]
\[+ \sum_{i=0}^{p} \gamma_i \Delta \text{EPU}_{t-i} + \theta \text{ECT}_{t-1} + \epsilon_t \]  
(3)

Model 4 – O
\[
\Delta \text{Oil}_t = c + \delta_{\text{Oil}} \text{Oil}_{t-1} + \delta_{\text{CNC}} \text{CNC}_{t-2} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Oil}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{CNC}_{t-i}
\]
\[+ \sum_{i=0}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \lambda_i \Delta \text{EPU}_{t-i} + \theta \text{ECT}_{t-1} + \epsilon_t \]  
(4)

Gold– Models

Model 1 – G
\[
\Delta \text{Gold}_t = c + \delta_{\text{Gold}} \text{Gold}_{t-1} + \delta_{\text{CNC}} \text{CNC}_{t-1} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Gold}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{CNC}_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \lambda_i \Delta \text{EPU}_{t-i}
\]
\[+ \theta \text{ECT}_{t-1} + \epsilon_t \]  
(5)

Model 2 – G
\[
\Delta \text{Gold}_t = c + \delta_{\text{Gold}} \text{Gold}_{t-1} + \delta_{\text{CND}} \text{CND}_{t-1} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Gold}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{CND}_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \lambda_i \Delta \text{EPU}_{t-i}
\]
\[+ \theta \text{ECT}_{t-1} + \epsilon_t \]  
(6)

Model 3 – G
\[
\Delta \text{Gold}_t = c + \delta_{\text{Gold}} \text{Gold}_{t-1} + \delta_{\text{PIX}} \text{PIX}_{t-1} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Gold}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{PIX}_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \lambda_i \Delta \text{EPU}_{t-i}
\]
\[+ \theta \text{ECT}_{t-1} + \epsilon_t \]  
(7)

Model 4 – G
\[
\Delta \text{Gold}_t = c + \delta_{\text{Gold}} \text{Gold}_{t-1} + \delta_{\text{CNC}} \text{CNC}_{t-2} + \delta_{\text{VIX}} \text{VIX}_{t-1} + \delta_{\text{EPU}} \text{EPU}_{t-2} + \sum_{i=1}^{p} \alpha_i \Delta \text{Gold}_{t-i} + \sum_{i=0}^{p} \beta_i \Delta \text{CNC}_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{p} \lambda_i \Delta \text{EPU}_{t-i}
\]
\[+ \theta \text{ECT}_{t-1} + \epsilon_t \]  
(8)

Where Oil and Gold present respectively crude oil and gold prices, CNC is the COVID-19 new cases, CND is the COVID-19 deaths, CPIX is the COVID-19 panic index, CMC is the COVID-19 media coverage index, VIX is the financial volatility index and EPU is the economic policy uncertainty index.

While c and ε are the intercept and the error term respectively, Δ denotes the short-run terms, δ defines the long-run terms, the error correction term is indicated by ECT (δ should be negative and significant in order to validate the long-run relationship). The maximum number of lags is determined using the Akaike Information Criteria (AIC). The existence of a long-run relationship is confirmed by the F-statistic where the null hypothesis of no cointegration is:

Table 3

| Bound test results (Oil). | F Statistic | Critical Values | Conclusion |
|--------------------------|------------|----------------|------------|
| Model specification     | Lower Bound | Upper Bound    | (5%)       |
|                         |           |                | (5%)       |
| M10– CMC                | 15.29871  | 3.23           | 4.35       | cointegration |
| M20– CND                | 16.11787  | 3.23           | 4.35       | Cointegration |
| M30– CPIX               | 16.06209  | 3.23           | 4.35       | Cointegration |
| M40– CMC                | 16.91756  | 3.23           | 4.35       | Cointegration |

Notes: (i) Critical values at 5% significance level, CNC: COVID-19 new cases, CND: COVID-19 deaths, CPIX: COVID-19 panic index, CMC: COVID-19 media coverage index.

We applied the Breusch-Godfrey LM test to check for the residual serial correlation, Engle ARCH-LM test to determine the presence of ARCH effects and Jarque-Bera test to check the normality. Before proceeding with the estimation, we applied the natural log to the variables of the study.
Table 4
Estimation of the ARDL specification OIL.

| Model | CNC | CND | CPIX | CMC | VIX | EPU | Δ | Oil t-3  | Oil t-2  | Oil t-1  |
|-------|-----|-----|------|-----|-----|-----|---|---------|---------|---------|
| 1-O   | 0.004623 [0.6717] | 0.021438 [0.0015]*** | -0.07144 [0.3121] | -0.40931 [0.003]*** | -0.20996 [0.0779]* | -0.18501 [0.0281]** | C 0.642431 [0.0000]*** |
| 2-O   | 0.728291 [0.0001]*** | 0.757725 [0.0001]*** | 0.747967 [0.0002]** | 0.811321 [0.001]** |
| 3-O   | 0.535705 [0.0016]** | 0.573993 [0.0007]*** | 0.715413 [0.0000]*** | 0.419294 [0.013]** |
| 4-O   | 0.016312 [0.6724] | -0.01555 [0.0964]* | -0.03014 [0.0628]* | -0.05345 [0.061]* |

Notes: significance at 1%, 5% and 10%; Breusch-Godfrey LM test for serial correlation is used; ARCH effects for conditional heteroscedasticity (with 3 lags); CNC: COVID-19 new cases, CND: COVID-19 deaths, CPIX: COVID-19 panic index, CMC: COVID-19 media coverage index, VIX: financial volatility index, EPU: Economic Policy Uncertainty index.

Table 5
Bounds test results (Gold).

| Model specification | F Statistic | Critical Values | Conclusion |
|---------------------|-------------|-----------------|------------|
|                     | Lower Bound | Upper Bound     |            |
|                     | Bound I(0)  | Bound I(1)      |            |
|                     | (10%)       | (10%)           |            |
| M1G- CNC            | 4.1546115   | 2.72            | 3.77       | cointegration |
| M2G- CND            | 0.775397    | 2.72            | 3.77       | No cointegration |
| M3G- CPIX           | 0.447180    | 2.72            | 3.77       | No cointegration |
| M4G- CMC            | 4.200514    | 2.72            | 3.77       | Cointegration |

Notes: (i) Critical values at 10% significance level CNC: COVID-19 new cases, CND: COVID-19 deaths, CPIX: COVID-19 panic index, CMC: COVID-19 media coverage.

4. Empirical results

4.1. Oil price and COVID-19 effects

To verify the existence of a long-term relationship, we have applied Bounds test, which adopt a lower bound for series I (0) and an upper bound for series I (1). The variables are cointegrated only when the value of the F statistic is greater than the critical value of the upper limit (5%) (Narayan, 2005).

According to Table 3, the F-statistic of the four models indicates the presence of a long-term relationship between the oil price and the daily new cases, deaths, panic index and media coverage of the COVID-19.

Table 4 presents the ARDL estimations for the four models examining the dynamic interactions between oil price and the CPVID-19 health crisis approximated respectively by: the COVID-19 new cases (Model 1-O), the COVID-19 deaths (Model 2-O), the COVID-19 panic index (Model 3-O) and the COVID-19 media coverage (Model 4-O). We find that the economic policy uncertainty index (EPU) and the financial volatility (VIX) have short and long-term negative effects on oil price. We realize that as long as economic uncertainty and financial volatility increase, so long as the oil price falls dramatically. This finding coincides with the results of Bakas and Triantafyllou (2020).

The result of the first model in Table 4 indicates that COVID-19 new confirmed cases do not have a significant effect on the oil price. However, this finding do not confirm the result of Albulescu (2020) and Musa et al. (2020) who found that COVID-19 infected cases have a negative impact on crude oil price.

According to the Model 2-O, we detect a negative short-term and a positive long-term impact of COVID-19 deaths on the oil price. Indeed, the declaration of the first coronavirus deaths caused the oil price deterioration in the short-term. Nonetheless, on the long-term, after removing COVID-19 lockdown and the return of economic activities, the crude oil price gradually recovered despite news of deaths.

We find that the COVID-19 panic index has a short-term negative effect on oil price (Model 3-O). The high number of daily deaths and infections, the lockdown and travel restrictions and the business closures all raised the level of anxiety and panic, which had a short-term negative impact on oil price. Our result controverts the conclusion of Salisu et al (2020), which indicates that commodity price returns rise as the COVID-19 fear surges. Our finding confirms the results of Deeney et al. (2015), Du and Zhao (2017), Ji et al. (2019), Qadan and Nama (2018), Shahzad et al. (2017) and Yang et al. (2019), which demonstrate that the oil price variations are explained by investor sentiment.

In addition, the results of Model 4-O show that the impact of the COVID-19 media coverage on the oil price is positive in the short term and negative in the long term. This finding points to the fact that the COVID-19 media coverage has a positive impact on the dynamic of the...
Table 6
Estimation of the ARDL specification -Gold.

| Long-run equation | Model 1-G | Model 2-G | Model 3-G | Model 4-G |
|-------------------|-----------|-----------|-----------|-----------|
| CNC(-1)           | 0.031912  | [0.0332]**| 0.5009    | [0.0504]* |
| CND(-1)           |           |           | -0.1200   | [0.1190] |
| CPIX              |           |           | -0.0940   | [0.2059] |
| CMC               |           |           | 0.2760    | [0.1489] |
| VIX               | 0.025446  | [0.5985]  |           |           |
| EPU(-1)           | -0.01631  | [0.7410]  |           |           |
| C                | 0.026303  | [0.0665]* |           |           |

| Short-run equation |          |          |          |          |
|-------------------|----------|----------|----------|----------|
| \(\Delta \text{Gold}\)       | 0.724619 | [0.000]**| 0.731825 | [0.000]**|
| \(\Delta \text{Gold}\)       | 0.453439 | [0.009]**| 0.447968 | [0.0251]**|
| \(\Delta \text{Gold}\)       | -0.19129 | [0.4002] | -0.35914 | [0.0858]*|
| \(\Delta \text{Gold}\)       | -0.18945 | [0.4221] |          |          |
| \(\Delta \text{CNC}\)        | 0.001334 | [0.8246] |          |          |
| \(\Delta \text{CNC}\)        | -0.00684 | [0.1920] |          |          |
| \(\Delta \text{CNC}\)        | -0.00080 | [0.9565] |          |          |
| \(\Delta \text{CNC}\)        | 0.030244 | [0.0749] |          |          |
| \(\Delta \text{CNC}\)        | -0.01745 | [0.0357]**|          |          |
| \(\Delta \text{CND}\)        | 0.008714 | [0.0815]*|          |          |
| \(\Delta \text{CND}\)        | 0.000651 | [0.9328] |          |          |
| \(\Delta \text{CND}\)        | -0.00172 | [0.8990] |          |          |
| \(\Delta \text{CND}\)        | 0.001245 | [0.9520] |          |          |
| \(\Delta \text{CND}\)        | -0.00287 | [0.7338] |          |          |
| \(\Delta \text{EPU}\)        | -0.01653 | [0.0885]*| -0.02131 | [0.0392]**|
| \(\Delta \text{EPU}\)        | 0.003204 | [0.5734] | -0.00013 | [0.9827] |
| \(\Delta \text{EPU}\)        | -0.00461 | [0.3933] | -0.00111 | [0.9865] |
| \(\Delta \text{EPU}\)        | 0.002593 | [0.6389] |          |          |
| \(\Delta \text{VIX}\)        | 0.014683 | [0.4446] | -0.00147 | [0.9372] |
| \(\Delta \text{VIX}\)        | 0.001237 | [0.9475] | 0.004761 | [0.8443] |
| \(\Delta \text{VIX}\)        | -0.05290 | [0.0890] | -0.05425 | [0.1039] |
| \(\Delta \text{VIX}\)        | 0.042143 | [0.0956]*| 0.055095 | [0.0521] |
| \(\Delta \text{CPIX}\)       |          |          | -0.00478 | [0.5385] |
| \(\Delta \text{CMC}\)        |          |          | 0.050590 | [0.006]*****|
| \(\Delta \text{ECT}\)        | -0.2026  | [0.0142]**| -0.1717  | [0.1745] |
| \(\Delta \text{ECT}\)        |          |          | -0.0433  | [0.1764] |
| Serial Correlation     | No       | No       | No       | No       |
| ARCH Effects           | No       | No       | No       | No       |
| Stability              | Yes      | Yes      | Yes      | Yes      |
| Observations           | 48       | 106      |          |          |

Notes: significance at 1%, 5% and 10%; Breusch-Godfrey LM test for serial correlation is used; ARCH effects for conditional heteroscedasticity (with 2 lags), CNC: COVID-19 new cases, CND: COVID-19 deaths, CPIX: COVID-19 panic index, CMC: COVID-19 media coverage index, VIX: financial volatility index, EPU: Economic Policy Uncertainty index.

Table 7
Estimation of the ARDL specification under two periods (Model 1-O).

| Long-run equation | Phase 1 | Phase 2 |
|-------------------|---------|---------|
| CNC(-1)           | -0.044889 | [0.0013]**| 0.232436 | [0.1256] |
| VIX               | -0.112753 | [0.0001]**| -0.379522 | [0.0494]**|
| EPU(-1)           | -0.015058 | [0.4043] | -0.154194 | [0.5596] |
| C                | 2.160897  | [0.0021]**| 0.295277 | [0.2387] |

| Short-run equation |          |          |          |          |
|-------------------|----------|----------|----------|----------|
| \(\Delta \text{Oil}\)       | 0.692914 | [0.0380]**| 0.812337 | [0.0000]**|
| \(\Delta \text{Oil}\)       | -0.759062 | [0.0868]**|           |          |
| \(\Delta \text{CNC}\)       | -0.016246 | [0.1223] | 0.043620 | [0.1103] |
| \(\Delta \text{CNC}\)       | 0.000394 | [0.5908] |          |          |
| \(\Delta \text{CNC}\)       | -0.035555 | [0.0047]**|          |          |
| \(\Delta \text{EPU}\)       | -0.021007 | [0.1033] |          |          |
| \(\Delta \text{VIX}\)       | -0.046242 | [0.1736] | -0.028936 | [0.5633] |
| \(\Delta \text{VIX}\)       | -0.079370 | [0.1218] |          |          |
| \(\Delta \text{ECT}\)       | -1.066149 | [0.0000]**| -0.180253 | [0.0000]**|

| Serial Correlation     | No       | No       | No       | No       |
| ARCH Effects           | No       | No       | No       | No       |
| Stability              | Yes      | Yes      | Yes      | Yes      |
| Observations           | 48       | 106      |          |          |

Notes: significance at 1%, 5% and 10%; Breusch-Godfrey LM test for serial correlation is used; ARCH effects for conditional heteroscedasticity (with 2 lags), CNC: COVID-19 new cases, VIX: financial volatility index, EPU: Economic Policy Uncertainty index.

oil market in the short term. However, the oil price falls in the long term because of the propaganda created by the media, which keeps banging non-stop on the threats of this dangerous virus. Generally, the economic uncertainty and the financial volatility affect oil price negatively during the COVID-19 health crisis.

4.2. Gold price and COVID-19 effects

We apply bound test (Table 5) and according to the critical values of Narayan (2005), the F statistic indicates a cointegration relation in Model 1-G and Model 4-G. For these two models dealing with the daily new infection cases and the pandemic media coverage.

We admit the existence of a long-run relationship between gold price, COVID-19 news, media coverage, financial volatility and the US economic uncertainty. However, the COVID-19 deaths and the panic generated by bad news around the pandemic can only have a short-term effect on gold price. We present, as follows, the ARDL estimations for four models examining the dynamic interactions between gold price and respectively, the COVID-19 new cases (Model 1-G), the COVID-19 deaths (Model 2-G), the COVID-19 panic index (Model 3-G) and the COVID-19 media coverage (Model 4-G).

Contrary to previous results concerning oil price, the results in Table 6 indicate a positive long-term relationship between the Coronavirus new cases and gold price (Model 1-G). This result largely confirms the findings of the previous studies of Ali et al. (2020) and Yousef and Shehadeh (2020). Furthermore, the COVID-19 deaths have a short-term
The neutrality of the effect of confirmed new infections on oil price, noted above in Table 4, are surprising. Contrary to our expectations, we did not find any significant relationship between the COVID-19 new cases and the oil price during the period January 23, 2020–June 23, 2020 (Model 1-O). Regarding the impact of the new COVID-19 confirmed cases on gold price, we did not define a clearly and ultimate association (Model 1-O). As a result, we wonder if the incidence of COVID-19 disease on these two commodities varies from January 2020 to June 2020.

On 11th March, the World Health Organization WHO declared the COVID-19 disease as a pandemic. Therefore, we proceeded to divide the study period on two intervals, by referring to the work of All et al. (2020). The phase 1 is from January 23, 2020 until March 10, 2020 when the COVID-19 disease is considered as an epidemic and phase 2 from March 11, 2020 until June 23, 2020 when it is confirmed as a pandemic.

In this section, we identify how the COVID-19 new cases affect oil and gold prices over time depending on the phase of the disease using the ARDL approach, which is still applicable post-division of the sample because the number of observations is greater than 30 for both phases. Table 5 indicates that the short and long run ARDL model reveal that the disclosure of the COVID-19 new cases has a negative effect on the oil price during the phase 1. This finding corroborates the result of the Albuès (2020)’s study indicating a negative relationship between new cases of COVID-19 and oil prices. We realize that when COVID-19 disease is declared pandemic (phase 2), the oil price is no longer influenced by the declaration of the number of new infected cases in the long-term.

We explain these findings by the fact that the high number of new infected cases declared and the seriousness of the COVID-19 prompted the taking of protective measures (lockdown, social distancing, travel interruption, closure of factories) which led to a decrease in demand for oil versus an abandoning supply as the oil extraction sites continued to operate at the beginning of phase 1. Therefore, the reporting of new cases of COVID-19 during phase 1 worsened the situation and led to a sharp drop in the oil price. While during phase 2, the protective measures became more flexible, which refreshed the oil market. Thus, we support the fact that new confirmed infections only impact the price of oil when the disease is declared an epidemic.

Table 8 shows that the new cases affect negatively the gold price at the phase 1. This first phase, when the new Coronavirus is considered as an epidemic, was characterized by a high level of uncertainty and distress caused by the panic and the lack of information about this disease. After March 11, 2020, when COVID-19 was declared as a pandemic (phase 2), the impact of COVID-19 new cases on the gold price has changed and becomes positive. The gold price is affected negatively

Table 8

|                | Phase 1                          | Phase 2                          |
|----------------|----------------------------------|----------------------------------|
| β              |                                  |                                  |
| CNE t−1        | −0.046036 [0.0517]               | 0.089329 [0.0000]               |
| VIX            | 0.003848 [0.8873]                | 0.007182 [0.7290]               |
| EPU t−1        | 0.093942 [0.0951]                | −0.009314 [0.4346]             |
| C              | −4.913313 [0.1938]              | 0.922007 [0.0004]               |

Short-run equation

| ΔGOLD t−1      | 0.033826 [0.9371]               | −0.328150 [0.0002]               |
| ΔGOLD t−2      | 1.783395 [0.2337]               |                                  |
| ΔGOLD t−3      | 0.737277 [0.3902]               |                                  |
| ΔCNE t−1       | 0.009472 [0.2114]               |                                  |
| ΔCNE t−2       | 0.014607 [0.2850]               | 0.029313 [0.0000]               |
| ΔEPU t−1       | 0.017116 [0.6471]               |                                  |
| ΔEPU t−2       | 0.030367 [0.2135]               |                                  |
| ΔEPU t−3       | −0.052779 [0.0328]              | −0.003057 [0.4225]              |
| ΔVIX t−1       | 0.037795 [0.5944]               | 0.002357 [0.7223]               |
| ΔVIX t−2       | −0.020434 [0.7210]              |                                  |
| ΔVIX t−3       | 0.072383 [0.3210]               |                                  |
| ΔVIX t−4       | −0.095727 [0.3415]              |                                  |
| ΔECT1          | 1.554498 [0.0144]               | −0.328150 [0.0000]               |

Serial Correlation

|                | No                                | No                                |
|----------------|-----------------------------------|-----------------------------------|
| ARCH Effects   | No                                | No                                |
| Stability      | Yes                               | Yes                               |

Observations

48 106

Notes: significance at 1%, 5% and 10%; Breusch-Godfrey LM test for serial correlation is used; ARCH effects for conditional heteroscedasticity (with 3 lags), CNC: COVID-19 new cases, VIX: financial volatility index, EPU: Economic Policy Uncertainty index.

positive effect on the gold price (Model 2-G). Therefore, the gold price rise by 3% in the long-term when new cases increase by 1% and decrease by 0.8% in the short-term after a growth about 1% of the COVID-19 deaths. Indeed, during COVID-19 health crisis, investors try to escape to a safe haven and find refuge in gold particularly. Our results show that the demand for gold is increasing, as is its price in the face of extreme negative market shocks. We argue that gold is the safer commodities and acts as a stabilizing force for the financial system in times of crisis. Our results corroborate the study by Baur and McDermott (2010).

Likewise, the COVID-19 media coverage has short and long-term positive effect on the gold price (Model 4-G). Therefore, an increase in media coverage around the Coronavirus by 1% leads to a raise in the gold price by 5% in the long term and 0.5% in the short term. The media coverage (scientific discoveries, debates, research, investigations, statistics, reports, etc.) about the COVID-19 pandemic considerably affect the gold price more than the direct announce of the number of new infected cases and deaths in the order of 5%. Our results do not agree with the findings of Elder et al. (2012) which indicated that declarations regarding a surprising progress in the economy are having a negative impact on gold prices.

We admit that the COVID-19 pandemic has been the greatest crisis for gold. We find that the price of this precious metal is not sensitive depressingly to the COVID-19 new cases, deaths or media coverage and tends to react unlike oil. According to our study, we demonstrate that gold resists despite the bad news and retains its status as a “safe haven” asset in times of health crisis as well as in times of economic and financial crisis. We recall the terrorist attack of September 11, 2001 against the World Trade Center and the financial crisis in 2008. This is consistent with the findings of Baur and McDermott (2010), who reveal that gold is a hedge against any economic or geopolitical crisis.
during an epidemic period and have started to show an increase during the pandemic phase, which supports the notion of “Gold is a safe-haven asset” (Reboredo, 2013; Baur and McDermott, 2010).

We conclude that like all previous crises, during the COVID-19 health crisis, investors are rushing to buy gold, to protect themselves during this time of high risk. We add that the impact of COVID-19 new confirmed infections on the gold price depend on the stage of the disease.

5. Conclusion

The existing literature on oil and gold prices mainly focuses on macroeconomic aspects and ignores the behavioral factors, health impact and the effect of media coverage, leaving three important questions unanswered: How do the prices of the major commodities respond to the COVID-19 pandemic news? What is the impact of the panic generated by the new Coronavirus on the oil and gold prices? What is the consequence of media coverage of COVID-19 on oil and gold prices?

This study is probably the first to examine the impact of the news, the panic and the media coverage of the major pandemic that rocked the world on commodity prices. The new contribution to the existing literature is to provide new evidence on the influence of the current health crisis on oil and gold prices, using four variables related to COVID-19 infections, deaths, panic and media coverage. This paper adopts an ARDL approach to examine the impact of COVID-19 pandemic on gold and oil over the period 23/01/2020–23/06/2020.

The empirical results provide substantial evidence of the impact of the COVID-19 pandemic on commodity prices. We find that COVID-19 has opposite effects on oil and gold prices. Our survey shows that the number of deaths and the COVID-19 panic have negative effects on crude oil price. Amid threat the COVID-19 health crisis, panic hits oil market and trig oil price slump. Contrarily, the COVID-19 media coverage has a positive impact on the oil price in the short term.

Additionally, results show that gold price is less sensible to “bad news”. We provide evidence that the gold price continues to increase despite the COVID-19 situation. We note that the COVID-19 new infections, deaths and media coverage have positive effects on the gold price. This commodity tends to react unlike other types of assets or commodities, which fall during this health crisis.

Our results point to the fact that the COVID-19 media coverage have a positive impact on the dynamics of the oil and gold market. Therefore, media play an important role in decreasing doubt and fear caused by the COVID-19 disease and improve the market sentiment in the period of a positive impact on the dynamics of the oil and gold market. Therefore, the pandemic phase, which supports the notion of during an epidemic period and have started to show an increase during this time of high risk. We add that the impact of COVID-19 new confirmed infections on the gold price depend on the stage of the disease.

We applied the ARDL model. Therefore, implications for future research to use other techniques (such as the NARDL approach) and more than one method and compare the results. The resulting estimates may offer improved results.

We find that during phase 2 the protective measures became more flexible, which refreshed the oil market. Thus, we recommend the authorities to revise certain restrictions to restore economic stability and oil market recovery.

What is the consequence of media coverage on oil and gold prices; it is also a question of looking more in depth and specifying which type of media is the most influential. This will help the authorities to manage the situation well, ensure balance and limit shocks.

Given the novelty of the Covid-19 event and its significant implications for the global economy, we are limited by a short but sufficient study period. Therefore, future research with longer study periods will be appreciated and recommended to evaluate additional the impact of the long-term of the Covid-19 health crisis and compare its repercussions with previous crises.

Authors statement

Hanen Atri: Conceptualization, Methodology, Formal Analysis, Investigation, Data, Writing-Original Draft, Writing-Review & Editing.

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