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Does safe haven exist? Tail risks of commodity markets during COVID-19 pandemic

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A B S T R A C T

This paper investigates the tail behavior patterns of commodity assets, the risk exposure of these assets, and how they rank given their safe haven properties. We use state-of-the-art dynamic generalized autoregressive score models to jointly estimate tail risk measures for ten commodity assets (aluminum, copper, crude oil, gasoline, gold, heating oil, lead, soybeans, tin, and wheat) over the period from September 14, 2011 to June 30, 2021. Our in-sample findings suggest that aluminum outperforms gold as a safe haven in both pre- and COVID-19 times. The out-of-sample results confirm that aluminum retains its leading role during the COVID-19 pandemic. These findings bear implications for constructing well-diversified portfolios which is vital for investors, portfolio managers, and financial advisors, and for policymakers to design policies that ensure financial stability during periods of market turmoil, such as the COVID-19 pandemic.

1. Introduction

The COVID-19 pandemic and its variants (from Delta to Omicron) has urged many countries to adopt strict measures (e.g., quarantines, lockdowns, travel restrictions, interruptions in the Supply chain industry) causing economic activities to be greatly restricted (Zhang and Hamori, 2021). Such rapid spread events have immensely affected the global economy, financial markets, and all humankind (Ashraf, 2020; Goodell, 2020; Fernandes, 2020; Gormsen and Koijen, 2020; Ramelli and Wagner, 2020; Zhang et al., 2020; Zaremba et al., 2021; Zhang and Hamori, 2021). The impact of the COVID-19 pandemic on the economic and financial spheres is expected to be exceedingly greater than that of the 1918 influenza pandemic (Barro et al., 2020) and substantially exacerbate than the Global Financial Crisis (GFC) (IMF, 2020), entitled by some as “economic catastrophe” (Akhtaruzzaman et al., 2021a).

Undoubtedly, since the outbreak of COVID-19 pandemic numerous financial markets have experienced high volatility and unforeseen deteriorating returns (Baker et al., 2020). In fact, only within a ten-day period in March 2020, the circuit-breakers have been triggered four times in the US stock market (Kinateder et al., 2021).[1] As the future remains uncertain, and forecasts are difficult to make, financial markets are expected to face great losses (see, Miller, 1977, for a discussion).

In times like these, investors adopt strategies to minimize portfolio losses, part of which is looking for safe havens. Although some

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[1] In 12 March 2020, stock markets such as the US, Japan, Hong Kong, Indonesia, the UK, Germany, France, Italy, Finland, Sweden, Latvia, have experienced a sharp drop in their shares exceeding 20% below the most recent peaks.

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research has been undertaken on safe havens during the COVID-19 pandemic, past studies have mainly focused on its first major wave, with mixed results on the safe haven characteristics of commodities, mostly gold (Bouri et al., 2020; Corbet et al., 2020; Ji et al., 2020; Wang and Enilov, 2020; Akhtaruzzaman et al., 2021b; Kinateder et al., 2021; Salisu et al., 2021a; Cheema et al., 2022). However, the literature has not yet established the safe haven characteristics of other commodities relative to gold during the COVID-19 pandemic, and has not extended this comparison beyond the initial phases of the pandemic. Our paper fills this gap in the flight-to-quality literature by answering the following questions: which investment assets serve as a safe haven during the COVID-19 pandemic? What is the risk exposure of these assets, and how they rank giving their safe haven properties? To address these questions, we consider a wider set of tail risk measures over a longer period of time than the existing literature and extend the list of commodities that could exhibit safe haven properties.

Defining safe haven assets can be challenging (Baur and Lucey, 2010; Bouri et al., 2020; Ji et al., 2020). A widely accepted definition is that a safe haven asset is those uncorrelated or negatively correlated with another asset or portfolio in extreme stock market declines (see, Baur and Lucey, 2010, for a discussion). In contrast to a hedge, investors purchase the safe haven asset only in times of market turmoil, with the asset not losing its value during such periods and, hence, works as a safe haven (Baur and McDermott, 2010; Hood and Malik, 2013). In that way, safe haven assets can help investors to build a portfolio that mitigates the downside market risk in times of economic uncertainty, such as the COVID-19 pandemic. Ji et al. (2020) argue that safe haven concept is actually assessing the dependence between assets on tail-quantiles of the return distribution as those should remain stable for an effective safe haven asset in times of market downswings. In other words, the risk premium of an investor's portfolio return should be associated with the tail risk of the considered safe haven asset. In this manner, Kwon (2020) determine that a decrease in risk premium of investor's portfolio return must have a positive association with the tail risk of a commodity if this commodity serves as a safe haven for the given portfolio. In detail, the tail risk represents the chance of a loss occurring due to a rare event, e.g., stock market crash, as predicted by a probability distribution, i.e., the tail of the distribution. Therefore, if there is a positive or no relationship between the stock market returns and the tail risk from a commodity, that same commodity can serve as a safe haven for the stock market returns. The commodity will be preferable for traders and practitioners in such instances. Alternatively, if the stock market returns and the tail risk from a commodity have a negative relationship, the commodity asset does not serve as a safe haven for the stock market returns. This approach to safe haven assets is consistent with the save haven definition by Baur and Lucey (2010) but focuses on the tail-quantiles of the distribution as in Ji et al. (2020) and Shahzad et al. (2020), among others. Our study follows the concept in defining safe haven asset via the prism of tail-quantiles as in the latter studies.

This paper simultaneously contributes to three streams of literature. First, it relates to the growing number of studies on safe haven assets (see, among others, Baur and Lucey, 2010; Baur and McDermott, 2010; Reboredo, 2013; Beckmann et al., 2015; Akhtaruzzaman et al., 2021a,b; Bouri et al., 2020; Ji et al., 2020; Ming et al., 2020; Cheema et al., 2022). Most academic work in the area has been, to a large extent, focused on cryptocurrencies and gold, and its larger family of precious metals. In this paper, we consider few potential safe haven assets that are usually ignored in the literature, and then empirically examine their effectiveness toward equity index in lines of the existing market vulnerability due to the COVID-19 pandemic. Moreover, considering the indispensable need of practitioners to use safe haven assets to offset downside risk, we evaluate the risk exposure of our commodity assets and rank them along their safe haven properties. Our results indicate the emergence of new safe haven commodities, such as aluminum, which have previously been ignored by the academic literature and policy makers alike. Intriguingly, our findings reveal that gold has been replaced by aluminum as the safest asset in the COVID-19 pandemic.

Second, this study contributes to the international finance literature by measuring the tail risk of gold and other commodities through the estimation of a joint dynamic model of expected shortfall (ES) and value-at-risk (VaR) (see, for example, Kwon, 2020; Mehlitz and Auer, 2021). The advantage of this joint modelling approach is in its explicit satisfaction of the subadditivity assumption. This assumption is commonly overlooked in past studies. But subadditivity is a necessary condition ensuring that the diversification principle of modern portfolio theory holds (Danielsson et al., 2005; Roccioletti, 2016). On one side, the past studies have mostly employed the tail risk of VaR, which ignores the shape and structure of the tail and is not a sub-additive risk measure (Artzner et al., 1997, 1999; Lazar and Xue, 2020). On the other side, fewer papers have incorporated estimations of tail risk in commodities through ES modelling (see, for example, Feng et al., 2018; Kwon, 2020; Mehlitz and Auer, 2021; Reboredo, 2013; Stavroyiannis, 2018). However, those papers solely estimate ES, but the ES is itself not elicitable as per the statistical decision theory (Gneiting, 2011; Fissler and Ziegel, 2016; Ziegel, 2016).[2] To overcome the problem of non-subadditivity, our paper adopts the newly developed model of Patton et al. (2019) that allows us to estimate ES jointly with VaR by minimizing the loss function, while the pair of ES and VaR is elicitable itself and, hence, subadditive, as shown by Acerbi and Székely (2014) and Fissler et al. (2016). To ensure the robustness of our results, we consider four semiparametric dynamic models as per Patton et al. (2019): the two-factor GAS (GAS-2F) model, the one-factor GAS (GAS-1F) model, the GARCH-FZ model and the hybrid GAS/GARCH (Hybrid) model, to jointly estimate the ES and VaR of commodities. By doing so, we are the first study to incorporate joint forecast of ES and VaR in the safe haven commodity assets literature.

Third, our paper relates to the seldom but rapidly growing literature on modelling and forecasting the tail risk behaviour of commodities in an out-of-sample context. Inoue and Kilian (2005) determine that in-sample tests tend to indicate rather spuriously the existence of predictability when there is none. In this sense, to strengthen the reliability of our in-sample results, we consider forecasting commodity tail risk out-of-sample, such as one-day-ahead VaR and ES. To further reinforce our results, we use a variety of

[2] As per the statistical decision theory, a risk measure is *elicitable* if exists a loss function for which the risk measure is the solution to minimizing the expected loss (Patton et al., 2019).

methods for comparing the models performance. We start with backtesting the VaR and ES individually via the dynamic quantile (DQ) regression of Engle and Manganelli (2004), and then use the dynamic ES (DES) test of Patton et al. (2019). In such a way, this paper complements the forecasting literature by documenting the importance of joint estimation of tail risk measures for predicting tail behaviour of commodities.

Our paper adds to the current knowledge on the tail behaviour of commodities in times of market turmoil which is vital for investors, portfolio managers, and financial advisors targeting lower risks in market turmoil, and for policymakers trying to mitigate adverse impacts of such events on the economy (see, Zhang and Hamori, 2021, for a discussion).

The rest of the paper is organized as follows. Section 2 provides an overview of the existing literature. Section 3 discusses the methodology. Section 4 describes the data and presents a preliminary statistical analysis. Section 5 discusses the empirical results. Section 6 concludes the paper with a summary of the main findings.

2. Related literature

Traditionally, precious metals, such as gold, and its larger family, commodities, are considered to maintain or appreciate in value during times of market turbulence (Bouri et al., 2020). The potential for gold to act as a safe haven asset is broadly recognised in the past literature (see, for example, Baur and Lucey, 2010; Baur and McDermott, 2010, 2016; Ciner et al., 2013; Hood and Malik, 2013; Reboredo, 2013; Areal et al., 2015; Beckmann et al., 2015; Bredin et al., 2015; O'Connor et al., 2015; He et al., 2018; Rehman et al., 2019; Shahzad et al., 2019a,b; Bouri et al., 2020; Ming et al., 2020; Ding and Zhang, 2021; Kumar and Padakandla, 2022; Naeem et al., 2022). However, the safe haven property of gold is found to vary across different stock markets. One of the pioneer studies on the topic was by Baur and Lucey (2010) who find that gold serves as a safe haven, only for a limited time, for stock markets in the UK and the US but not in Germany. Comparatively, Baur and McDermott (2010) determine that gold is a safe haven for the US and major European stock markets (including Germany) but not for Australia, Canada, Japan and the large emerging markets of Brazil, Russia, India and China (BRIC). In contrast, Bekiros et al. (2017) show that gold acts as a safe haven asset for stock markets of the leading emerging economies, the BRICS, in both crisis and non-crisis times. Similarly, Chkili (2016) and Mensi et al. (2018) show that gold play a crucial role as a safe haven during extreme stock market movements in BRICS economies. Choudhry et al. (2015) show the gold lost its ability to act as a safe haven in the UK, the US and Japan during the GFC. Shahzad et al. (2019b) declare that gold does not act as a safe haven asset for G7 stocks, but Shahzad et al. (2020) determine the opposite for all G-7 markets but Canada. Further, Shahzad et al. (2019a) discover that the general commodity index but gold act as a safe haven for China and the US stock markets.

Much of the field literature has found mixed evidence about the safe haven property of gold. Therefore, the literature has started exploring whether other commodities possess safe haven properties in times of financial turmoil. For example, Lucey and Li (2015) show that silver, platinum and palladium act as a safe haven for the US stocks at some periods when gold does not. In contrast, Hood and Malik (2013) find that platinum and silver do not serve as a safe haven for the US stock market but gold does. Creti et al. (2013) show that gold acts as a safe haven, but for oil, coffee, and cocoa correlations decrease in times of downswings in stock markets. Li and Lucey (2017) explore the time-variable safe haven property of precious metals, gold, silver, platinum and palladium. They found that silver is a safe haven for Canada, Switzerland, and the US, gold for Germany, Japan, Italy, and the UK, platinum for China, France, and South Africa, and palladium for India stock markets. Klein (2017) determines that gold and silver serve as a safe haven in developed stock markets while this characterization does not hold in general after 2013. Rehman et al. (2019) also confirm that gold and silver provide maximum diversification benefits among a sample of nine different commodities, i.e., gold, silver, copper, platinum, palladium, wheat, crude oil, gas and coal. Peng (2020) finds that gold outperforms silver and platinum, as a safe haven, against stock market risk in China. As we can see above, a substantial number of studies provide mixed results on gold as a safe haven asset, while little research has considered the role of other commodities as safe haven assets in market turmoil.

The COVID-19 pandemic has reignited the interest in safe haven assets. Recent studies re-examine the safe haven features of commodities during the COVID-19 pandemic. For example, Bouri et al. (2020) find that the most promising safe haven asset during the COVID-19 pandemic is gold, followed by commodities, represented by a composite commodity index, for the US, China, the world, the developed, and emerging stock markets. Similarly, Salisu et al. (2021b) show that gold acts as a safe haven asset against oil price risks during the pandemic. Salisu et al. (2021a) confirm that gold provides the best safe investment option during the COVID-19 pandemic relative to other financial assets such as silver, palladium and platinum. At the same time, numerous recent studies have challenged the view that gold is a safe haven during turmoil. Akhtaruzzaman et al. (2021b) find that gold serves as a safe haven asset for the US, Japan, China, and Eurozone stock markets at the early stages of the COVID-19 pandemic, but its safe haven property is lost later. Cheema et al. (2022) assess the safe haven role of gold and silver against the US stock market during the GFC and COVID-19 pandemic. They find that gold serves as a safe haven during the GFC, but not in the course of COVID-19 turmoil. Meanwhile, silver does not act as a safe haven asset in either of the two crises. Similarly, Hasan et al. (2021) find that gold and silver are safe haven assets for US stock market during the GFC, but not in the course of COVID-19 turmoil, with oil not acting as safe haven asset at either time. Likewise, Disli et al. (2021) find that neither gold nor oil exhibit safe haven characteristics during COVID-19 pandemic.

The literature has extensively explored the safe haven properties of gold. However, it has paid little attention to the other commodities and their role as safe haven assets during the COVID–19 pandemic. Ji et al. (2020) find that not only gold but also soybeans can act as a safe haven asset against stocks from the US, China and Europe during the COVID-19 turmoil, while oil does not. Iqbal et al. (2022) also discover that agricultural futures can offer some hedge against the extreme left tails of traditional equity assets during COVID-19, whereas energy commodities exhibit an exactly opposite behavior in those scenarios. Ding and Zhang (2021) find that agricultural commodities have remained stable and less volatile during the early stages of COVID-19 pandemic. Bouri et al. (2021b) find strong and moderate levels of volatility connectedness among energy and metals, and moderate connectedness levels within the group of agricultural commodities, precisely, gold followed by soybeans have the lowest standard deviation. Intriguingly, Farid et al. (2021) reveal that natural gas emerges as a superior safe haven against the US stocks during the COVID-19, compared to gold, silver and oil. Ezeaku and Asongu (2020) and Rubbaniy et al. (2022) show that soft commodities such as wheat, corn, cotton and cocoa can be used as safe haven assets towards the uncertainty imposed by the COVID-19 pandemic. More recently, Kumar and Padakandla (2022) find that gold is a better safe haven tool compared to Bitcoin against stock market turmoil, irrespective of timescales. Naeem et al. (2022) show that gold plays the role of a safe haven for metals and agricultural markets. Above all, past studies on the matter, mostly, concentrated on gold and, to a lesser extent, on non-precious metals. Therefore, testing the safe haven properties of commodities, such as gold, but also other potential safe haven assets is worth investigating.

The prevalent methodological issue the safe haven literature faces is that VaR dominates the modelling choice. To the best of our knowledge, the existing literature has been mainly focused on the tail behaviour of gold and cryptocurrencies (see, for example, Reboredo, 2013; Osterrieder and Lorenz, 2017; Feng et al., 2018; Gkillas and Katsiampa, 2018; Selmi et al., 2018; Shahzad et al., 2019b; Stavroyiannis, 2018; Conlon and McGee, 2020; Conlon et al., 2020; Kwon, 2020). Not many studies consider other commodities, such as, silver, platinum and palladium (Hammoudeh et al., 2011), oil (Patra, 2021), and overall commodity indexes (Bouri et al., 2020; Mehlitz and Auer, 2021). Besides, only few among them investigate the average of all losses which are greater or equal than VaR, that is to consider the ES modelling, in a separate setting to their VaR estimation. However, the main downside of using purely ES models is their failure on elicitability property (Gneiting, 2011; Weber, 2006; Emmer et al., 2015). This problem is overcome by the novel framework for joint estimation of VaR and ES of Patton et al. (2019) who combine the general class of GAS models and the dynamic conditional score models by, respectively, Creal et al. (2013) and Harvey (2013). Though, the literature on the relevance of VaR and ES tail behaviour models within the confines of commodity markets is rather limited and further investigation is needed.

To sum up, past studies on safe haven assets concentrated on gold and, to a lesser extent, on non-precious metals. These studies have also provided mixed results on the safe haven properties of gold, and other commodities, for stock market investments. However, investors may readjust their portfolios in favour of commodities that are considered to have safe haven characteristics in an attempt to protect their investments during the COVID-19 and any future crisis (Salisu et al., 2021a). Hence, testing the safe haven properties of gold, but also other potential safe haven assets is worth investigating, and is what this paper does. The next section illustrates how we perform these tests.

3. Methodology

To investigate the tail riskiness of commodity assets, we rely on the dynamic joint models of VaR and ES introduced by Patton et al. (2019). The vital novelty in their framework is the use of a scaled score to drive the time variation in the target parameter (see, Lazar and Xue, 2020, for a discussion). It, therefore, can be estimated by minimizing the loss function of Fissler and Ziegel (2016), namely L_{FZ0}:

$$L_{FZ0}(Y_t, \nu, e, \alpha) = -\frac{1}{\alpha e}\mathbf{1}\{Y_t \leq \nu\}(\nu - Y_t) + \frac{\nu}{e} + \log(-e) - 1, \tag{1}$$

where Y_t is the asset returns at time t, α is the probability level for the tail loss distribution, $\alpha = 0.05$ as per Patton et al. (2019), ν and e are the values of VaR and ES, respectively, and $\mathbf{1}$ is an indicator function which returns 1 when $Y_t \leq \nu$ and 0 otherwise. As such, the asset returns do not affect the estimation if $Y_t > \nu$, but when $Y_t \leq \nu$, forecasts of ES and VaR react to asset returns through the score variable. In this study, we consider four semiparametric dynamic models: the two-factor GAS (GAS-2F) model, the one-factor GAS (GAS-1F) model, the GARCH-FZ model and the hybrid GAS/GARCH (Hybrid) model to estimate VaR and ES jointly by minimizing L_{FZ0}. Specifically, we assume that both ES (e_t) and VaR (v_t) are driven by a common factor κ_t:

$$v_t = a\exp\{\kappa_t\}, \tag{2}$$

$$e_t = b\exp\{\kappa_t\}, b < a < 0, \tag{3}$$

where b is the probability level for the e_t distribution, and the common factor, κ_t, follows a dynamic process, defined as:

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma H_{t-1}^{-1}s_{t-1}. \tag{4}$$

The forcing variable, $H_{t-1}^{-1}s_{t-1}$, is obtained from the FZ0 loss function, L_{FZ0}, plugging in $(a\exp\{\kappa_t\}, b\exp\{\kappa_t\})$ for (v_t, e_t). Then, the score, s_t, and Hessian, I_t, are:

$$s_t = \frac{\partial L_{FZ0}}{\partial \kappa_t} = -\frac{1}{e_t}\left(\frac{1}{\alpha}\mathbf{1}\{Y_t \leq v_t\}Y_t - e_t\right), \tag{5}$$

$$I_t = \frac{\partial^2 E_{t-1}[L_{FZ0}]}{\partial^2 \kappa_t} = \frac{\alpha - \kappa_\alpha a_\alpha}{\alpha}, \tag{6}$$

where κ_α is a negative constant and $a_\alpha \in (0,1)$. The Hessian, I_t, is constant so the scaling matrix, H_t, is set to one (see, Patton et al., 2019, for a discussion).

Based on the above, the GAS-1F model is specified as:

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma \frac{1}{b\exp\{\kappa_{t-1}\}}\left(\frac{1}{\alpha}\mathbf{1}\{Y_{t-1} \leq a\exp\{\kappa_{t-1}\}\}Y_{t-1} - b\exp\{\kappa_{t-1}\}\right). \tag{7}$$

Then, following the setting of GAS-1F model, the GAS-2F model is defined as:

$$\begin{bmatrix} v_t \\ e_t \end{bmatrix} = \mathbf{w} + \mathbf{B}\begin{bmatrix} v_{t-1} \\ e_{t-1} \end{bmatrix} + \mathbf{A}\boldsymbol{\lambda}_t, \tag{8}$$

where $\mathbf{w}$ is a $(2x1)$ vector, $\mathbf{B}$ and $\mathbf{A}$ are $(2x2)$ matrices, $\boldsymbol{\lambda}_t \equiv [\lambda_{v,t-1}, \lambda_{e,t-1}]^{'}$ is a forcing variable, where

$$\lambda_{v,t} = -v_t(\mathbf{1}\{Y_t \leq v_t\} - \alpha), \tag{9}$$

$$\lambda_{e,t} = \frac{1}{\alpha}\mathbf{1}\{Y_t \leq v_t\}Y_t - e_t, \tag{10}$$

The aforementioned models are extended through the incorporation of GARCH features and, hence, the GARCH-FZ model can be expressed as:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \gamma Y_{t-1}^2, \tag{11}$$

where σ_t^2 is the conditional variance and is assumed to follow a GARCH(1,1) process. The parameters of Eq. (11) are estimated by minimizing the loss function L_{FZ0} from Eq. (1). The parameter ω is unidentified and, following Patton et al. (2019), is set to one. Hence, the parameter vector to be estimated becomes (β, γ, a, b).

Next, we combine the GAS-1F model, as described in Eq. (7), and a standard GARCH model to formulate the hybrid GAS/GARCH (Hybrid) model denoted as:

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma\frac{1}{e_{t-1}}\left(\frac{1}{\alpha}\mathbf{1}\{Y_{t-1} \leq v_{t-1}\}Y_{t-1} - e_{t-1}\right) + \delta\log|Y_{t-1}|, \tag{12}$$

where κ_t is the log volatility, described by the one-period-lagged log volatility, score factor and the logarithm of absolute return, δ is the GARCH forcing variable. The intercept in the GAS equation is unidentified and following Patton et al. (2019) it is fixed to zero for the GAS-1F and Hybrid models. The five parameters of the GAS/GARCH model $(\beta, \gamma, \delta, a, b)$ are estimated using L_{FZ0} minimization.

To evaluate the forecasting performance of the four models for ES and VaR, we use two different frameworks: first, the dynamic quantile (DQ) test proposed by Engle and Manganelli (2004) and, second, the dynamic ES (DES) test of Patton et al. (2019).

The DQ test is robust against the impacts of serial correlation on estimation results and is derived from Eq. (9), as follows:

$$\lambda_{v,t}^s = a_0 + a_1\lambda_{v,t-1}^s + a_2 v_t + u_{v,t}, \tag{13}$$

where $\lambda_{v,t}^s = \mathbf{1}\{Y_t \leq v_t\} - \alpha$,

$\lambda_{v,t}^s$ is an independent and identically distributed Bernoulli variable with probability $\alpha = 5\%$ and mean of zero, $\boldsymbol{a} = [a_0, a_1, a_2]^{'}$ are regression parameters, and $u_{v,t}$ is the error term. The null hypothesis of DQ test is that all regression parameters are equal to zero against the corresponding alternative hypothesis.

The second method is the DES regression test that allows evaluating the ES estimates individually. The DES test is derived from Eq. (10), as follows:

$$\lambda_{e,t}^s = b_0 + b_1\lambda_{e,t-1}^s + b_2 e_t + u_{e,t}, \tag{14}$$

where $\lambda_{e,t}^s = \frac{1}{\alpha}\mathbf{1}\{Y_t \leq v_t\}Y_t - e_t$,

$\lambda_{e,t}^s$ is an independent and identically distributed Bernoulli variable with probability of $\alpha = 5\%$ and mean of zero; $\boldsymbol{b} = [b_0, b_1, b_2]^{'}$ are regression parameters; $u_{e,t}$ is the error term. The null hypothesis of DES test is that all regression parameters are equal to zero against the corresponding alternative hypothesis. Overall, both DQ and DES test forecast optimality by testing that all regression parameters are equal to zero, against the usual two-sided alternative.

4. Data and preliminary statistics

To examine the tail behavior of commodity assets in times of the pre- and during COVID-19 pandemic, we use data on daily closing prices for 10 commodity assets: aluminum, copper, crude oil, gasoline, gold, heating oil, lead, soybeans, tin, and wheat. We consider the LME-Aluminum 99.7% Cash, copper LME-Copper Grade A Cash, WTI Spot Cushing, Gasoline Reg. Unld. FOB NYH, gold Gold Bullion LBM, NY No. 2 Heating Oil Spot Price FOB, LME-Lead Cash, Soybeans, No.1 Yellow, LME-Tin 99.85% Cash, and Wheat US No.2 HRS Del Kansas, extracted from *Thomson Reuters Datastream* database (see, Appendix A.1 for a detailed list on the series definitions).[3] Our sample covers a broad set of commodity assets, including ones considered as strategic, such as oil, wheat, and gold, and others with different levels of risk and intensity of trading. Some are also major inputs into the production process and households' consumption baskets. The sample period spans from September 14, 2011 to June 30, 2021, as dictated by data availability and, covers the turbulent phase of the COVID-19 pandemic. Similar to Bouri et al. (2021a), our main focus is on very recent advances of the COVID-19 outbreak and its difference to the "normal" pre-crisis period, i.e., pre-COVID-19 announcement. Therefore, our study follows Bouri et al. (2021a) in the choice of the sample period and excludes the effect of the Global Financial Crisis in the "normal" times period, so that our sample period covers the last nearly 10 years of data. The only difference from our sample period selection and those of Bouri et al. (2021a) is that theirs starts in May 2011, whereas ours starts in September 2011. The latter starting date is chosen as, in contrast to Bouri et al. (2021a), our sample includes agricultural commodities which prices are very sensitive to demand and supply factors. The main supply factors affecting agricultural prices is crop harvesting and, thus, prices of agricultural commodities are uncertain and volatile before the end of the harvesting period. The harvesting period for the U.S. hard red spring wheat ends at mid-September (U.S. Wheat Associates, 2022), therefore, the starting period for our sample is chosen to be September 14. Following the literature in the field, the sample is split into pre- and post-COVID-19 announcement periods, as due by the date, December 31, 2019, on which the novel virus was first identified from an outbreak in the Chinese city of Wuhan (see, among others, Corbet et al., 2020; Akhtaruzzaman et al., 2021b; Zaremba et al., 2021).[4] To ensure the applicability of our empirical models, we perform the standard procedures described by Barndorff-Nielsen et al. (2009) to clean the data, by removing the market-specific non-trading days and exactly zero returns from all series. The percentage returns series, Y_t, are calculated by taking the natural logarithm of the daily closing prices, $Y_t = (\ln(P_t) - \ln(P_{t-1})) \times 100$, where P_t is the closing price of commodity asset at day t.[5]

Fig. 1 displays the commodity price series during the full sample period. It can be noted that all of them exhibit somewhat similar trend during the COVID-19 period, with strong upsurge in the last months. Notably, the smallest fluctuations can be notes in the gold prices, which is not surprising as numerous studies list it as the best safe haven in times of market turbulence.

Table 1 presents the summary statistics of the daily commodity return series before and during COVID-19 announcement period. We can observe that commodities are highly volatile during the COVID-19 period, with an annualized mean returns ranging from −2.633% for heating oil to 62.987% for crude oil, while in normal times, the annualized returns range is much narrower from −5.629% for gasoline to −2.153% for gold. The summary statistics of the return series in Table 1 indicate that crude oil has the highest standard deviation of 83.915%, followed by gasoline of 71.715%, with these two being the riskiest assets in normal times as well, as also highlighted in the past literature (see, Rehman et al., 2019; Ding and Zhang, 2021). This is not surprising given the deplorable impact of the COVID-19 pandemic on energy prices (Dutta et al., 2020; Bouri et al., 2021a). Important to note is that gold, followed by aluminum, have the smallest standard deviation both before and during COVID-19 announcement periods. For the COVID-19 period, the difference in their standard deviations is almost negligible, for gold 17.908%, and for aluminum 18.086%. Furthermore, the aluminum exhibits a decrease in its standard deviation during the COVID-19 period relative to normal times, but this is not true for the gold returns. All daily return series exhibit non-zero skewness and substantial kurtosis, especially in COVID-19 times, which implies asymmetry in the return series. The last part in Table 1 shows the sample VaR and ES for 5% significance level. The gold and aluminum prove to be different from the other commodities since their quantile and ES are lower than the sample risk measures of the other commodities. Notably, the gold returns indicate the lowest values for VaR and ES among all commodities in the pre-COVID-19 times, while the things have been changes since the outbreak of the COVID-19 pandemic. In fact, the results for VaR and ES in COVID-19 times indicate that investment in aluminum is safer than all other nine commodities considered in this study, which is an exceptional finding for the safe haven literature in turmoil times. This result is somewhat consistent with the outcomes of Agyei-Ampomah et al. (2014) and Sakemoto (2018), but those studies use aggregate industrial metal indices (including aluminum within the index basket) to find the best safe haven assets. In contrast, our study differs by providing disaggregated results that precisely evaluate the safe haven property of each individual commodity.

5. Empirical results

Before discussing the empirical results, we provide a brief glance of what to follow up. Our study considers two separate periods, pre- and post-COVID-19 announcement, and we also divide each of these periods into in-sample and out-of-sample sub-periods, for estimation and backtesting, respectively. Therefore, for pre-COVID-19 announcement period, the *in-sample* period starts from September 14, 2011 to December 31, 2017, while the forecast (*out-of-sample*) period covers January 1, 2018 to December 31, 2019.

[3] First, we have initially selected 16 commodities covering all globally main commodity markets, and some that have already been commonly considered as safe haven assets in past literature: aluminium, copper, corn, crude oil, gasoline, gold, heating oil, lead, nickel, palladium, platinum, silver, soybeans, tin, wheat, and zinc. Second, as the current analysis is related to the COVID-19 pandemic, to illustrate the impact of the epidemic on the safe haven properties of assets, we select those commodities that satisfy the elicitable condition of minimizing the loss function as specified at Eq. (1) for the post-COVID-19 period, which results in a sample of 10 commodities.

[4] https://www.who.int/news/item/27-04-2020-who-timeline—covid-19.

[5] All of the commodity return series satisfy the stationarity condition due to the results of the augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests. Thus, no ARMA filter is applied to the data. Results are available from the authors upon request.

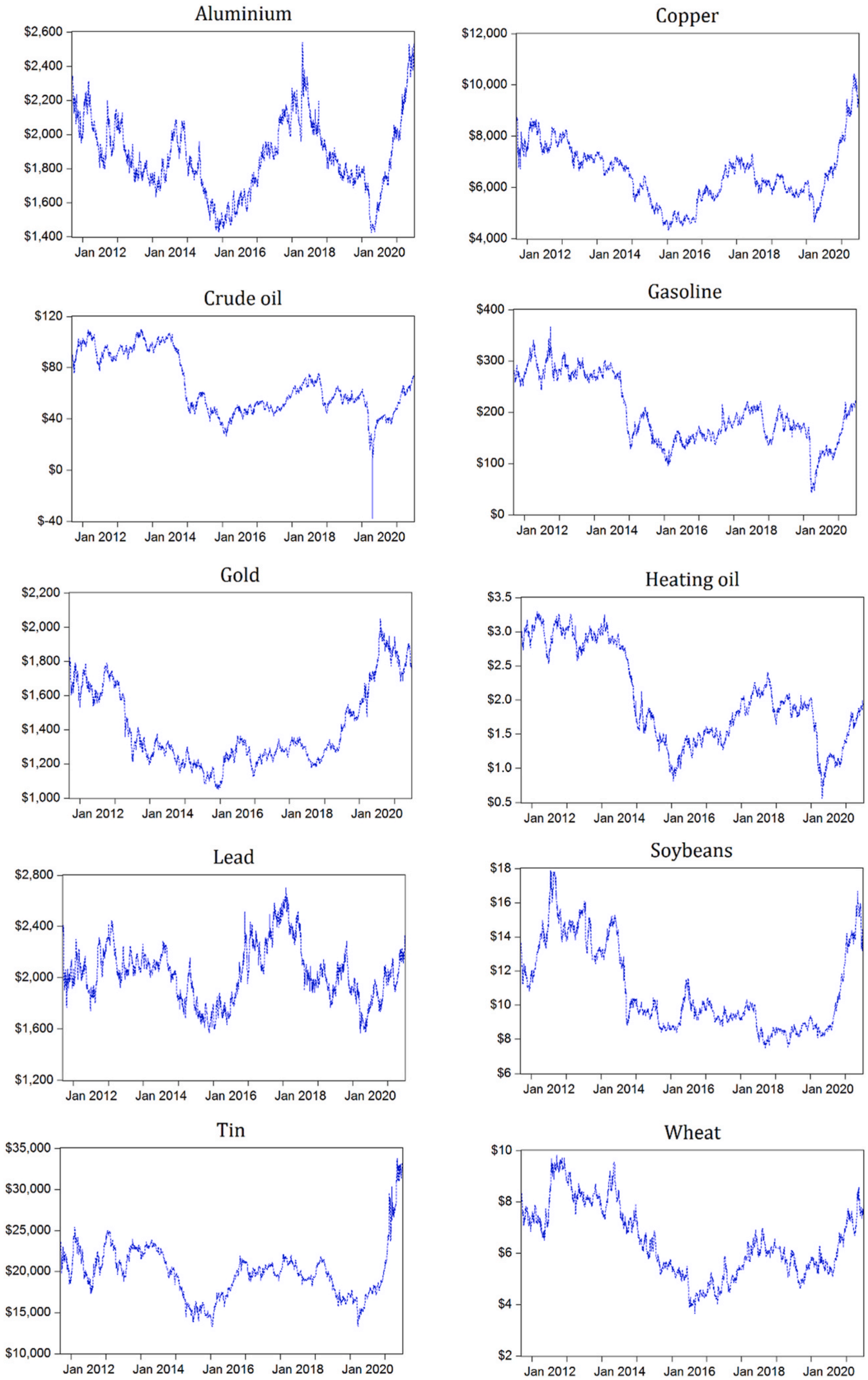

Fig. 1. Time-series graph of raw U.S. dollar commodity prices.

Likewise, for post-COVID-19 announcement period, the *in-sample* period starts from January 1, 2020 to February 28, 2021, while the forecast (*out-of-sample*) period covers March 1, 2021 to June 30, 2021. We start with an in-sample estimation of our specified models and assess the safe haven properties of the ten commodities. Past literature claims that in-sample predictive ability often fails to translate into out-of-sample success (Timmermann, 2006). Therefore, the analysis is extended to an out-of-sample framework and also performs one-day-ahead ES and VaR forecasts.

As a robustness check, we assess the safe heaven properties of our sampled commodities by juxtaposing the tail measures of the ten commodities against the movements of the major US stock market index – S&P500, during the COVID-19 pandemic using rolling-window regressions. In addition, we use spectral risk measures for downside risk (Acerbi, 2002, 2004) to check the robustness of our main results.

Table 1
The descriptive statistics of the log returns of the ten commodity assets.

	Soybeans	Wheat	Crude oil	Gasoline	Heating oil	Aluminum	Copper	Lead	Tin	Gold
Panel A: Pre-COVID-19 announcement										
Mean	−4.870	−4.626	−4.740	−5.629	−4.645	−3.275	−4.234	−2.776	−3.841	−2.153
StdDev	22.333	26.934	34.202	35.914	31.025	18.985	20.350	24.559	21.639	14.959
Skewness	−0.500	−0.001	0.147	−0.425	0.253	0.226	0.074	0.098	−0.081	−0.772
Kurtosis	8.388	5.866	6.778	16.883	10.015	5.344	5.983	4.776	6.741	12.441
VaR	−2.170	−2.461	−3.553	−3.450	−2.951	−1.827	−2.063	−2.435	−2.132	−1.537
ES	−3.282	−3.662	−5.003	−5.162	−4.515	−2.435	−2.890	−3.233	−3.250	−2.307
Nº obs.	1943	1960	2073	2083	2046	2084	2096	2094	2081	2131
Panel B: Post-COVID-19 announcement										
Mean	30.750	18.380	62.987	16.016	−2.633	22.851	27.950	11.303	43.363	9.751
StdDev	22.061	28.713	83.915	71.715	54.44	18.086	22.605	24.560	34.230	17.908
Skewness	−0.429	−0.033	0.633	−1.475	−0.995	0.152	−0.843	−0.301	0.394	−0.719
Kurtosis	9.454	3.503	15.513	18.044	9.032	3.547	6.127	3.819	14.038	6.978
VaR	−2.042	−2.893	−6.543	−6.362	−4.970	−1.631	−2.421	−2.610	−3.093	−1.806
ES	−3.135	−3.743	−12.27	−12.209	−8.919	−2.223	−3.538	−3.486	−5.159	−2.989
Nº obs.	355	355	362	376	370	378	378	376	378	386

Note: This table presents the summary statistics of the ten daily commodity return series studied over the pre- and post-COVID-19 announcement period from September 13, 2011 to June 30, 2021. The table has two panels, A and B, corresponding to pre- and post-COVID-19 announcement periods, respectively. It reports the annualized mean returns (Mean), standard deviation of the returns as percentages (StdDev), skewness (Skewness), kurtosis (Kurtosis) and the sample VaR and ES estimates for α equal to 5% significance level. The number of observations (Nº obs.) presents the effective sample size after performing the procedures of Barndorff-Nielsen et al. (2009) to clean the data.

5.1. In-sample estimation

Table 2 presents the outcomes from standard time series models for the ten commodity return series over the in-sample pre- and post-COVID-19 announcement periods. In panels A.1 and B.1, we investigate the existence of an autoregressive moving average (ARMA) process, where the lags (p, q) are selected via the Bayesian information criterion (BIC). We determine the existence of ARMA process only in the case of crude oil, for the post-COVID-19 announcement period, and AR process for both crude oil and heating oil, in the pre-COVID-19 years. Panels A.2 and B.2 of Table 2 provide the estimated parameters of the GARCH(1,1) model, indicating the existence of conditional variances in our series for both periods under investigation.[6] Panels A.3 and B.3 of Table 2 display the degrees of freedom (DoF) and skew-t density for the standardized residuals. The findings suggest the presence of, mainly negative, asymmetry in the skew-t distribution, confirming the occurrence of non-normality in our series, which is consistent with past literature (see, Erb and Harvey, 2006). Overall, the parameter estimates reported in Table 2 are similar to those found in the literature (see, Deaton and Laroque, 1992; Cheng and Hung, 2011; Nissanke, 2012; Fernandez-Perez et al., 2018).

Tables 3 and 4 present the GAS-2F parameters and their standard errors for pre- and post-COVID-19 periods, respectively. The parameters for both VaR and ES are determined individually to facilitate interpretability. For both periods, we notice the presence of high persistence for all commodities, ranging from 0.826 for Copper to 0.998 for Wheat, with the estimated b parameters being statistically significantly different from zero at the 5% significance level. Compared to the standard time series models, i.e., GARCH, as given in Table 2, the parameters from GAS-2F model exhibit a higher persistence, see Table 3. This reveals evidence of a long-range dependence. In Table 3, the coefficients a_e anda_v, are relatively small in magnitude and only about a quarter of them are found to be statistically significant at 5% significance level. Conversely, the period of COVID-19 exhibit all coefficients a_e anda_v to be insignificant at 5% level for either of the model specifications but they remain relatively small, similar to their pre-COVID-19 values.

The average loss generated by the GAS-2F model for aluminum is the smallest amongst all commodity markets in both pre- and COVID-19 periods. This suggests that aluminum is the safest asset for investment in times of market turbulence, i.e., the COVID-19 pandemic. Interesting to note is that aluminum (0.813) is followed up by gold (0.853) as the second safest commodity in normal times, but during the COVID-19 times, soybeans (0.889) overtakes gold (1.040) as the second safest commodity. Our findings are consistent with those of Cheema et al. (2022) implying that gold has weakened its safe haven status during COVID-19 pandemic. Likewise, Iqbal et al. (2022) show that agricultural commodities wheat, soybeans, and corn exhibit relatively lower volatility during the COVID-19 period, as compared to other energy and metal futures, which signifies diversification characteristics. Similar to our results, Ji et al. (2020) find that gold and soybeans futures have strong safe haven role in the COVID-19 crisis. Another study that confirms the diversification properties of soybeans has been undertaken by Bouri et al. (2021b). The authors investigate the realized volatility of 16 different commodity futures and determine that gold followed by soybeans have the lowest standard deviation, 0.0815 and 0.0820, respectively, with both having negligible difference from each other. A potential reason for this is the growing importance of agricultural commodities during the COVID-19 pandemic and their stable or even increased demand, with less uncertainty about consumers' desire to acquire the good (OECD/FAO, 2021). As such, soybeans asset has been proven to exhibit safe haven properties

[6] The existence of conditional variances in our series provides strong grounding for employing a battery of GARCH-type models further in our study, i.e., GARCH-FZ and hybrid GAS/GARCH models. The choice of GARCH model of order (1,1) is based on the findings by Hansen and Lunde (2005) for the inferiority of the GARCH (1,1) to alternative models.

Table 2
ARMA, GARCH, and Skew-t results.

	Soybeans	Wheat	Crude oil	Gasoline	Heating oil	Aluminum	Copper	Lead	Tin	Gold
Panel A: Pre-COVID-19 announcement										
A.1: Conditional mean										
Constant	−0.027	−0.029	−0.025	−0.026	−0.025	−0.002	−0.012	0.002	−0.010	−0.021
AR (1)	–	–	−0.134	–	−0.103	–	–	–	–	–
MA (1)	–	–	–	–	–	–	–	–	–	–
A.2: Conditional variance										
Constant	0.063	0.104	0.035	0.184	0.028	0.035	0.031	0.027	0.014	0.013
ARCH	0.068	0.032	0.078	0.147	0.069	0.038	0.047	0.047	0.048	0.049
GARCH	0.904	0.932	0.916	0.822	0.927	0.936	0.935	0.942	0.945	0.940
A.3: Skew-density										
DoF	5.671	5.643	8.144	7.015	5.574	14.399	6.022	11.636	4.976	4.261
Skewness	−0.029	0.109	−0.095	−0.036	−0.002	0.120	−0.004	−0.012	−0.071	−0.048
Panel B: Post-COVID-19 announcement										
B.1: Conditional mean										
Constant	0.147	0.089	0.271	0.030	−0.054	0.064	0.135	0.022	0.148	0.043
AR (1)	–	–	−0.814	–	–	–	–	–	–	–
MA (1)	–	–	0.955	–	–	–	–	–	–	–
B.2: Conditional variance										
Constant	0.067	0.238	0.351	0.427	0.679	0.456	0.383	0.318	0.085	0.152
ARCH	0.087	0.045	0.283	0.247	0.325	0.147	0.210	0.090	0.133	0.102
GARCH	0.864	0.883	0.717	0.753	0.647	0.447	0.606	0.788	0.867	0.796
B.3: Skew-density										
DoF	6.134	12.062	5.756	5.283	12.017	49.998	6.537	11.430	3.213	3.926
Skewness	−0.018	0.025	−0.172	−0.130	−0.169	0.049	−0.207	−0.056	−0.030	−0.178

Note: This table presents the marginal distribution estimates over the in-sample period for the ten daily commodity returns. The table has two panels, A and B, corresponding to pre- and post-COVID-19 announcement periods, respectively. Each panel contains three parts. Part 1 reports the parameter estimates for autoregressive (AR(p)) and moving average (MA(q)) models of the conditional means of these returns. Part 2 shows parameter estimates for GARCH (1,1) model. Part 3 presents parameter estimates of the skew-*t* density for the standardized residuals.

Table 3
Estimated parameters of two-factor GAS model for VaR and ES, pre-COVID-19 announcement.

	Soybeans		Wheat		Crude oil		Gasoline		Heating oil	
	VaR	ES	VaR	ES	VaR	ES	VaR	ES	VaR	ES
ω	−0.041	−0.140	−0.007	−0.007	−0.042	−0.048	−0.027	−0.061	−0.013	−0.024
(s.e.)	(0.022)	(0.088)	(0.009)	(0.009)	(0.026)	(0.020)	(0.013)	(0.027)	(0.005)	(0.013)
b	0.981	0.958	0.998	0.998	0.986	0.988	0.989	0.984	0.996	0.995
(s.e.)	(0.010)	(0.026)	(0.003)	(0.003)	(0.009)	(0.005)	(0.005)	(0.006)	(0.002)	(0.003)
a_v	−0.010	−0.006	−0.125	−0.219	−0.008	−0.004	−0.371	−0.841	−0.043	−0.095
(s.e.)	(0.117)	(0.418)	(0.095)	(0.200)	(0.135)	(0.200)	(0.163)	(0.262)	(0.114)	(0.282)
a_e	0.005	0.013	−0.004	−0.008	0.007	0.008	−0.008	−0.018	0.006	0.008
(s.e.)	(0.004)	(0.015)	(0.004)	(0.006)	(0.003)	(0.008)	(0.004)	(0.006)	(0.003)	(0.008)
Average loss	**1.194**		**1.268**		**1.434**		**1.557**		**1.402**	
	Aluminum		**Copper**		**Lead**		**Tin**		**Gold**	
	VaR	**ES**	**VaR**	**ES**	**VaR**	**ES**	**VaR**	**ES**	**VaR**	**ES**
ω	−0.032	−0.031	−0.035	−0.102	−0.032	−0.03	−0.048	−0.035	−0.008	−0.045
(s.e.)	(0.021)	(0.028)	(0.016)	(0.065)	(0.014)	(0.017)	(0.020)	(0.023)	(0.003)	(0.018)
b	0.981	0.986	0.983	0.964	0.986	0.990	0.978	0.988	0.996	0.982
(s.e.)	(0.012)	(0.012)	(0.007)	(0.023)	(0.006)	(0.006)	(0.009)	(0.008)	(0.002)	(0.008)
a_v	0.349	0.435	0.189	0.566	−0.005	−0.002	−0.007	0.000	0.191	0.214
(s.e.)	(0.318)	(0.338)	(0.251)	(0.693)	(0.081)	(0.170)	(0.232)	(0.254)	(0.070)	(0.259)
a_e	0.014	0.015	0.013	0.034	0.004	0.005	0.007	0.004	0.008	0.017
(s.e.)	(0.012)	(0.012)	(0.012)	(0.028)	(0.003)	(0.005)	(0.008)	(0.009)	(0.002)	(0.008)
Average loss	**0.813**		**1.030**		**1.109**		**1.142**		**0.853**	

Note: This table presents the estimated parameters and standard errors for the two-factor GAS model (GAS-2F) model from Equation (8) in the methods section for VaR and ES for the ten commodity returns over the in-sample pre-COVID-19 announcement period. The last row of this table presents the average (in-sample) losses for each of the ten commodities. The standard errors are provided in brackets.

and our findings from Table 4 that list soybeans as the second safest commodity during the COVID-19 pandemic should not be surprise but seen as a further support to the recent literature (i.e., Rubbaniy et al., 2022) that identifies soft commodities to grow their importance as safe haven assets during times of COVID-19.

However, neither of the above studies include aluminum as potential safe haven asset, so a direct comparison is not possible. But

Table 4
Estimated parameters of two-factor GAS model for VaR and ES, post-COVID-19 announcement.

	Soybeans		Wheat		Crude oil		Gasoline		Heating oil	
	VaR	ES	VaR	ES	VaR	ES	VaR	ES	VaR	ES
ω	−0.023	−0.038	−0.016	−0.061	−0.209	−0.286	−0.157	−0.264	−0.080	−0.389
(s.e.)	(0.027)	(0.146)	(0.533)	(0.481)	(1.073)	(1.297)	(1.096)	(0.606)	(0.115)	(0.324)
b	0.988	0.986	0.994	0.983	0.965	0.965	0.976	0.974	0.978	0.938
(s.e.)	(0.017)	(0.058)	(0.211)	(0.133)	(0.141)	(0.118)	(0.136)	(0.063)	(0.025)	(0.049)
a_v	0.005	0.003	0.011	0.000	−0.007	0.007	−0.057	0.008	−0.004	−0.003
(s.e.)	(0.090)	(0.932)	(1.653)	(1.330)	(35.090)	(4.098)	(5.580)	(5.419)	(0.701)	(1.386)
a_e	−0.007	−0.006	−0.002	0.002	0.053	0.071	0.028	0.053	0.007	0.024
(s.e.)	(0.004)	(0.029)	(0.072)	(0.047)	(1.981)	(0.207)	(0.265)	(0.126)	(0.024)	(0.053)
Average loss	**0.889**		**1.317**		**1.988**		**2.028**		**1.924**	
	Aluminum		**Copper**		**Lead**		**Tin**		**Gold**	
	VaR	**ES**	**VaR**	**ES**	**VaR**	**ES**	**VaR**	**ES**	**VaR**	**ES**
ω	−0.013	−0.013	−0.125	−0.544	−0.023	−0.03	−0.118	−0.137	−0.038	−0.035
(s.e.)	(0.014)	(0.030)	(0.253)	(0.456)	(0.030)	(1.323)	(0.219)	(0.101)	(0.096)	(0.031)
b	0.991	0.994	0.941	0.826	0.988	0.991	0.966	0.983	0.983	0.989
(s.e.)	(0.009)	(0.015)	(0.108)	(0.134)	(0.013)	(0.391)	(0.111)	(0.049)	(0.041)	(0.011)
a_v	0.005	0.007	0.011	0.020	0	0	−0.106	0.073	0.003	0.007
(s.e.)	(0.426)	(0.725)	(0.844)	(2.607)	(0.482)	(1.765)	(1.802)	(2.304)	(0.545)	(0.977)
a_e	−0.003	−0.006	0.012	0.041	0.002	−0.001	0.033	0.063	−0.006	−0.011
(s.e.)	(0.014)	(0.024)	(0.033)	(0.102)	(0.016)	(0.058)	(0.047)	(0.092)	(0.025)	(0.040)
Average loss	**0.733**		**1.137**		**1.250**		**1.113**		**1.040**	

Note: This table presents the estimated parameters and standard errors for the two-factor GAS model (GAS-2F) from Equation (8) in the methods section for VaR and ES for the ten commodity returns over the in-sample post-COVID-19 announcement period. The last row of this table presents the average (in-sample) losses for each of the ten commodities. The standard errors are provided in brackets.

the importance of aluminum, as represented by its global demand, has increased significantly during the COVID-19 pandemic. This is factual as the investment in the aluminum-intensive industries such as electrical vehicles (EV) and consumer electronics has surged tremendously due to the increased demand in these sectors. In fact, in less than two years the price of aluminum has increased by 41% from $1781 per tonne to $2509, respectively, from the outbreak of the COVID-19 pandemic on January 1, 2020 to June 30, 2021. The deceleration of production and distribution runs due to widespread lockdowns and other strict measures to contain COVID-19 at early stages has influenced the supply of the commodity. In that way, the imbalance between supply and demand for aluminum led to its notable price appreciation in the post-COVID-19 announcement period, and enhance its value on the world market. Consistent with this shift, our study determines aluminum to be the safest haven asset during the COVID-19 period, which is desired for diversification, and accelerates aluminum as important investment vehicle and diversifier in the years of the COVID-19 pandemic. This finding benefits investors and risk managers who could consider it constructing more robust portfolios and hedging strategies based on tail-loss derivatives.

With respect to energy commodities, our findings in Tables 3 and 4 determine that energy commodities are the riskiest investment assets, regardless the estimation period, which is consistent with the recent studies by Hasan et al. (2021) and Iqbal et al. (2022). A possible explanation for this finding, as highlighted by Iqbal et al. (2022), is that the recessionary forecasts can induce market participants to short energy commodities.

In sum, our evidence is consistent with many previous studies (see, Disli et al., 2021; Hasan et al., 2021; Cheema et al., 2022, among others) and contrasts with others (Bouri et al., 2020; Salisu et al., 2021a) in finding that gold steps down from its first place to other assets, i.e., aluminum, as the safest commodity in the COVID-19 times.

Tables 5 and 6 report the estimated parameters of alternative GAS models: GAS-1F, GARCH-FZ, and Hybrid, for both pre- and post-COVID-19 announcement periods, respectively. Focusing first on the pre-COVID-19 results in Table 5, we find that the three models comprise β parameters that are highly persistent and statistically significantly different from zero at the 5% significance level, which is very alike to the b paratemers of the GAS-2F models, given in Table 3. This finding implies a close interrelationship between the current estimated risk measures and their previous estimations. This also reveals that an increase will tend to be followed by an increase and vice versa which is a signal of predictability of future prices. Our finding denies weak-form efficiency hypothesis. Beyond that, all three GAS models reveal that the safest asset is aluminum, followed by gold – which is consistent with the results from the GAS-2F model for the pre-COVID-19 times. In contrast, our findings determine that investments in crude oil and gasoline have been the riskiest one in the pre-COVID-19 years, as can be seen in Table 5. This is consistent with the study of Rehman et al. (2019) who determine that crude oil offers the least diversification benefits for a portfolio of assets. Shifting our attention to the post-COVID-19 announcement period, the three models in Table 6 determine aluminum as the safest asset among all 10 commodities. Interestingly, gold has been replaced by soybeans as the second safest asset, a result consistent with the GAS-2F estimations, and mildly agreeing with Ji et al. (2020) on the role of soybeans as safe haven asset in times of the COVID-19 pandemic. In similar manner, Ding and Zhang (2021) and Luo et al. (2022) claim that agricultural products, as daily necessities, are stable and remain less volatile compared to other commodity futures during the COVID-19 pandemic. Unsurprisingly, the riskiest assets for investment, as found by all three models in Table 6, are energy commodities and, in particular, crude oil and gasoline. This is consistent with the study of Bouri et al. (2021b) and Hasan et al. (2021), who determine strong levels of volatility among energy commodities, with the highest standard deviation reported for crude oil. The

Table 5
Estimated parameters of alternative GAS models for VaR and ES, pre-COVID-19 announcement.

	Soybeans	Wheat	Crude oil	Gasoline	Heating oil	Aluminum	Copper	Lead	Tin	Gold
GAS-1F										
β	0.947	0.989	0.997	0.989	0.997	0.991	0.968	0.993	0.983	0.965
(s.e.)	(0.032)	(0.009)	(0.001)	(0.004)	(0.001)	(0.006)	(0.014)	(0.006)	(0.005)	(0.022)
γ	0.012	0.002	0.007	0.009	0.009	0.003	0.010	0.007	0.009	0.016
(s.e.)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.009)
δ	–	–	–	–	–	–	–	–	–	–
(s.e.)	–	–	–	–	–	–	–	–	–	–
a	−2.225	−2.519	−3.093	−2.705	−2.710	−1.754	−2.209	−2.679	−2.178	−1.572
(s.e.)	(1.547)	(2.234)	(2.033)	(3.152)	(1.106)	(1.426)	(1.538)	(8.410)	(0.765)	(7.982)
b	−3.203	−3.651	−4.304	−4.251	−3.861	−2.297	−2.922	−3.397	−2.951	−2.357
(s.e.)	(2.250)	(3.250)	(2.765)	(4.902)	(1.583)	(1.896)	(2.189)	(10.578)	(1.061)	(11.941)
Average loss	**1.188**	**1.289**	**1.440**	**1.576**	**1.403**	**0.828**	**1.037**	**1.103**	**1.136**	**0.868**
GARCH-FZ										
β	0.882	0.932	0.949	0.767	0.936	0.918	0.900	0.928	0.932	0.900
(s.e.)	(0.214)	(0.381)	(0.129)	(0.165)	(0.114)	(0.169)	(0.098)	(0.164)	(0.119)	(0.383)
γ	0.059	0.019	0.039	0.102	0.181	0.028	0.014	0.018	0.007	0.018
(s.e.)	(0.014)	(0.012)	(0.008)	(0.030)	(0.052)	(0.027)	(0.006)	(0.011)	(0.003)	(0.027)
δ	–	–	–	–	–	–	–	–	–	–
(s.e.)	–	–	–	–	–	–	–	–	–	–
a	−1.786	−1.594	−1.647	−2.128	−0.954	−1.926	−2.857	−2.421	−3.574	−2.948
(s.e.)	(0.700)	(1.417)	(0.457)	(0.810)	(0.189)	(1.131)	(0.844)	(1.311)	(1.412)	(2.385)
b	−2.627	−2.355	−2.286	−2.918	−1.363	−2.409	−3.833	−3.058	−4.913	−4.294
(s.e.)	(1.620)	(3.203)	(0.907)	(1.484)	(0.430)	(1.738)	(1.406)	(2.053)	(2.472)	(4.882)
Average loss	**1.144**	**1.277**	**1.441**	**1.510**	**1.383**	**0.812**	**1.032**	**1.073**	**1.132**	**0.848**
Hybrid										
β	0.894	0.963	0.952	0.916	0.972	0.973	0.960	0.981	0.983	0.946
(s.e.)	(0.063)	(0.025)	(0.023)	(0.035)	(0.011)	(0.010)	(0.039)	(0.005)	(0.005)	(0.027)
γ	0.011	0.001	0.008	0	0.005	0	0.010	0.005	0.009	0.012
(s.e.)	(0.007)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)	(0.010)	(0.001)	(0.002)	(0.005)
δ	0.050	0.017	0.028	0.062	0.024	0.020	0.014	0.012	0	0.025
(s.e.)	(0.030)	(0.004)	(0.016)	(0.021)	(0.006)	(0.003)	(0.010)	(0.002)	(0.000)	(0.013)
a	−2.711	−2.557	−3.027	−3.154	−3.152	−2.568	−2.651	−2.817	−2.180	−2.396
(s.e.)	(3.123)	(1.765)	(3.574)	(2.653)	(2.674)	(1.273)	(12.886)	(4.215)	(5.300)	(4.562)
b	−3.840	−3.794	−4.296	−4.523	−4.491	−3.299	−3.507	−3.580	−3.028	−3.553
(s.e.)	(4.459)	(2.630)	(5.157)	(3.816)	(3.999)	(1.629)	(16.819)	(5.371)	(7.372)	(6.820)
Average loss	**1.175**	**1.282**	**1.434**	**1.526**	**1.399**	**0.823**	**1.031**	**1.096**	**1.136**	**0.862**

Note: This table presents the estimated parameters and standard errors for the three alternative GAS models specified in the methods section for VaR and ES for the ten commodity returns over the in-sample pre-COVID-19 announcement period. The top panel presents the results for the one-factor GAS (GAS-1F) model in Equation (7). The middle panel presents the results for the GARCH model estimated by FZ loss minimization (GARCH-FZ), as specified in Equation (11), and "hybrid" one-factor GAS (Hybrid) model that includes an additional GARCH-type forcing variable, as specified in Equation (12). The last row of each sub-panel presents the average (in-sample) losses from each of these three models. The standard errors are provided in brackets.

expectancy of this result comes from the fact that the energy prices have experienced a tremendous meltdown in the early months of the pandemic, signified with the historic event of negative crude oil prices on April 20, 2020. Overall, our findings from all four GAS models, reported in Tables 3–6, suggest with high consistency that the riskiest asset is gasoline (in few cases, crude oil) and the safest asset is undoubtedly aluminum regardless of whether the estimation period is pre- or post-COVID-19 announcement.

5.2. *Out-of-sample estimation*

This section aims to elaborate on the past claims in the forecasting literature that the in-sample predictive ability often fails to translate into out-of-sample success, see Timmermann (2006). Therefore, we use the four GAS models to estimate one-day-ahead forecasts for the commodity returns and juxtapose their relative performance based on out-of-sample average losses, for $\alpha = 5\%$, using the L_{FZ0} function from Eq. (1).

Table 7 presents the out-of-sample performance rankings based on average out-of-sample losses for each of the ten commodities. Interestingly, our findings reveal gold as the safest asset in the pre-COVID-19 announcement period (ranked 1), according to the out-of-sample models, but its being ranked as the 2nd best safe haven by its in-sample counterparts. Meanwhile, aluminum steps back to 5th position as the safest asset in the non-pandemic years. However, in the post-COVID-19 announcement period aluminum (ranked 1) unarguably holds its position as the safe haven commodity, according to both in- and out-of-sample models. This finding suggests that gold should not been blindly accepted as the safest asset for investment during any type of market turbulence, e.g. caused by pandemic, currency crises, sudden stops, debt crises, banking crises, and etc. The latter finding about the weaken safe haven properties of gold in the recent COVID-19 pandemic is in line with Cheema et al. (2022). Table 7 also suggests that, unsurprisingly, the energy commodities remain the riskiest investment assets in both periods. Indeed, the out-of-sample estimations determine crude oil as the riskiest asset,

Table 6
Estimated parameters of alternative GAS models for VaR and ES, post-COVID-19 announcement.

	Soybeans	Wheat	Crude oil	Gasoline	Heating oil	Aluminum	Copper	Lead	Tin	Gold
GAS-1F										
β	0.946	0.548	0.978	0.998	0.966	0.917	0.894	0.963	0.947	0.532
(s.e.)	(0.123)	(0.228)	(0.022)	(0.002)	(0.009)	(0.211)	(0.159)	(0.094)	(0.009)	(1.068)
γ	0.001	0.020	0.035	0.028	0.026	0.008	0.016	0.005	0.042	0.011
(s.e.)	(0.007)	(0.028)	(0.002)	(0.000)	(0.002)	(0.012)	(0.008)	(0.004)	(0.001)	(0.008)
δ	–	–	–	–	–	–	–	–	–	–
(s.e.)	–	–	–	–	–	–	–	–	–	–
a	−1.576	−2.818	−5.864	−1.555	−4.694	−1.667	−2.015	−2.533	−3.422	−1.846
(s.e.)	(3.529)	(3.497)	(6.168)	(1.406)	(4.923)	(4.707)	(2.911)	(5.326)	(1.117)	(0.095)
b	−2.608	−3.764	−8.971	−1.656	−6.157	−2.165	−3.115	−3.532	−3.889	−3.095
(s.e.)	(6.045)	(4.588)	(9.841)	(1.439)	(6.403)	(5.982)	(4.837)	(7.463)	(1.115)	(0.741)
Average loss	**0.958**	**1.322**	**2.009**	**1.978**	**1.851**	**0.760**	**1.154**	**1.265**	**1.137**	**1.130**
GARCH-FZ										
β	0.849	0.925	0.439	0.650	0.759	0.857	0.528	0.609	0.645	0.836
(s.e.)	(0.166)	(0.255)	(0.392)	(0.396)	(0.340)	(0.124)	(0.399)	(0.285)	(0.208)	(0.457)
γ	0.106	0.046	0.116	1.960	0.721	0.842	0.127	0.132	0.143	0.084
(s.e.)	(0.183)	(0.054)	(0.138)	(0.845)	(0.874)	(0.749)	(0.090)	(0.045)	(0.099)	(0.038)
δ	–	–	–	–	–	–	–	–	–	–
(s.e.)	–	–	–	–	–	–	–	–	–	–
a	−1.714	−1.310	−3.924	−0.868	−0.988	−0.551	−2.047	−1.935	−2.808	−1.450
(s.e.)	(1.116)	(0.656)	(1.104)	(0.568)	(0.677)	(0.095)	(0.586)	(0.516)	(1.378)	(0.960)
b	−2.362	−1.695	−5.313	−1.142	−1.373	−0.715	−2.996	−2.834	−3.386	−2.522
(s.e.)	(1.453)	(1.129)	(3.159)	(1.250)	(1.141)	(0.178)	(1.515)	(1.597)	(1.926)	(3.228)
Average loss	**0.965**	**1.339**	**2.123**	**2.066**	**1.915**	**0.741**	**1.202**	**1.252**	**1.124**	**1.140**
Hybrid										
β	0.889	0.970	0.980	0.998	0.889	0.808	0.862	0.615	0.694	0.772
(s.e.)	(0.241)	(0.047)	(0.006)	(0.011)	(0.011)	(0.130)	(0.158)	(0.125)	(0.189)	(0.562)
γ	0	0	0.027	0.030	0.027	0.003	0.014	0.021	0.021	0.007
(s.e.)	(0.017)	(0.001)	(0.011)	(0.021)	(0.003)	(0.003)	(0.012)	(0.022)	(0.020)	(0.007)
δ	0.089	0.053	0.011	0.001	0.075	0.058	0.026	0.081	0.187	0.038
(s.e.)	(0.130)	(0.030)	(0.005)	(0.003)	(0.017)	(0.022)	(0.021)	(0.037)	(0.202)	(0.014)
a	−2.528	−2.749	−4.767	−2.612	−3.637	−1.939	−2.175	−2.582	−2.891	−2.145
(s.e.)	(7.959)	(0.695)	(49.764)	(593.797)	(1.916)	(0.512)	(3.256)	(2.989)	(2.882)	(0.746)
b	−3.767	−3.645	−5.710	−3.012	−4.551	−2.482	−3.305	−3.642	−3.938	−3.462
(s.e.)	(11.167)	(1.226)	(59.874)	(685.212)	(2.528)	(0.757)	(5.483)	(4.082)	(4.623)	(1.546)
Average loss	**0.916**	**1.307**	**1.944**	**1.963**	**1.840**	**0.723**	**1.143**	**1.243**	**1.108**	**1.123**

Note: This table presents the estimated parameters and standard errors for the three alternative GAS models specified in the methods section for VaR and ES for the ten commodity returns over the in-sample post-COVID-19 announcement period. The top panel presents the results for the one-factor GAS (GAS-1F) model in Equation (7). The middle panel presents the results for the GARCH model estimated by FZ loss minimization (GARCH-FZ), as specified in Equation (11), and "hybrid" one-factor GAS (Hybrid) model that includes an additional GARCH-type forcing variable, as specified in Equation (12). The last row of each sub-panel presents the average (in-sample) losses from each of these three models. The standard errors are provided in brackets.

Table 7
Out-of-sample performance rankings for the ten commodities.

	Soybeans	Wheat	Crude Oil	Gasoline	Heating Oil	Aluminum	Copper	Lead	Tin	Gold
Panel A: Pre-COVID-19 announcement										
GAS-2F	3	10	8	9	7	5	2	6	4	1
GAS-1F	3	8	9	10	7	5	2	6	4	1
GARCH-FZ	3	8	10	9	7	4	2	6	5	1
Hybrid	3	8	9	10	7	4	2	6	5	1
Average ranking	**3**	**8**	**9**	**10**	**7**	**=5**	**2**	**6**	**=5**	**1**
Panel B: Post-COVID-19 announcement										
GAS-2F	7	4	10	6	8	1	5	3	9	2
GAS-1F	10	4	9	6	8	1	5	3	7	2
GARCH-FZ	8	4	10	5	9	2	6	3	7	1
Hybrid	6	4	10	8	9	1	5	3	7	2
Average ranking	**8**	**4**	**10**	**6**	**9**	**1**	**5**	**3**	**7**	**2**

Note: This table has two panels, A and B, corresponding to pre- and post-COVID-19 announcement periods, respectively. The table presents the rankings (with the safest commodity asset ranked 1 and the riskiest ranked 10) based on the four GAS models, i.e., two-factor GAS (GAS-2F) model, one-factor GAS (GAS-1F) model, the GARCH model estimated by FZ loss minimization (GARCH-FZ), and "hybrid" one-factor GAS (Hybrid) model that includes an additional GARCH-type forcing variable. The "average ranking" row presents the average rank across the four forecasting models.

overall, with average losses that ranks it on 9th and 10th position for the pre- and post-COVID-19 announcement periods, respectively. The minimal diversification benefits from crude oil and natural gas for the pre-COVID-19 years are also highlighted in Rehman et al. (2019). Looking further into the results for other commodities the ranking is fairly mixed. Overall, we can conclude that gold remains the safest asset in non-pandemic years, while in the recent times of COVID-19 pandemic, its leading role has been challenged by metals, such as aluminum. Somehow our finding mildly agrees with Disli et al. (2021) who claim that neither gold nor oil exhibit safe haven characteristics during COVID-19 pandemic. Lastly, the findings for soybeans remain doubtful, as shown by the mixed results from in- and out-of-sample estimations. Therefore, further investigation incorporating out-of-sample models is needed on the safe haven properties of agricultural commodities.

Table 8 presents the p-values from the DQ and DES tests of the VaR and ES forecasts, respectively, at $\alpha = 5\%$, for the ten commodities. The p-values larger than 0.01 (0.05) indicate no evidence against optimality at the 1% (5%) significance level. The results from Panel A in Table 8 are relatively mixed. Although numerous cases of rejection of the null hypothesis can be seen at 1% (5%) level of significance, there are about 45 (35) percent of all tests indicating evidence for optimality from the DQ tests. Similarly, the results from the DES tests of ES forecasts show that 45 (40) percent of all tests suggest evidence for optimality at 1% (5%) level of significance. The model ranking performance remains strongly consistent at 1% level of significance suggesting that GAS-1F and GAS-2F have the highest pass rate in both the goodness-of-fit tests, i.e., DQ and DES tests. Looking at the 5% level results, the highest pass rate is found for the GARCH-FZ model. The test pass rate of the four models becomes even weaker considering the COVID-19 period. In fact, only for 12.5 (10) percent of all tests pass the optimality condition at 1% (5%) level of significance for both the goodness-of-fit tests. Overall, the best-performing model after the onset of the COVID-19 pandemic is found to be the GAS-1F model, followed by GAS-2F, considering altogether the results from both DQ and DES tests.

6. Robustness check

6.1. Commodity-stock relationship in the COVID-19 market downturn

The above analysis determines the tail behavior of commodities in times of market turbulence, and ranks their riskiness level in both in- and out-of sample scenarios. However, it does not indicate whether commodities have worked as safe haven assets against movements in the stock markets during the COVID-19 pandemic. To support the notion, we consider the US stock market, while the US stock returns are calculated using S&P 500 index (see, Choudhry et al., 2015; Lucey and Li, 2015; Salisu et al., 2021a).[7]

Past studies have determined that commodity-stock relationship is not stable over time and is affected by structural breaks (see, Chen et al., 2010; Ji et al., 2018; Shahzad et al., 2019a; Enilov et al., 2021; Iqbal et al., 2022). As such, leaving the presence of possible parameter instability unaddressed may result in estimation errors and unreliability of the model in general (see, Rossi, 2006, among others). A common method in the existing literature to overcome the problem of parameter instability is adoption of a rolling window procedure. Chen et al. (2010) highlight that rolling window approach is relatively robust to the presence of time-varying parameters and requires no explicit assumption about the nature of the time variation in the data. Examples of rolling estimation include: in commodity futures and volatility connectedness, Iqbal et al. (2022) to investigate the time-varying connectedness among the realized volatility of various energy, metals, and agricultural commodities; in finance, Enilov et al. (2021) to determine the power of commodity prices in predicting stock market returns; in exchange rate forecasting, Chen et al. (2010) to investigate the extent to which exchange rates predict global commodity prices; and in digital currency, Shahzad et al. (2019a) to examine the safe haven properties of Bitcoin, gold, and the commodity index across various stock market indices. To this end, we follow the past literature and address the time-varying nature of the stock-commodity relationship in times of economic turbulence using a rolling-window strategy.

The following is the specification of the rolling-window regression:

$$Tail_{t,t+\xi} = \beta_1 + \beta_2 SP_{t,t+\xi} + \varepsilon_{t,t+\xi}, \tag{15}$$

where *Tail* is the tail movement of the commodity assets based on the four estimation models we used above (GAS-2F, GAS-1F, GARCH-FZ, Hybrid),[8] $Tail_{t,t+\xi} = Tail_t, Tail_{t+1}, \ldots, Tail_{t+\xi}$, SP denotes the US stock returns, $SP_{t,t+\xi} = SP_t, SP_{t+1}, \ldots, SP_{t+\xi}$, and ξ is the size of the rolling window. The size of the rolling window is set to 40 (see, for a discussion, Liu and Song, 2018; Enilov and Wang, 2021). Following the preceding literature in the field (see, Baur and Lucey, 2010; Baur and McDermott, 2010), if the estimated parameters β_2 in Equation (15) are insignificant (regardless positive or negative) or positive significant, commodity can be regarded as a safe haven asset during crisis. For example, if the coefficient β_2 is positive significant then in case of stock prices decline, the tail risk from commodity trading is reduced, or if the coefficient β_2 is not significant (regardless positive or negative), it does not exist a link between the commodities and US stocks. Likewise, if β_2 is both negative and significant, then the commodity asset does not act as a safe haven for the US stocks.

Table 9 reports the percentage frequency of significant negative coefficients β_2 from Equation (15), based on 5% and 10% level of significance. The percentage frequency is calculated as the total number of negative significant coefficients β_2 is divided by the total

[7] The daily data for the S&P500 is obtained from *Thomson Reuters Datastream* database. The percentage returns series of the S&P500 are calculated consistently with those for the commodity assets as described in the data section above.

[8] The Tail estimates are calculated based on the 5% VaR modelling, the 5% ES results are available from the authors upon request. Tail is calculated as the absolute value of VaR estimates, for interpretability purposes.

Table 8

P-values from goodness-of-fit tests for the VaR and ES out-of-sample models.

	Soybeans	Wheat	Crude Oil	Gasoline	Heating Oil	Aluminum	Copper	Lead	Tin	Gold	Model Ranking (1% sig. lvl)	Model Ranking (5% sig. lvl)
Panel A: Pre-COVID-19 announcement												
DQ test (VaR)												
GAS-2F	0.000	0.000	0.276	0.086	0.298	0.007	0.000	0.013	0.000	0.000	**=1**	**=1**
GAS-1F	0.000	0.075	0.104	0.008	0.211	0.851	0.000	0.000	0.000	0.000	**=1**	**=2**
GARCH-FZ	0.000	0.457	0.665	0.177	0.036	0.000	0.000	0.011	0.001	0.000	**=2**	**=1**
Hybrid	0.000	0.048	0.140	0.158	0.343	0.346	0.000	0.006	0.000	0.000	**=2**	**=2**
DES test (ES)												
GAS-2F	0.000	0.000	0.366	0.084	0.201	0.002	0.000	0.008	0.002	0.173	**=1**	**=2**
GAS-1F	0.000	0.082	0.185	0.002	0.152	0.320	0.000	0.001	0.004	0.000	**=1**	**=2**
GARCH-FZ	0.000	0.325	0.518	0.162	0.032	0.000	0.000	0.006	0.031	0.000	**=2**	**1**
Hybrid	0.000	0.055	0.246	0.129	0.317	0.551	0.000	0.003	0.002	0.000	**=2**	**3**
Panel B: Post-COVID-19 announcement												
DQ test (VaR)												
GAS-2F	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.210	0.002	0.000	**=1**	**=2**
GAS-1F	0.022	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**=1**	**1**
GARCH-FZ	0.074	0.000	0.000	0.000	0.000	0.000	0.055	0.000	0.000	0.000	**2**	**3**
Hybrid	0.194	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	**=1**	**=2**
DES test (ES)												
GAS-2F	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.247	0.000	0.000	**=1**	**2**
GAS-1F	0.069	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.002	0.000	**=1**	**=1**
GARCH-FZ	0.002	0.000	0.000	0.000	0.000	0.000	0.042	0.000	0.000	0.000	**=1**	**=1**
Hybrid	0.088	0.000	0.000	0.000	0.065	0.000	0.000	0.000	0.000	0.000	**2**	**=1**

Note: This table has two panels, A and B, corresponding to pre- and post-COVID-19 announcement periods, respectively. The table presents p-values from dynamic quantile (DQ) regression of Engle and Manganelli (2004), and the dynamic ES (DES) test of Patton et al. (2019) for VaR and ES for the ten commodity returns based on the four GAS models, i.e., two-factor GAS (GAS-2F) model, one-factor GAS (GAS-1F) model, the GARCH model estimated by FZ loss minimization (GARCH-FZ), and "hybrid" one-factor GAS (Hybrid) model that includes an additional GARCH-type forcing variable. The "average ranking" row presents the average rank across the four forecasting models. The p-values greater than 0.05 indicate no evidence against optimality at the 5% significance level. The last two columns presents the model ranking, with the best-performing model ranked 1 and the worst ranked 4. In case of equivalence in ranking, the equality sign is stated. The ranking is calculated as the numerical sum of null hypothesis non-rejections is divided by the total number of tests for each model, i.e. ten.

number of rolling window tests. For instance, the percentage frequency for soybeans from GAS-2F at 5% significance level is 0.023. This implies that 2.3% of all coefficients β_2 are both negative and significant and thus soybeans does not act as a safe haven for the US stocks in 2.3% of the cases. The results determine the energy commodities as the riskiest assets for investments, overall. This is in contrast to metals that emerge as a good diversifier to the US market, according to GAS-1F and GARCH-FZ. Comparing the results for gold and aluminum, aluminum shows better safe haven properties than gold according to three out of the four models at both 5% and 10% significance level.

To illustrate our results, we provide visual representation on the time-varying β_2 coefficients from Eq. (15) over the COVID-19 period. Fig. 2 shows the results for all ten commodities. The largest fluctuations are perceived for the energy commodities, consistent with the aforementioned findings. Fig. 3 presents the results for aluminum and gold. The coefficients of gold are visually determined to be more volatile than those of aluminum, although the former are more likely to position at the positive side of the graphs. This suggests that both aluminum and gold can act as safe haven assets during the COVID-19 pandemic. The evidence for gold is consistent with the past studies of Ji et al. (2020), Akhtaruzzaman et al. (2021b), and Hasan et al. (2021).

6.2. *Alternative measures for downside risks: spectral risk measures*

To further support the validity of our findings, we employ spectral risk measures for downside risks (see, Acerbi, 2002, 2004, for a discussion). The spectral risk measures are known as coherent measures that are a weighted average of the quantiles of the portfolio returns with a non-increasing weight function (Artzner et al., 1997, 1999), which delivers more precise estimates than the standard VaR risk measure (Cotter and Dowd, 2006). As such, spectral risk measures have gained popularity in estimating downside risk during the COVID-19 pandemic (see, for example, Akhtaruzzaman et al., 2022). Our study follows Cotter and Dowd (2006) in defining a spectral risk measure M_ψ as:

$$M_\psi = \int_0^1 \psi(p) q_p \mathrm{d}p, \tag{16}$$

where $\psi(p)$ is weighting function that reflects the user's risk aversion, for which, $\psi(p) \geq 0$ for $p \in [0, 1]$; $\int_0^1 \psi(p)\mathrm{d}p = 1$; $\psi(p_1) \leq \psi(p_2)$ for all $0 \leq p_1 \leq p_2 \leq 1$; q_p is the p loss quantile, where $q_p = VaR_p$.[9] $\psi(p)$ is determined from the following exponential utility risk-aversion function:

$$\psi(p) = \frac{Re^{-R(1-p)}}{1 - e^{-R}}, \tag{17}$$

where $R \in (0, \infty)$ is the user's coefficient of absolute risk-aversion. We follow both well-established and recent studies of Cotter and Dowd (2006) and Akhtaruzzaman et al. (2022) and choose varying coefficients of absolute risk aversion, $R \in (20, 100, 200)$. This further reassures that our results are not sensitive to the choice of the coefficient of absolute risk-aversion, R.

Table 10 reports the spectral risk measures for the ten commodities in our sample, for each coefficient of absolute risk-aversion, $R \in (20, 100, 200)$, where p starts at 95%. The empirical outcomes provide evidence that aluminum is the safest commodity during the COVID-19 pandemic, which is consistent with our main findings. Besides, we find that aluminum is followed up by gold and soybeans, which shows qualitatively similar results. This once again highlights the safe haven properties of agricultural commodities in a market downturn and, more specifically, during the period of the COVID-19 pandemic. The latter is consistent with the findings of Ji et al. (2020), which is one of the pioneer studies to emphasize safe haven properties of agricultural commodities during the COVID-19 pandemic. The results from pre-COVID-19 announcement period are rather mixed, but still highlight that the safest commodities in normal times are gold and aluminum, which have very close estimates. In sum, energy commodities are found to be the riskiest investment shown in Table 10, which is in line with the results from our main analysis, as well as literature in the field, e.g., Rehman et al. (2019), Disli et al. (2021), Hasan et al. (2021), Iqbal et al. (2022).

7. Conclusion

This study contributes to the current literature by investigating the tail behavior patterns in commodity markets, in particular, of ten commodity assets (aluminum, copper, crude oil, gasoline, gold, heating oil, lead, soybeans, tin, and wheat), the risk exposure of these assets, and ranks their relative performance in acting as safe haven assets in times of market turbulence. The study spans from September 14, 2011 to June 30, 2021, covering the COVID-19 pandemic. Using four dynamic generalized autoregressive score (GAS) models, i.e., the two-factor GAS (GAS-2F), the one-factor GAS (GAS-1F), the GARCH-FZ and the hybrid GAS/GARCH, for joint estimation of the expected shortfall (ES) and value-at-risk (VaR) for commodities, we confirm that the tail behavior of commodities exhibits different patterns in the pre- and post-COVID-19 announcement times. Given these points, we assess the safe haven properties of the ten commodities, and rank their relative riskiness in both pre- and post-COVID-19 announcement periods. Expanding our analysis, the study uses an out-of-sample framework to perform one-day-ahead ES and VaR forecasts. Lastly, we evaluate the

[9] For a detailed discussion, see Acerbi (2002, 2004) and Cotter and Dowd (2006). We thank Kevin Dowd for providing us the MATLAB code used in the computation.

Table 9
Share of significant parameter estimates in rolling-window commodity-stock regressions during the COVID-19 market downturn.

	GAS-2F		GAS-1F		GARCH-FZ		Hybrid	
	5%	*10%*	*5%*	*10%*	*5%*	*10%*	*5%*	*10%*
Soybeans	0.023	0.081	0.003	0.017	0.035	0.066	0.037	0.086
Wheat	0.009	0.009	0.029	0.072	0	0	0	0.003
Crude Oil	0.035	0.063	0.032	0.058	0.012	0.035	0.055	0.078
Gasoline	0.063	0.144	0.037	0.110	0.035	0.138	0.061	0.144
Heating Oil	0.014	0.095	0.023	0.066	0.052	0.101	0.049	0.135
Aluminum	0	0.003	0.020	0.029	0	0.006	0.003	0.017
Copper	0.012	0.029	0.023	0.029	0.012	0.035	0	0.003
Lead	0.052	0.112	0.026	0.035	0	0.012	0.107	0.115
Tin	0	0.003	0.006	0.026	0	0.003	0.046	0.101
Gold	0.095	0.124	0	0	0.014	0.029	0.023	0.066

Note: The table reports the percentage frequency of significant negative coefficients β_2 from Equation (15), based on 5% and 10% level of significance. The percentage frequency is calculated as the total number of negative significant coefficients β_2 is divided by the total number of rolling window tests. The table report the results based on tail risk measures from the four GAS models, i.e., two-factor GAS (GAS-2F) model, one-factor GAS (GAS-1F) model, the GARCH model estimated by FZ loss minimization (GARCH-FZ), and "hybrid" one-factor GAS (Hybrid) model that includes an additional GARCH-type forcing variable.

forecasting performance of the dynamic GAS models. To do so, we juxtapose the relative performance of the tail risk models to determine the most parsimonious one in forecasting one-day-ahead VaR and ES commodity returns in COVID-19 times.

Given this framework, our in-sample results determine aluminum to be the safest asset for investment in times of market turbulence, i.e., during the COVID-19 pandemic. In the meantime, aluminum is followed up by gold as the second safest commodity in normal times, but during the COVID-19 times, soybeans outperforms gold as the second safest commodity. The latter finding is consistent with the previous literature examining the safe haven properties of agricultural commodities. A potential reason for this is the growing importance of agricultural commodities during the COVID-19 pandemic and their stable or even increased demand, with less uncertainty about consumers' desire to acquire the good. Our results also suggest that the riskiest investment assets are energy commodities regardless of whether the estimation period is pre- or post-COVID-19 announcement. In sum, our in-sample evidence determines that gold has stepped down from its dominant place to other assets (i.e., aluminum) as the safest commodity during the COVID-19 pandemic.

Notably, our study also evaluates the out-of-sample performance rankings based on the average out-of-sample losses for each of the ten commodities. Consistent with its traditional role, our results confirm gold as the safest asset in the pre-COVID-19 announcement period. In contrast, during the COVID-19 pandemic, aluminum retains its position as the safest commodity asset for portfolio investments, according to both in- and out-of-sample models. Overall, we can conclude that gold is the safest asset in non-pandemic years, but its leading role has been challenged by metals, such as aluminum, during the COVID-19 pandemic. This finding suggests that gold should not be *a priori* accepted as the safest investment asset in periods of market turbulence.

Unsurprisingly, the out-of-sample estimates determine energy commodities as the riskiest investment assets, in line with the in-sample results. In fact, crude oil is found to be the riskiest asset, overall, with average losses that ranks it on 9th and 10th position in the pre- and post-COVID-19 announcement periods, respectively. The results for soybeans remain mixed and are heavily dependent on the estimation methods. Nonetheless, our study shows that aluminum outperforms gold in turbulent times and could therefore expand the range of safe haven commodities in investment portfolios. Broadening strategic options for turbulent times is good news for investors, policymakers and the general public alike. Those newer options mitigate the risk of portfolio losses, weaken the taxpayer exposure to expensive bailouts, and curtails commodity price volatility, delivering broader overall stability.

Additionally, we use the out-of-sample period to evaluate the dynamic GAS models' forecasting performance. The model ranking performance remains strongly consistent at 1% level of significance suggesting that GAS-1F and GAS-2F have the highest pass rate according to both goodness-of-fit tests, i.e., DQ and DES tests. Looking at the 5% significance level results, the highest pass rate is found for the GARCH-FZ model. The test pass rate of the four models becomes weaker considering the COVID-19 period. Overall, the best-performing model after the onset of the COVID-19 pandemic is signified to be GAS-1F model, followed by GAS-2F, considering altogether the results from both DQ and DES tests.

Several implications for investors, portfolio managers, financial advisors, and policymakers can be derived from our research. First, our results can benefit both investors and portfolio managers to formulate effective investment strategies for protecting their investments in times of market turbulence. The investors may then design specific portfolio strategy to minimize financial risk and maximize financial return. From the aspect of risk management, it also contributes to systemic risk monitoring to help identify risks to financial stability. Second, given the fundamental shift in consumer and industrial preferences into more environmentally-friendly technologies, the emergence of green investments as safe haven assets can improve financial stability and performance, particularly during the periods of market downswings driven by the recent pandemic. Also, our results bear policy implications. Policymakers can, especially in times of crisis, create relative stability in the commodity market by controlling the foreign exchange market at commodity export dependent economies. With these actions, policymakers can direct the businesses to include these safe havens for portfolio and risk management.

The limitation of this study is that the analysis is constrained by testing the safe haven properties of our sample of commodities

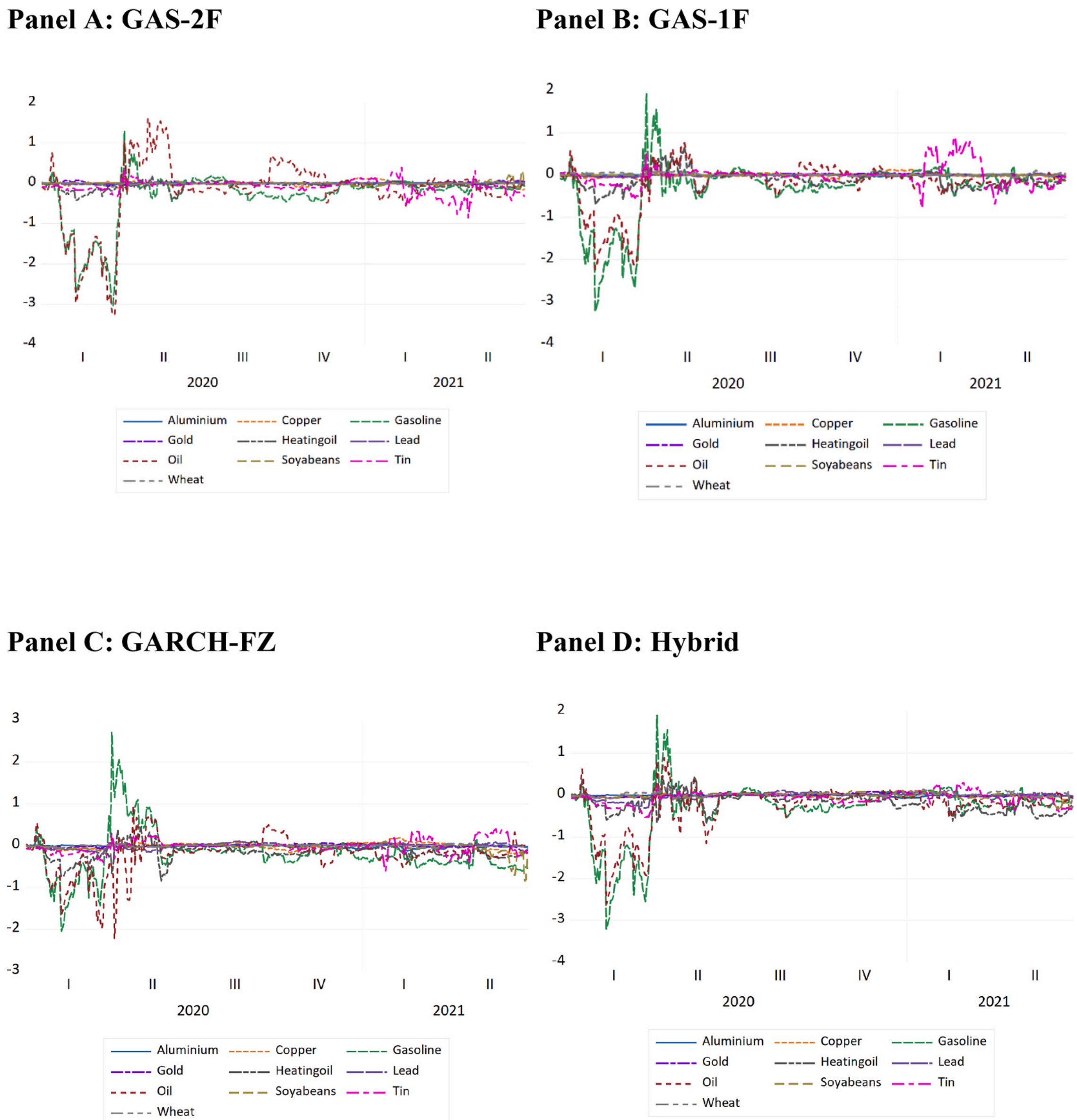

Fig. 2. Rolling-window coefficient estimations during the COVID-19 pandemic.

against only the US stock market, though it is the largest stock exchange in the world. To provide a more comprehensive scenario regarding the safe haven properties of different commodities, future researchers should incorporate a broader set of stock markets in their studies.

Our paper suggests several avenues for future research. Firstly, in order to fully explore the safe haven characteristics of commodities, this study solely focuses on commodity assets, which implies some missed opportunities for understanding the safe haven potential of other assets during the COVID-19 period. A future study can consider simultaneous analysis of, for example, bonds, cryptocurrency, foreign exchange, and the recently become quite popular clean energy investments that have the potential to serve as a safe haven as well. Secondly, our study focuses on the first stages of the COVID-19 pandemic, however, the spread of COVID-19 is still ongoing and thus a wider dataset would deepen the knowledge about safe haven assets, and their persistently as such. Thirdly, using alternative frequencies of observation, e.g., intra-day data, for the tail risk measures may capture intra-day aspects of potential safe haven assets. Finally, from a methodological standpoint, recent advances in the flight-to-quality literature based on semi-parametric dynamic asymmetric method have facilitated incorporation of realized measures for tail risk forecasting. It would also be interesting to investigate the safe haven characteristics of the commodity assets, and their behavior in the times of the COVID-19 pandemic by applying this method.

Credit author statement

Martin Enilov: Supervision, Formal analysis, writing, review & editing. **Walid Mensi**: Conceptualization, revision and writing of

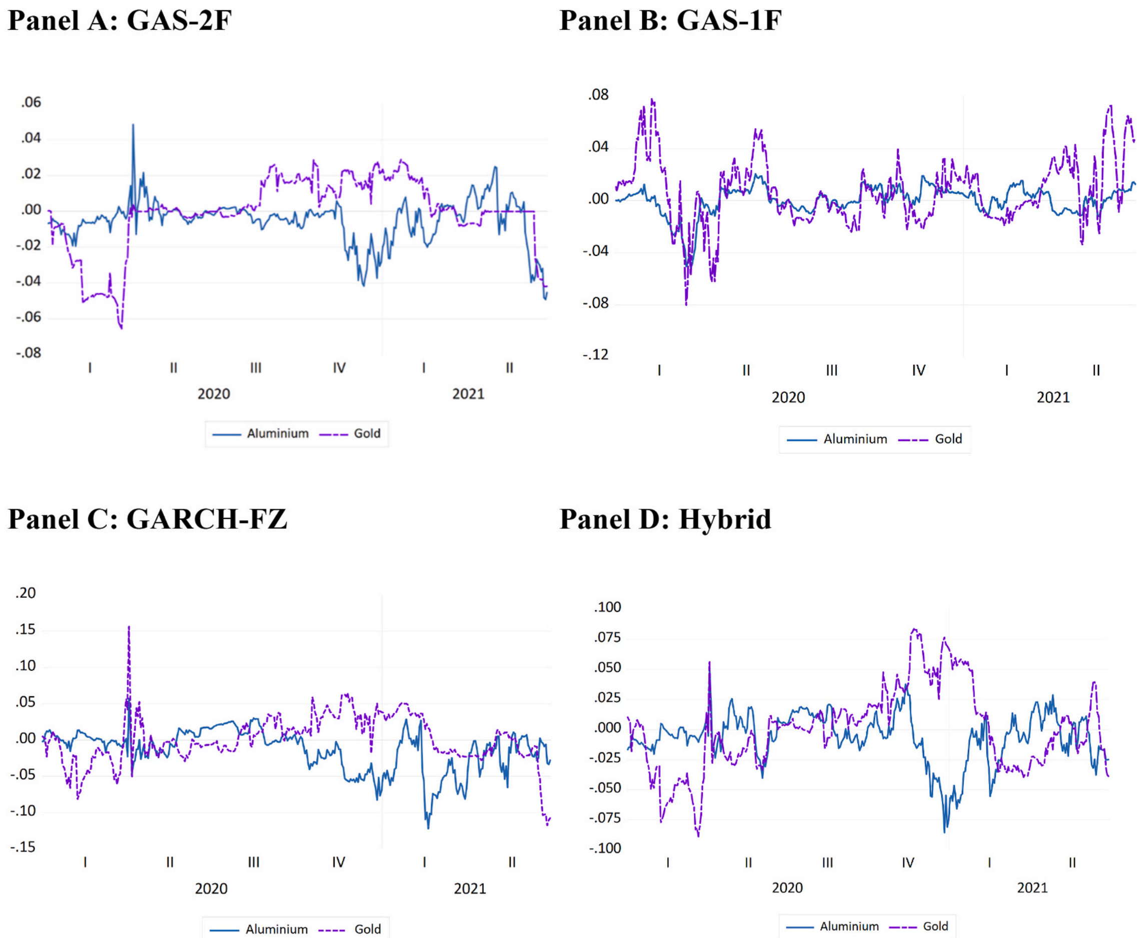

Fig. 3. Rolling-window coefficient estimations during the COVID-19 pandemic, aluminum and gold. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 10
Estimates of exponential spectral risk measures.

	Soybeans	Wheat	Crude Oil	Gasoline	Heating Oil	Aluminum	Copper	Lead	Tin	Gold
Panel A: Pre-COVID-19 announcement										
R = 20	16.799	18.751	25.640	26.417	23.097	12.462	14.806	16.564	16.639	11.831
R = 100	16.481	18.397	25.156	25.917	22.660	12.227	14.527	16.251	16.325	11.607
R = 200	16.441	18.353	25.096	25.855	22.606	12.198	14.492	16.212	16.286	11.579
Average ranking	**6**	**7**	**9**	**10**	**8**	**2**	**3**	**4**	**5**	**1**
Panel B: Post-COVID-19 announcement										
R = 20	16.130	19.223	62.660	62.826	46.219	11.396	18.143	17.896	26.466	15.214
R = 100	15.825	18.861	61.472	61.632	45.343	11.181	17.801	17.559	25.964	14.926
R = 200	15.787	18.816	61.324	61.484	45.234	11.154	17.759	17.517	25.902	14.89
Average ranking	**3**	**6**	**9**	**10**	**8**	**1**	**5**	**4**	**7**	**2**

Note: This table has two panels, A and B, corresponding to pre- and post-COVID-19 announcement periods, respectively. Estimates are in daily % returns terms based on the parameter values, using the trapezoidal integration method with N = 1 million (see, Cotter and Dowd, 2006). *R* is the absolute risk-aversion, which takes values of 20,100, and 200, and the cumulative probability *p* starts at 95%. The "average ranking" row presents the average rank across the ten commodity assets (with the safest commodity asset ranked 1 and the riskiest ranked 10).

the paper. **Petar Stankov**: Conceptualization, write-up development, review & editing.

Financial disclosure

My coauthors and I declare there are no financial disclosure related to our paper.

Data availability

Data will be made available on request.

Appendix

Table A.1
Data description

Name	Description	Datastream Code	Currency
Soybeans	Soyabeans, No.1 Yellow $/Bushel	SOYBEAN	U$
Wheat	Wheat US No.2 HRS Del Kansas U$/Bsh	WHTKANS	U$
Crude oil	Crude Oil-WTI Spot Cushing U$/BBL	CRUDOIL	U$
Gasoline	Gasoline Reg. Unld. FOB NYH UC/GAL	GSRUNYH	UC
Heating oil	NY No. 2 HO Spot Price FOB U$/GAL	EIANYHO	U$
Aluminum	LME-Aluminum 99.7% Cash U$/MT	LAHCASH	U$
Copper	LME-Copper Grade A Cash U$/MT	LCPCASH	U$
Lead	LME-Lead Cash U$/MT	LEDCASH	U$
Tin	LME-Tin 99.85% Cash U$/MT	LTICASH	U$
Gold	Gold Bullion LBM $/t oz DELAY	GOLDBLN	U$

References

Acerbi, C., 2002. Spectral measures of risk: a coherent representation of subjective risk aversion. J. Bank. Finance 26 (7), 1505–1518.
Acerbi, C., 2004. Coherent representations of subjective risk aversion. In: Szegö, G. (Ed.), Risk Measures for the 21st Century. John Wiley & Sons, New York, pp. 148–207.
Acerbi, C., Székely, B., 2014. Back-testing expected shortfall. Risk 27 (11), 76–81.
Agyei-Ampomah, S., Gounopoulos, D., Mazouz, K., 2014. Does gold offer a better protection against losses in sovereign debt bonds than other metals? J. Bank. Finance 40, 507–521.
Akhtaruzzaman, M., Benkraiem, R., Boubaker, S., Zopounidis, C., 2022. COVID-19 crisis and risk spillovers to developing economies: evidence from Africa. J. Int. Dev. 34 (4), 898–918.
Akhtaruzzaman, M., Boubaker, S., Chiah, M., Zhong, A., 2021a. COVID– 19 and oil price risk exposure. Finance Res. Lett. 42, 101882.
Akhtaruzzaman, M., Boubaker, S., Lucey, B.M., Sensoy, A., 2021b. Is gold a hedge or a safe-haven asset in the COVID–19 crisis? Econ. Modell. 102, 105588.
Areal, N., Oliveira, B., Sampaio, R., 2015. When times get tough, gold is golden. Eur. J. Finance 21 (6), 507–526.
Artzner, P., Delbaen, F., Eber, J.M., Heath, D., 1997. Thinking coherently. Risk 10 (11), 68–71.
Artzner, P., Delbaen, F., Eber, J.M., Heath, D., 1999. Coherent measures of risk. Math. Finance 9 (3), 203–228.
Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? Res. Int. Bus. Finance 54, 101249.
Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C., Viratyosin, T., 2020. *The Unprecedented Stock Market Impact of COVID-19* (No. W26945). National Bureau of Economic Research.
Barndorff-Nielsen, O.E., Hansen, P.R., Lunde, A., Shephard, N., 2009. Realized kernels in practice: trades and quotes. Econom. J. 12 (3), C1–C32.
Barro, R.J., Ursúa, J.F., Weng, J., 2020. *The Coronavirus and the Great Influenza Pandemic: Lessons From the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity* (No. W26866). National Bureau of Economic Research.
Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ. Rev. 45 (2), 217–229.
Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Finance 34 (8), 1886–1898.
Baur, D.G., McDermott, T.K., 2016. Why is gold a safe haven? J. Behav. Exp. Finance 10, 63–71.
Beckmann, J., Berger, T., Czudaj, R., 2015. Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. Econ. Modell. 48, 16–24.
Bekiros, S., Boubaker, S., Nguyen, D.K., Uddin, G.S., 2017. Black swan events and safe havens: the role of gold in globally integrated emerging markets. J. Int. Money Finance 73, 317–334.
Bouri, E., Cepni, O., Gabauer, D., Gupta, R., 2021a. Return connectedness across asset classes around the COVID-19 outbreak. Int. Rev. Financ. Anal. 73, 101646.
Bouri, E., Lucey, B., Saeed, T., Vo, X.V., 2021b. The realized volatility of commodity futures: interconnectedness and determinants. Int. Rev. Econ. Finance 73, 139–151.
Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L., Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: new insight through wavelet analysis. Q. Rev. Econ. Finance 77, 156–164.
Bredin, D., Conlon, T., Potì, V., 2015. Does gold glitter in the long-run? Gold as a hedge and safe haven across time and investment horizon. Int. Rev. Financ. Anal. 41, 320–328.
Cheema, M.A., Faff, R., Szulczyk, K.R., 2022. The 2008 global financial crisis and COVID-19 pandemic: how safe are the safe haven assets? Int. Rev. Financ. Anal. 83, 102316.
Chen, Y.C., Rogoff, K.S., Rossi, B., 2010. Can exchange rates forecast commodity prices? Q. J. Econ. 125 (3), 1145–1194.
Cheng, W.H., Hung, J.C., 2011. Skewness and leptokurtosis in GARCH-typed VaR estimation of petroleum and metal asset returns. J. Empir. Finance 18 (1), 160–173.
Chkili, W., 2016. Dynamic correlations and hedging effectiveness between gold and stock markets: evidence for BRICS countries. Res. Int. Bus. Finance 38, 22–34.

Choudhry, T., Hassan, S.S., Shabi, S., 2015. Relationship between gold and stock markets during the global financial crisis: evidence from nonlinear causality tests. Int. Rev. Financ. Anal. 41, 247–256.
Ciner, C., Gurdgiev, C., Lucey, B.M., 2013. Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates. Int. Rev. Financ. Anal. 29, 202–211.
Conlon, T., Corbet, S., McGee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. Res. Int. Bus. Finance 54, 101248.
Conlon, T., McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. Finance Res. Lett. 35, 101607.
Corbet, S., Larkin, C., Lucey, B., 2020. The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies. Finance Res. Lett. 35, 101554.
Cotter, J., Dowd, K., 2006. Extreme spectral risk measures: an application to futures clearinghouse margin requirements. J. Bank. Finance 30 (12), 3469–3485.
Creal, D., Koopman, S.J., Lucas, A., 2013. Generalized autoregressive score models with applications. J. Appl. Econom. 28 (5), 777–795.
Creti, A., Joëts, M., Mignon, V., 2013. On the links between stock and commodity markets' volatility. Energy Econ. 37, 16–28.
Danielsson, J., Jorgensen, B.N., Mandira, S., Samorodnitsky, G., De Vries, C.G., 2005. Subadditivity Re-examined: the Case for Value-At-Risk. Cornell University Operations Research and Industrial Engineering.
Deaton, A., Laroque, G., 1992. On the behaviour of commodity prices. Rev. Econ. Stud. 59 (1), 1–23.
Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74, 427–431.
Ding, Z., Zhang, X., 2021. The impact of geopolitical risk on systemic risk spillover in commodity market: an EMD-based network topology approach. Complexity 1–17.
Disli, M., Nagayev, R., Salim, K., Rizkiah, S.K., Aysan, A.F., 2021. In search of safe haven assets during COVID-19 pandemic: an empirical analysis of different investor types. Res. Int. Bus. Finance 58, 101461.
Dutta, A., Bouri, E., Uddin, G.S., Yahya, M., 2020. Impact of COVID-19 on global energy markets. In: IAEE Energy Forum Covid, 19, pp. 26–29.
Emmer, S., Kratz, M., Tasche, D., 2015. What is the best risk measure in practice? A comparison of standard measures. J. Risk 18 (2), 31–60.
Engle, R.F., Manganelli, S., 2004. CAViaR: conditional autoregressive value at risk by regression quantiles. J. Bus. Econ. Stat. 22 (4), 367–381.
Enilov, M., Fazio, G., Ghoshray, A., 2021. Global connectivity between commodity prices and national stock markets: a time-varying MIDAS analysis. Int. J. Finance Econ.
Enilov, M., Wang, Y., 2021. Tourism and economic growth: multi-country evidence from mixed-frequency Granger causality tests. Tourism Econ. 28 (5), 1216–1239.
Erb, C.B., Harvey, C.R., 2006. The strategic and tactical value of commodity futures. Financ. Anal. J. 62 (2), 69–97.
Ezeaku, H., Asongu, S., 2020. Covid-19 and Cacophony of Coughing: Did International Commodity Prices Catch Influenza? European Xtramile Centre of African Studies WP/20/040.
Farid, S., Kayani, G.M., Naeem, M.A., Shahzad, S.J.H., 2021. Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. Resour. Pol. 72, 102101.
Feng, W., Wang, Y., Zhang, Z., 2018. Can cryptocurrencies be a safe haven: a tail risk perspective analysis. Appl. Econ. 50 (44), 4745–4762.
Fernandes, N., 2020. Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy. *Available at: SSRN 3557504*.
Fernandez-Perez, A., Frijns, B., Fuertes, A.M., Miffre, J., 2018. The skewness of commodity futures returns. J. Bank. Finance 86, 143–158.
Fissler, T., Ziegel, J.F., 2016. Higher order elicitability and Osband's principle. Ann. Stat. 44 (4), 1680–1707.
Fissler, T., Ziegel, J.F., Gneiting, T., 2016. Expected Shortfall is jointly elicitable with Value at Risk-Implications for backtesting. Risk Magazine 29, 58–61.
Gkillas, K., Katsiampa, P., 2018. An application of extreme value theory to cryptocurrencies. Econ. Lett. 164, 109–111.
Gneiting, T., 2011. Making and evaluating point forecasts. J. Am. Stat. Assoc. 106 (494), 746–762.
Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett. 35, 101512.
Gormsen, N.J., Koijen, R.S., 2020. Coronavirus: impact on stock prices and growth expectations. Rev. Asset Pricing Stud. 10 (4), 574–597.
Hammoudeh, S., Malik, F., McAleer, M., 2011. Risk management of precious metals. Q. Rev. Econ. Finance 51 (4), 435–441.
Hansen, P.R., Lunde, A., 2005. A forecast comparison of volatility models: does anything beat a GARCH (1,1)? J. Appl. Econom. 20 (7), 873–889.
Harvey, A.C., 2013. Dynamic Models for Volatility and Heavy Tails: with Applications to Financial and Economic Time Series. Cambridge University Press, Cambridge.
Hasan, M.B., Hassan, M.K., Rashid, M.M., Alhenawi, Y., 2021. Are safe haven assets really safe during the 2008 global financial crisis and COVID-19 pandemic? Global Finance J. 50, 100668.
He, Z., O'Connor, F., Thijssen, J., 2018. Is gold a sometime safe haven or an always hedge for equity investors? A markov-switching CAPM approach for US and UK stock indices. Int. Rev. Financ. Anal. 60, 30–37.
Hood, M., Malik, F., 2013. Is gold the best hedge and a safe haven under changing stock market volatility? Rev. Financ. Econ. 22 (2), 47–52.
IMF, 2020. *World Econ. Outlook Update, June 2020*. International Monetary Fund, Washington, DC.
Inoue, A., Kilian, L., 2005. In-sample or out-of-sample tests of predictability: which one should we use? Econom. Rev. 23 (4), 371–402.
Iqbal, N., Bouri, E., Grebinevych, O., Roubaud, D., 2022. Modelling extreme risk spillovers in the commodity markets around crisis periods including COVID19. Ann. Oper. Res. 1–30.
Ji, Q., Bouri, E., Gupta, R., Roubaud, D., 2018. Network causality structures among Bitcoin and other financial assets: a directed acyclic graph approach. Q. Rev. Econ. Finance 70, 203–213.
Ji, Q., Zhang, D., Zhao, Y., 2020. Searching for safe-haven assets during the COVID-19 pandemic. Int. Rev. Financ. Anal. 71, 101526.
Kinateder, H., Campbell, R., Choudhury, T., 2021. Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. Finance Res. Lett. 43, 101951.
Klein, T., 2017. Dynamic correlation of precious metals and flight-to-quality in developed markets. Finance Res. Lett. 23, 283–290.
Kumar, A., Padakandla, S., 2022. Testing the safe-haven properties of gold and bitcoin in the backdrop of COVID-19: a wavelet quantile correlation approach. Finance Res. Lett. 47, 102707.
Kwon, J.H., 2020. Tail behavior of Bitcoin, the dollar, gold and the stock market index. J. Int. Financ. Mark. Inst. Money 67, 101202.
Lazar, E., Xue, X., 2020. Forecasting risk measures using intraday data in a generalized autoregressive score framework. Int. J. Forecast. 36 (3), 1057–1072.
Li, S., Lucey, B.M., 2017. Reassessing the role of precious metals as safe havens–What colour is your haven and why? J. Commod. Mark. 7, 1–14.
Liu, H., Song, H., 2018. New evidence of dynamic links between tourism and economic growth based on mixed-frequency granger causality tests. J. Trav. Res. 57 (7), 899–907.
Lucey, B.M., Li, S., 2015. What precious metals act as safe havens, and when? Some US evidence. Appl. Econ. Lett. 22 (1), 35–45.
Luo, J., Klein, T., Ji, Q., Hou, C., 2022. Forecasting realized volatility of agricultural commodity futures with infinite Hidden Markov HAR models. Int. J. Forecast. 38 (1), 51–73.
Mehlitz, J.S., Auer, B.R., 2021. Time-varying dynamics of expected shortfall in commodity futures markets. J. Futures Mark. 41 (6), 895–925.
Mensi, W., Hkiri, B., Al-Yahyaee, K.H., Kang, S.H., 2018. Analyzing time–frequency co-movements across gold and oil prices with BRICS stock markets: a VaR based on wavelet approach. Int. Rev. Econ. Finance 54, 74–102.
Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. J. Finance 32 (4), 1151–1168.
Ming, L., Zhang, X., Liu, Q., Yang, S., 2020. A revisit to the hedge and safe haven properties of gold: new evidence from China. J. Futures Mark. 40 (9), 1442–1456.
Naeem, M., Hasan, M., Arif, M., Suleman, T., Kang, S.H., 2022. Oil and gold as a hedge and safe-haven for metals and agricultural commodities with portfolio implications. Energy Econ. 105, 105758.
Nissanke, M., 2012. Commodity market linkages in the global financial crisis: excess volatility and development impacts. J. Dev. Stud. 48 (6), 732–750.
O'Connor, F.A., Lucey, B.M., Batten, J.A., Baur, D.G., 2015. The financial economics of gold—a survey. Int. Rev. Financ. Anal. 41, 186–205.
OECD/FAO, 2021. OECD-FAO Agricultural Outlook 2021-2030. OECD Publishing, Paris.
Osterrieder, J., Lorenz, J., 2017. A statistical risk assessment of Bitcoin and its extreme tail behavior. Ann. Financ. Econ. 12 (1), 1–19.
Patra, S., 2021. Revisiting value-at-risk and expected shortfall in oil markets under structural breaks: the role of fat-tailed distributions. Energy Econ. 101, 105452.
Patton, A.J., Ziegel, J.F., Chen, R., 2019. Dynamic semiparametric models for expected shortfall (and value-at-risk). J. Econom. 211 (2), 388–413.

Peng, X., 2020. Do precious metals act as hedges or safe havens for China's financial markets? Finance Res. Lett. 37, 101353.
Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346.
Ramelli, S., Wagner, A.F., 2020. Feverish stock price reactions to COVID-19. Rev. Corporate Finance Stud. 9 (3), 622–655.
Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. J. Bank. Finance 37 (8), 2665–2676.
Rehman, M.U., Bouri, E., Eraslan, V., Kumar, S., 2019. Energy and non-energy commodities: an asymmetric approach towards portfolio diversification in the commodity market. Resour. Pol. 63, 101456.
Roccioletti, S., 2016. Backtesting Value at Risk and Expected Shortfall. Springer.
Rossi, B., 2006. Are exchange rates really random walks? Some evidence robust to parameter instability. Macroecon. Dyn. 10 (1), 20–38.
Rubbaniy, G., Khalid, A.A., Syriopoulos, K., Samitas, A., 2022. Safe-haven properties of soft commodities during times of COVID-19. J. Commod. Mark. 27, 100223.
Sakemoto, R., 2018. Do precious and industrial metals act as hedges and safe havens for currency portfolios? Finance Res. Lett. 24, 256–262.
Salisu, A.A., Raheem, I.D., Vo, X.V., 2021a. Assessing the safe haven property of the gold market during COVID-19 pandemic. Int. Rev. Financ. Anal. 74, 101666.
Salisu, A.A., Vo, X.V., Lawal, A., 2021b. Hedging oil price risk with gold during COVID-19 pandemic. Resour. Pol. 70, 101897.
Selmi, R., Mensi, W., Hammoudeh, S., Bouoiyour, J., 2018. Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Econ. 74, 787–801.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin. Econ. Modell. 87, 212–224.
Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L., Lucey, B., 2019a. Is Bitcoin a better safe-haven investment than gold and commodities? Int. Rev. Financ. Anal. 63, 322–330.
Shahzad, S.J.H., Raza, N., Roubaud, D., Hernandez, J.A., Bekiros, S., 2019b. Gold as safe haven for G-7 stocks and bonds: a Revisit. J. Quant. Econ. 17 (4), 885–912.
Stavroyiannis, S., 2018. Value-at-risk and related measures for the Bitcoin. J. Risk Finance 19 (2), 127–136.
Timmermann, A., 2006. Forecast combinations. Handb. Econ. Forecast. 1, 135–196.
Wheat Associates, U.S., 2022. Planting the crop: U.S. Wheat seeding involves careful planning. Available at: https://www.uswheat.org/wheatletter/u-s-wheat-seeding-involves-careful-planning-and-varietal-selection/. (Accessed 22 August 2022). accessed.
Wang, W., Enilov, M., 2020. The Global Impact of Covid-19 on Financial Markets. *Available at: SSRN 3588021*.
Weber, S., 2006. Distribution-invariant risk measures, information, and dynamic consistency. Math. Finance 16 (2), 419–441.
Zaremba, A., Kizys, R., Tzouvanas, P., Aharon, D.Y., Demir, E., 2021. The quest for multidimensional financial immunity to the COVID-19 pandemic: evidence from international stock markets. J. Int. Financ. Mark. Inst. Money 71, 101284.
Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 36, 101528.
Zhang, W., Hamori, S., 2021. Crude oil market and stock markets during the COVID-19 pandemic: evidence from the US, Japan, and Germany. Int. Rev. Financ. Anal. 74, 101702.
Ziegel, J.F., 2016. Coherence and elicitability. Math. Finance 26 (4), 901–918.