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Comparing gold’s and Bitcoin’s safe-haven roles against energy commodities during the COVID-19 outbreak: A vine copula approach

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A R T I C L E   I N F O

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A B S T R A C T

This paper aims to compare the safe-haven roles of gold and Bitcoin for energy commodities, including oils and petroleum, during COVID-19. Specifically, we examine the presence of reduction in downside risk after mixing gold/Bitcoin with such energy commodities. To do this, we account for dependence among energy commodities and gold/Bitcoin returns by applying a (vine) copula. The findings show that gold substantially reduces the downside risk of a portfolio containing any allocation to gold and energy commodities, indicating its safe-haven ability. In contrast, Bitcoin’s safe-haven functionality is inconsistent since the downside risk reduction is achieved for Bitcoin’s small allocation only.

1. Introduction

Since being first discovered in Wuhan, China, in December 2019, COVID-19 has lasted more than one and half a year and has negatively affected almost all sectors in the world, including energy markets. Specifically, this turmoil has brought a fall in international energy commodity prices. From the demonstration of Dutta et al. (2020) for December 2014 to March 2020, Brent and WTI crude oils were observed to slip to the lowest level less than US$23 per barrel at the end of March 2020. The WTI oil price further continued to turn negative on April 20, 2020 (Corbet et al., 2020). Besides, Devpura and Narayan (2020) reported that oil price volatility increased following the onset of COVID-19. These situations indicate that investments in these markets become riskier and may produce more acute losses. Accordingly, investors are motivated to prepare capital allocation for bearing a worse extreme downside risk (Bredin et al., 2017). The amount of such capital may be determined by forecasting an accurate measure of downside risk (see, e.g., Del Brio et al., 2020; Velásquez-Gaviria et al., 2020; Syuhada et al., 2021) as in financial risk management.

In addition to doing risk quantification, energy commodity investors may also make a decision of adding other investment instruments, acting as safe havens, into their portfolios. This strategy is expected to help them reduce the downside risk they are exposed to. To achieve this goal, gold that has been one of the leading commodities may be considered. The reason is that this precious metal is well known to be a bad news lover, a store of value, and, hence, a safe haven in times of market turmoil (Baur and McDermott, 2010). Its safe-haven role may be indicated from its negative or zero correlation with other financial instruments during such turmoil periods (Baur and Lucey, 2010). Gold’s image as a safe haven has been documented, for instance, for investors.
holding the US and major European equities when facing extremely negative shocks (Baur and Lucey, 2010; Baur and McDermott, 2010) and amidst financial crises (Bredin et al., 2015). As revealed by Bredin et al. (2017), this evidence was present across both short and longer horizons, contrary to what they found in other precious metals, including silver and platinum, whose safe-haven characteristics disappeared at long intervals.

In the last decade, investors also decided to invest in Bitcoin, the most prominent and major cryptocurrency ever since its introduction by Nakamoto (2008). Amidst its growing popularity, Bitcoin was regarded as a digital gold due to its many similarities with gold in terms of its potential safe-haven functionality (Popper, 2015). Recently, it was found to be suitable as a safe haven for the S&P 500 in times of COVID-19 (Mariana et al., 2021) and against downturns in US equity sectors (Bouri et al., 2020a). Bitcoin’s safe-haven capacity for the world, developed, emerging, US, and Chinese stock markets was even superior over both gold and commodity index (Bouri et al., 2020b). In contrast, Klein et al. (2018) argued that Bitcoin might behave as an opposite to gold since it correlated positively with downward markets, implying that it is not the new gold. Additionally, during the COVID-19 bear market, Bitcoin’s small allocation increased the magnitude of downside risk of a portfolio containing the S&P 500 and Bitcoin (Conlon and McGee, 2020), different from Mariana et al. (2021) considering a short period.

To the best of our knowledge, the studies examining the safe-haven properties of gold and Bitcoin for oils and other energy commodities, particularly during the ongoing COVID-19, are, however, still scarce. One of the few recent studies was conducted by Bouri et al. (2017) investigating the relationship between Bitcoin and energy commodity indices. They revealed that Bitcoin functioned as a safe haven before the December 2013 crash. Meanwhile, Selmi et al. (2018) focused on oil commodity and found that the Bitcoin–oil relationship was observed to be negatively stronger than the gold–oil relationship, suggesting the superiority of Bitcoin over gold. The former relationship, however, became positive over the beginning of the COVID-19 period when oil price went down (Dutta et al., 2020).

This paper contributes to the literature by assessing the roles of gold and Bitcoin to be safe havens against the downside risk of energy commodities, including oils and petroleum, during the outbreak of COVID-19. Following the works of Bredin et al. (2017) and Conlon and McGee (2020), we aim at comparing their safe-haven roles by examining the occurrence of downside risk reduction after mixing gold and blending Bitcoin with such energy commodities. To do this task, the dependence among the returns of all the energy commodity instruments and gold/Bitcoin are taken into account by adopting a vine copula. This model has been popular in describing high-dimensional risk dependence in energy commodities, precious metals, cryptocurrencies, and other markets; see, e.g., Sukcharoen and Leatham (2017), Dai et al. (2020), and Syuhada and Hakim (2020). For comparison, we simplify this problem by firstly combining the overall energy commodities into a portfolio and then capturing the dependence between this portfolio and gold/Bitcoin returns using a simple two-dimensional copula.

2. Data and methodology

2.1. Data

This study utilized data sets from three energy commodity markets. Specifically, Brent crude oil, heating oil in the New York Harbor, and RBOB gasoline in the US Gulf Coast are considered. Their daily spot price data were extracted from EIA.gov. In addition, we involve gold and Bitcoin whose daily closing prices were sourced from NASDAQ.com and CoinMarketCap.com, respectively. The price data period spans from September 29, 2018, to March 31, 2021. Into date with no trading activity, we insert the last observed price. The daily price data that have been completed are then transformed into the data of daily returns, i.e., \(\{R_{ij}\}_{i=1}^{n}\) with \(R_{ij} = 100 \ln(P_{ij}/P_{i-1,j})\), where \(P_{ij}\) is the price of the \(j\)th instrument at day \(i\) \((i=1)\). Fig. 1 demonstrates that all the energy commodity prices exhibited downward movements over the first two quarters of the COVID-19 period. They even reached the lowest level and became more volatile amidst this subperiod. This extreme volatility indicates a great impact of the COVID-19 outbreak on global energy supply and demand.

Statistics of the return data are summarized in Table 1. In addition to being more volatile with a higher standard deviation, the returns during COVID-19 tend to have heavier tails with a higher kurtosis as compared to those spanning over the pre-COVID-19 period. The highest kurtosis is recorded in the data from energy commodity and Bitcoin markets. Furthermore, all the returns are also found to be asymmetric due to a nonzero skewness. These non-normality indications are confirmed by the Jarque–Bera test reject the null hypothesis of normality at a 5% significance level. Additionally, Fig. 2 displays a weak serial correlation of the returns and the features of volatility persistence, volatility clustering, and conditional heteroscedasticity. The energy commodity returns, in particular, also seem to have a leverage effect, indicating that negative shocks lead to a more rise in future volatility as compared to positive ones of the same magnitude. In other words, energy commodity investors exhibit asymmetric responses to shocks.

2.2. Methodological frameworks

To capture the empirical facts investigated before, we propose a marginal model of the form

\[
R_{ij} = \mu_{ij} + \sigma_{ij} \varepsilon_{ij},
\]

for the \(i\)th return process, where \(\mu_{ij}\) \((\sigma_{ij}^{2})\) denotes the conditional mean (volatility) of \(R_{ij}\), given previous information \(\tilde{\delta}_{i,j-1}\), whilst \(\varepsilon_{ij}\) is an error term denoting an innovation independent of \(\tilde{\delta}_{i,j-1}\). We assume the conditional mean to satisfy an AR(1) equation, that is \(\mu_{ij} = a_{i} + \beta_{i} R_{i,j-1}\), with \((a_{i}, \beta_{i})\) \(\in \mathbb{R}^{2}\). Meanwhile, a heteroscedastic model of Glosten et al. (1993) is set up for \(\sigma_{ij}^{2}\), as below:

\[
\sigma_{ij}^{2} = \alpha_{i} + \delta_{i} (R_{i,j-1} - \mu_{i,j-1})^{2} + \beta_{i} \sigma_{i,j-1}^{2} + \gamma_{i} (R_{i,j-1} - \mu_{i,j-1})^{2} I_{i,j-1},
\]
Fig. 1. The daily price and return plots (blue and red lines, respectively) of energy commodities, gold, and Bitcoin. Note: The prices of crude oil, heating oil (gasoline), and gold are denominated in US dollars per barrel, in US dollars per gallon, and in US dollars per troy ounce, respectively. Meanwhile, Bitcoin is priced in US dollars. The shaded region represents the COVID-19 period, starting from December 31, 2019, to March 31, 2021.

Fig. 2. The plots of empirical $\text{Corr}(R_i, R_{i+k})$ (blue point), $\text{Corr}(R_i^2, R_{i+k}^2)$ (red point), and $\text{Corr}(R_i, R_{i+k})$ (green point) at lag $k \in \{1, 2, \ldots, 10\}$. Note: The shaded region represents their 95%-confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
The summary of statistics of energy commodities, gold, and Bitcoin returns.

|                | Crude Oil | Heating Oil | Gasoline | Gold | Bitcoin |
|----------------|----------|-------------|----------|------|---------|
| **Before COVID-19** |          |             |          |      |         |
| Mean           | −0.042   | −0.032      | −0.049   | 0.052| 0.022   |
| Standard Deviation | 1.798    | 1.347       | 1.910    | 0.628| 3.623   |
| Skewness       | 0.224    | 0.628       | −0.341   | 0.439| 0.037   |
| Kurtosis       | 8.101    | 12.155      | 7.545    | 7.588| 6.950   |
| Jarque–Bera   | 518.528*  | 1684.336*    | 417.875* | 431.379*| 309.108* |
| **During COVID-19** |          |             |          |      |         |
| Mean           | −0.016   | −0.048      | 0.023    | 0.027| 0.457   |
| Standard Deviation | 5.451    | 3.029       | 5.038    | 1.107| 4.165   |
| Skewness       | −2.854   | −1.134      | −1.880   | −0.344| −2.847  |
| Kurtosis       | 56.754   | 11.917      | 26.207   | 9.301| 38.607  |
| Jarque–Bera   | 57,509.015* | 1668.539*  | 10,881.149* | 793.684*| 25,590.460* |

*Indicates statistical significance at a 5% level.

where $(\omega_j, \delta_j, \beta_j, \gamma_j)^T \in (0, \infty) \times (0, \infty)^2 \times \mathbb{R}$. The term $I_{i,i-1}$ denotes an indicator variable with the value of one when $R_{i,i-1} - \mu_{i,i-1}$ is negative, and zero elsewhere. If $\gamma_j \neq 0$, the above model called GJR-GARCH(1,1) can handle the leverage effect. Furthermore, the innovation $\epsilon_{i,i}$ is assumed to follow a standardized Skewed Student’s $t$ distribution (SSTD) with a distribution function $F_{\epsilon_i}$.
parameterized by $\theta_j = (0, 1, v_j, \xi_j)^T$, where $v_j, \xi_j \in (0, \infty)$. All the parameters of each marginal AR(1)-GJR-GARCH(1,1)-SSTD model are first estimated. We then compute the standardized error $\hat{\varepsilon}_{ij} = (R_{ij} - \hat{\mu}_i) / \hat{\sigma}_i$ and its probability integral transformation:

$$U_{ij} = F_i(\hat{\varepsilon}_{ij}; \hat{\theta}_i),$$

so that $\{U_{ij}\}$ obeys a uniform distribution over $[0, 1]$.  

We further assume the innovations or the standardized errors for different instruments to be dependent. Due to their non-normality, we take a flexible dependence model, namely copula, into consideration. For two instruments $i$ and $j$, a bivariate copula $C_{ij}$ is a joint distribution function of $\{U_{ij}, U_{ji}\}$ uniformly distributed over $[0, 1]^2$ with a joint probability function $c_{ij}$ called copula density. According to the Sklar's theorem stated in Joe (2015), this approach allows us to define the joint distribution function of $w = (w_{R_{ij}}, w_{R_{ji}}, w_{\varepsilon_{ij}}, w_{\varepsilon_{ji}})$ as $F_{w}(w_{R_{ij}}, w_{R_{ji}}, w_{\varepsilon_{ij}}, w_{\varepsilon_{ji}})$. This means that, by using the copula method, this dependence modeling can be separated from the marginal innovation modeling before. A copula for a higher-dimensional innovation is then constructed from unidentical bivariate copulas. For instance, $(\varepsilon_{1i}, \varepsilon_{2i}, \varepsilon_{3i})^T$ building the return models for crude oil ($R_{1i}$), heating oil ($R_{2i}$), and gasoline ($R_{3i}$) may be assumed to have a trivariate copula $C_{123}$ with the following density:

$$c_{123}(u_{1i}, u_{2i}, u_{3i}) = c_{12}(u_{1i}, u_{2i}) \times c_{13}(u_{1i}, u_{3i}) \times c_{23}(u_{2i}, u_{3i}),$$

where $C_{ij}(u_{ki}, u_{kj}) = \partial C_{ij}(u_{ki}, u_{kj}) / \partial u_{ki}$, for each $(i, j) = (1, 2), (1, 3)$. If another instrument, gold/Bitcoin ($R_{4i}$), is involved, the above decomposition is extended to construct a four-dimensional copula density for $(\varepsilon_{1i}, \varepsilon_{2i}, \varepsilon_{3i}, \varepsilon_{4i})^T$ as below:

$$c_{1234}(u_{1i}, u_{2i}, u_{3i}, u_{4i}) = c_{123}(u_{1i}, u_{2i}, u_{3i}) \times c_{14}(u_{1i}, u_{4i}) \times c_{24}(u_{2i}, u_{4i}) \times c_{34}(u_{3i}, u_{4i}),$$

where $C_{4ij}(u_{ki}, u_{kj}) = \partial C_{4ij}(u_{ki}, u_{kj}) / \partial u_{ki}$, for each $(i, j, k) = (1, 2, 3), (1, 2, 4), (1, 3, 4), (2, 3, 4)$, and $C_{44}(u_{ki}, u_{kj}) = \partial C_{44}(u_{ki}, u_{kj}) / \partial u_{ki}$, for $(i, j, k) = (2, 3, 4)$; see Aas et al. (2009). Since the construction of the copula densities in Eqs. (4)–(6) depends on the permutation of 1, 2, 3 and 4, a graphical representation is required to help choose the appropriate one. Through this approach, the marginal distributions and the bivariate copulas are, respectively, represented by nodes and edges building a vine couple $T_v$ of nested tree graphs, called regular vine, with certain conditions. Absolute pairwise dependence measures are attached to the edges to find a maximum spanning tree as the first tree graph, $T_1$, of the regular-vine copula as illustrated by Dißmann et al. (2013).

The returns from different markets stored in a vector $R_i$, then form a portfolio $S_i = w^T R_i$ with a certain weighting vector $w$. For a given vector $w \in [0, 1]$, we put a portion $w$ on gold/Bitcoin and allocate the remaining $1 - w$ to energy commodities equally, i.e.,

$$S_i = (1 - w)\left(\frac{1}{3} R_{1i} + \frac{1}{3} R_{2i} + \frac{1}{3} R_{3i}\right) + w R_{4i},$$

which means $w = \left(\frac{1 - w}{3}, \frac{1 - w}{3}, \frac{1 - w}{3}, w\right)^T$ and $R_i = (R_{1i}, R_{2i}, R_{3i}, R_{4i})^T$ whose dependence is accounted for through the vine copula approach described before. As a benchmark, we consider $w^* = (1 - w, w)^T$ and $R_i^* = (R_{1i}, R_{4i})^T$ whose dependence is simply captured by a bivariate copula, where $R_{4i} = \frac{1}{3} R_{1i} + \frac{1}{3} R_{2i} + \frac{1}{3} R_{3i}$ assumed to have a marginal model of Eq. (1). If $w = 0$, we get a portfolio composed of energy commodities only.

Our aim is to forecast future portfolio downside risk at day $n + 1$, given the available information up to day $n$. Such a risk is measured by utilizing the standard deviation premium principle (SDPP) formulated by

$$SDPP = w^T \mu_{w1} + \Phi^{-1}(\alpha) \sqrt{w^T \Sigma_{w1} w},$$

The terms $\mu_{w1}$ and $\Sigma_{w1}$ denote a vector of conditional means and a matrix of conditional covariances, respectively, at day $n + 1$. Meanwhile, $\Phi^{-1}(\alpha)$ is the quantile of the standard normal distribution evaluated at a significance level of $\alpha \in (0, 1)$. Following Bredin et al. (2017) and Conlon and McGee (2020), a relative SDPP (RSDPP) defined by

$$RSDPP = \frac{SDPP_{\text{mix}}}{SDPP_{\text{energy}}}$$

is then computed to quantify the portfolio downside risk reduction after blending gold/Bitcoin with energy commodities. If this ratio is below one, the downside risk reduction is achieved.

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3 The constants $v_i$ and $\xi_i$, respectively, characterize the heavy-tailedness and the skewness of the individual return $R_i$.

4 The terms $\hat{\mu}_i$ and $\hat{\sigma}_i$ denote the fitted conditional mean and volatility, respectively, whilst $\hat{\theta}_i$ is the estimate for $\theta_i$.

5 The parameter of the copula $C_{ij}$ is estimated based on a collection $\{U_{ij}, U_{ji}, \varepsilon_{ij}, \varepsilon_{ji}\}$ of uniformly distributed pseudo observations given in Eq. (3) by using a sequential maximum likelihood method of Aas et al. (2009). The best-fit bivariate copulas are selected from the well-known family of Archimedean copulas, including (rotated) Clayton, (rotated) Gumbel, and Frank, provided in Table A.1 in Appendix.
3. Empirical findings

We first observe the correlation between the returns of each energy commodity and gold/Bitcoin measured by using Pearson’s $\rho$ and Kendall’s $\tau$. It is found from Fig. 3 that gold return is negatively correlated with energy commodity returns before COVID-19, but their correlation becomes insignificantly positive (at a 5% significance level) in the period of COVID-19. An exception is for the commodities of crude oil and gold with a significant Pearson’s $\rho$ but an insignificant Kendall’s $\tau$. In general, gold is indicated to serve as a safe haven for an energy commodity portfolio amidst COVID-19, but this effect is not strong (see Table 2). Meanwhile, Bitcoin is not found to be a safe-haven investment instrument. This preliminary indication is drawn based on its significantly positive correlation with this energy commodity portfolio in COVID-19 times.

We fit a marginal AR(1)-GJR-GARCH(1,1) with a skewed-$t$ innovation to each individual return series and provide its estimated parameters in Table 3, showing that highly persistent and asymmetric volatility is evident. A positive leverage parameter for energy commodities and gold during COVID-19 suggests that investors in these markets overreact to bad news rather than to good news. Bitcoin volatility, on the other hand, has an inverse leverage effect. From this modeling of individual returns, we compute their
### Table 3

The estimated parameters of marginal AR(1)-GJR-GARCH(1,1)-SSTD models for individual returns of energy commodities, gold, and Bitcoin.

|                | Crude Oil | Heating Oil | Gasoline | Gold     | Bitcoin  |
|----------------|-----------|-------------|----------|----------|----------|
| **Before COVID-19** |           |             |          |          |          |
| \(a\)           | 0.015 (0.072) | 0.018 (0.054) | -0.016 (0.080) | 0.055 (0.023) | -0.025 (0.113) |
| \(b\)           | -0.010 (0.033) | -0.003 (0.035) | -0.036 (0.034) | -0.081 (0.031) | -0.041 (0.040) |
| \(\omega\)      | 0.106 (0.168) | 0.005 (0.009) | 0.011 (0.047) | 0.005 (0.001) | 0.173 (0.310) |
| \(\delta\)      | 0.072 (0.061) | 0.000 (0.019) | 0.009 (0.010) | 0.081 (0.026) |          |
| \(\beta\)       | 0.933 (0.067) | 0.972 (0.013) | 0.974 (0.007) | 0.988 (0.005) | 0.894 (0.067) |
| \(\gamma\)      | -0.010 (0.084) | 0.056 (0.022) | 0.052 (0.035) | -0.016 (0.018) | 0.050 (0.057) |
| \(\nu\)         | 2.390 (0.109) | 2.643 (0.203) | 2.556 (0.182) | 2.502 (0.112) | 2.758 (0.349) |
| \(\zeta\)       | 0.994 (0.041) | 0.983 (0.040) | 0.964 (0.041) | 1.088 (0.046) | 0.975 (0.053) |
| \(LL\)          | -834.814 | -713.485 | -883.315 | -352.406 | -1127.512 |
| **During COVID-19** |           |             |          |          |          |
| \(a\)           | 0.111 (0.091) | 0.028 (0.098) | 0.161 (0.122) | 0.073 (0.041) | 0.404 (0.128) |
| \(b\)           | -0.016 (0.036) | 0.016 (0.041) | 0.013 (0.037) | -0.012 (0.027) | -0.109 (0.040) |
| \(\omega\)      | 0.456 (0.387) | 0.139 (0.083) | 0.873 (0.554) | 0.011 (0.007) | 0.148 (0.117) |
| \(\delta\)      | 0.000 (0.080) | 0.063 (0.103) | 0.000 (0.137) | 0.006 (0.017) | 0.096 (0.032) |
| \(\beta\)       | 0.894 (0.037) | 0.912 (0.033) | 0.923 (0.113) | 0.979 (0.060) | 0.942 (0.016) |
| \(\gamma\)      | 0.211 (0.171) | 0.050 (0.092) | 0.147 (0.152) | 0.030 (0.033) | -0.076 (0.030) |
| \(\nu\)         | 2.320 (0.376) | 2.762 (0.516) | 2.216 (0.270) | 2.295 (0.089) | 2.966 (0.378) |
| \(\zeta\)       | 1.007 (0.040) | 0.987 (0.041) | 1.023 (0.041) | 1.024 (0.044) | 1.041 (0.060) |
| \(LL\)          | -1036.355 | -1005.504 | -1107.763 | -584.660 | -1171.236 |

**Note:** The estimated parameters for each instrument alone is obtained by using the conditional maximum likelihood method applied to its individual return data, with a maximized conditional log-likelihood denoted by \(LL\) and a standard error given in parentheses.

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#### Fig. 4

The regular-vine copula structures for return dependence. Note: CO, HO, GAS, GLD, and BTC stand for crude oil, heating oil, gasoline, gold, and Bitcoin, respectively. At each edge, C, G, and F refer to bivariate Clayton, Gumbel, and Frank copulas, respectively, with the best fit. Meanwhile, C90/180/270 and G90/180/270 are rotated Clayton and Gumbel copulas, respectively, with a clockwise rotation of 90/180/270 degrees. Their estimated parameters are given in Tables A.2 and A.3 in Appendix.

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The probability integral transformation employed to determine their dependence model. Specifically, we describe, in Fig. 4, the high-dimensional dependence structure for (i) energy commodities, (ii) energy commodities and gold, and (iii) energy commodities and Bitcoin through regular-vine copulas. The first tree in each vine structure shows the strongest connection between different markets.
and indicates that heating oil becomes a center connected to other markets. In times of COVID-19, its dependence with other energy commodities seems to be symmetric with a Frank copula. Meanwhile, a Clayton copula for a pair of heating oil and Bitcoin tells us the presence of their lower-tail dependence, suggesting that their extremely negative returns are positively dependent.

The above vine copulas are applied to compute the downside risk measure forecasts. The computation is carried out for a portfolio made up of energy commodities and gold/Bitcoin with various weights allocated to gold/Bitcoin at a 1% significance level. The results, displayed by the solid lines in Fig. 5, demonstrate that the inclusion of gold in energy commodity investments before and during COVID-19 produces a reduced downside risk level for all the gold weights. Relative to investing in energy commodities only, the downside risk of a mixed portfolio containing energy commodities and gold is lower. This relative downside risk declines as the weight increases. In contrast, the involvement of Bitcoin makes the relative downside risk go up, although it initially decreases. These findings imply that gold consistently acts as a safe haven against the downside risk of energy commodities. Meanwhile, the safe-haven property of Bitcoin is inconsistent since its ability to reduce the downside risk is limited for a small Bitcoin’s allocation only. This conclusion is similarly drawn when considering the simplified energy commodity portfolio return\(^6\) although there is a gap close enough between the two (relative) downside risk forecasts as detailed in Fig. 5. In particular, the adoption of bivariate copula

\[ RSDDP = SDPP_{mix}/SDPP_{maxx} \]

Note: The family of Archimedean copulas.

Table A.1
The family of Archimedean copulas.

| Copula          | Copula Function | Parameter |
|-----------------|-----------------|-----------|
| Clayton         | \( C_{12}^{\theta}(u_1, u_2) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta} \) | \( \theta \in (0, \infty) \) |
| 90°-rotated Clayton | \( C_{12}^{\theta}(u_1, u_2) = u_1 - C_{12}^{\theta}(1 - u_1, u_2) \) | \( \theta \in (0, \infty) \) |
| 180°-rotated Clayton | \( C_{12}^{\theta}(u_1, u_2) = u_1 + u_2 + C_{12}^{\theta}(1 - u_1, 1 - u_2) - 1 \) | \( \theta \in (0, \infty) \) |
| 270°-rotated Clayton | \( C_{12}^{\theta}(u_1, u_2) = u_2 - C_{12}^{\theta}(u_1, 1 - u_2) \) | \( \theta \in (0, \infty) \) |
| Gumbel          | \( C_{12}^{\theta}(u_1, u_2) = \exp[-((\ln u_1)^{\theta} + (\ln u_2)^{\theta})^{1/\theta}] \) | \( \theta \in [1, \infty) \) |
| 90°-rotated Gumbel | \( C_{12}^{\theta}(u_1, u_2) = u_1 - C_{12}^{\theta}(1 - u_2, u_2) \) | \( \theta \in [1, \infty) \) |
| 180°-rotated Gumbel | \( C_{12}^{\theta}(u_1, u_2) = u_1 + u_2 + C_{12}^{\theta}(1 - u_1, 1 - u_2) - 1 \) | \( \theta \in [1, \infty) \) |
| 270°-rotated Gumbel | \( C_{12}^{\theta}(u_1, u_2) = u_2 - C_{12}^{\theta}(u_1, 1 - u_2) \) | \( \theta \in [1, \infty) \) |
| Frank           | \( C_{12}^{\theta}(u_1, u_2) = -\theta^{-1} \ln[1 + (e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)(e^{-\theta} - 1)^{-1}] \) | \( \theta \in \mathbb{R} \setminus \{0\} \)

Note: The rotated copulas are derived based on a clockwise rotation.

\[ \text{SDPP} \]

\[ \text{RSDPP} = SDPP_{mix}/SDPP_{maxx} \]

\[ \text{Mix of Overall Energy Commodities and Gold} \]

\[ \text{Mix of Energy Commodity Portfolio and Gold} \]

\[ \text{Mix of Energy Commodity Portfolio and Bitcoin} \]

\[ \text{Mix of Overall Energy Commodities and Bitcoin} \]

\[ \text{Note} \]

\[ \text{For brevity, the estimated parameter of the marginal model } \]

\[ \text{R}_t \]

\[ \text{for the combined energy commodity portfolio return and the best-fit bivariate copula for} \]

\[ \text{this portfolio and gold/Bitcoin returns are not reported in this paper but are available from the authors upon request.} \]
Table A.2
The estimated parameters of the best-fit copulas of regular vine for dependent return models before COVID-19.

| Tree Edge Copula          | $\theta$  | LL     | Kendall's $\tau$ |
|---------------------------|-----------|--------|------------------|
| Energy Commodities        |           |        |                  |
| $T_1$ CO,HO 180°-rotated Gumbel | 1.670    | 123.971| 0.401            |
| HO,GAS Frank              | 8.523     | 224.892| 0.621            |
| $T_2$ CO,GAS|HO 180°-rotated Gumbel | 1.072    | 5.556 | 0.067            |

| Energy Commodities and Gold|           |        |                  |
| $T_1$ CO,HO 180°-rotated Gumbel | 1.670    | 123.971| 0.401            |
| HO,GAS Frank              | 8.523     | 224.892| 0.621            |
| GAS,GAS 270°-rotated Gumbel | 1.109    | 11.649 | -0.098           |

| Energy Commodities and Bitcoin|           |        |                  |
| $T_1$ CO,GAS|HO 180°-rotated Gumbel | 1.072    | 5.556 | 0.067            |
| HO,GAS Frank              | 1.029     | 1.758  | 0.028            |
| $T_3$ CO,BTC|HO,GAS 270°-rotated Gumbel | 1.033    | 1.808 | -0.032           |

Note: CO, HO, GAS, GLD, and BTC stand for crude oil, heating oil, gasoline, gold, and Bitcoin, respectively. Meanwhile, LL refers to the maximized log-likelihood.

Table A.3
The estimated parameters of the best-fit copulas of regular vine for dependent return models during COVID-19.

| Tree Edge Copula          | $\theta$  | LL     | Kendall's $\tau$ |
|---------------------------|-----------|--------|------------------|
| Energy Commodities        |           |        |                  |
| $T_1$ HO,GAS Frank        | 8.523     | 224.892| 0.621            |
| $T_2$ CO,GAS|HO 180°-rotated Gumbel | 1.220    | 29.571 | 0.180            |

| Energy Commodities and Gold|           |        |                  |
| $T_1$ GLD,CO 180°-rotated Gumbel | 1.070    | 5.778 | 0.065            |
| HO,GAS Frank              | 8.535     | 228.539| 0.622            |
| $T_2$ GLD,GAS|HO 270°-rotated Gumbel | 1.034    | 1.547 | -0.033           |
| $T_3$ GLD,GAS|CO,HO Gumbel | 1.220    | 29.571 | 0.180            |

| Energy Commodities and Bitcoin|           |        |                  |
| $T_1$ HO,CO Frank           | 8.535     | 228.539| 0.622            |
| $T_2$ CO,GAS|HO 180°-rotated Gumbel | 1.220    | 29.571 | 0.180            |
| $T_3$ GAS,BTC|HO,CO 180°-rotated Clayton | 0.131    | 4.285 | 0.062            |

Note: CO, HO, GAS, GLD, and BTC stand for crude oil, heating oil, gasoline, gold, and Bitcoin, respectively. Meanwhile, LL refers to the maximized log-likelihood.

for this portfolio and Bitcoin returns produces better downside risk reductions than the previous vine copula approach. However, the former neglects strong dependence among the overall energy commodity instruments, whose measures have been provided before in Fig. 3, and, therefore, may be less appropriate.

4. Conclusions

The gold’s and Bitcoin’s safe-haven roles for international energy commodities are examined since turbulence in their markets occurred following the COVID-19 outbreak. The risk measure of SDPP and the corresponding relative SDPP have been used to assess these roles. Specifically, we compare the portfolio downside risk reduction ability of gold and Bitcoin after being blended with energy commodities under dependence assumption through a vine copula approach. It is found that the inclusion of gold and the involvement of Bitcoin in energy commodity investments bring different structures of dependence. We further show that gold with any allocation is capable of serving as a safe-haven asset for energy commodities in times under consideration. In contrast, the safe-haven functionality of Bitcoin appears to be inconsistent and, therefore, Bitcoin is not the new gold as noted by Klein et al. (2018). These findings are in line with those of Dutta et al. (2020) who investigated the relationship between gold/Bitcoin and crude oil. However, the investigation of gold–oil interaction may come to different findings (e.g., Reboredo, 2013) when using an approach based on average dependence or tail dependence. It revealed that gold was not able to hedge against oil price movements on average,
but it acted effectively as a safe haven during extreme movements in the oil market due to evidence of tail independence. In practice, hedging may be carried out by not only investors but also portfolio managers and policy designers. According to our findings above, investors and portfolio managers should add more gold (rather than Bitcoin) in their portfolio risk management. Meanwhile, policy designers may make use of this precious metal to stabilize the purchasing power and to maintain energy commodity values (see Reboredo, 2013).

CRediT authorship contribution statement

Khreshna Syuhada: Conceptualization, Methodology, Formal analysis, Writing – original draft, Validation, Writing – review & editing, Supervision. Djoko Suprijanto: Funding acquisition, Project administration. Arief Hakim: Conceptualization, Methodology, Formal analysis, Writing – original draft, Validation, Writing – review & editing, Software.

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Appendix

See Tables A.1–A.3.

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