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Is gold a hedge or safe haven against oil price movements?

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ABSTRACT

This paper assesses the role of gold as a hedge or safe haven against oil price movements. We use an approach based on copulas to analyse the dependence structure between these two markets. Empirical evidence for weekly data from January 2000 to September 2011 revealed the following: (a) there is positive and significant average dependence between gold and oil, which would indicate that gold cannot hedge against oil price movements; and (b) there is tail independence between the two markets, indicating that gold can act as an effective safe haven against extreme oil price movements. These results are useful for both portfolio risk managers and designers of policies aimed at using gold to preserve or stabilise oil exporter purchasing power.

Introduction

Recent joint movements in gold and oil prices have renewed interest in examining linkages between the corresponding markets, given that gold and oil are major commodities and their price movements have important implications for the real economy and the financial markets.[1] Starting in early 2000 (Fig. 1), the crude oil spot price—measured for West Texas Intermediate (WTI)—gradually rose from about 25 US dollars to a historic maximum of about 145 US dollars in mid-July 2008. Meanwhile the price of gold also increased steadily until the first half of 2008 to around 1000 US dollars per ounce. Joint movement in gold and crude oil prices was also observed during the financial crisis: by December 2008, oil prices had fallen to a low of about 30 US dollars and gold prices had dropped to 800 US dollars. Related price movements persisted to a great extent after oil and gold prices turned upwards again from 2009, to reach about 112 US dollars and 1500 US dollars, respectively, by the end of April 2011.

Explanations in the literature regarding the link between gold and oil markets refer to different mechanisms associated with the impact of oil price movements on economic variables and the use of gold as an investment asset. First, the link between gold and oil markets can be explained in inflationary terms. When oil prices rise, the general price level rises (see, e.g., Hooker, 2002; Hunt, 2006) and the price of gold also goes up, opening up the possibility of using this metal as a hedge against inflation (Jaffe, 1989). The relationship between gold and inflation has been widely studied in the literature (see, e.g., Chua and Woodward, 1982; Ghosh et al., 2004; Worthington and Pahlavani, 2007, Tully and Lucey (2007); Blose, 2010 and references therein). A second mechanism reflects how oil prices affect economic growth and asset values (Reboredo, 2010). High oil prices adversely affect economic growth and reduce asset prices, so investors turn to gold as an alternative asset to store value. Empirical studies examining gold's safe-haven status with respect to stock market movements include those by Baur and McDermott (2010) and Baur and Lucey (2010). A third mechanism was proposed by Melvin and Sultan (1990), who observed that oil-exporting countries, in particular, include gold in their international reserve portfolios; when oil prices and revenues rise, they increase their investment in gold in order to maintain its share in their diversified portfolios and this increased demand for gold leads to an increase in its price that mirrors the

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[1] Large oil price hikes have been blamed for economic recessions, trade deficits, high inflation, high investment uncertainty and low stock and bond values. Gold, on the other hand, is traded as an investment asset to hedge against inflation risk and against increasing financial market risk; more particularly, it can be used as a safe haven from market turbulence. Gold and oil may also drive the prices of other commodities (see, e.g., Sari et al., 2010).

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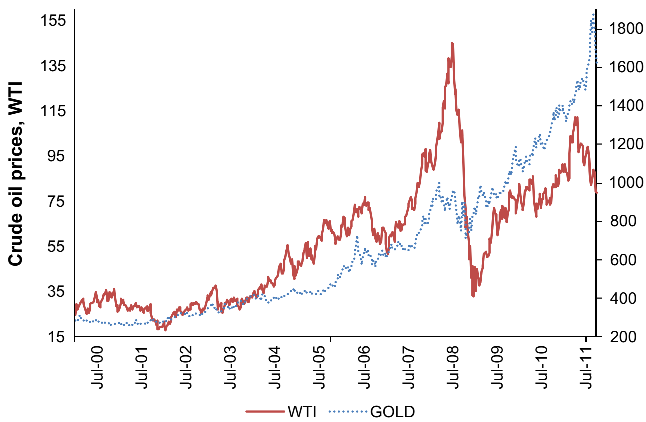

Fig. 1. West Texas Intermediate crude oil spot prices and gold prices in US dollars for the period 4 January 2000 to 29 July 2011.

increase in the oil price. Yet another mechanism reflects the fact that gold and oil are linked through the US dollar exchange rate. When the US dollar depreciates against other major currencies, investors may choose to use gold as a safe haven (see, e.g., Capie et al., 2005; Joy, 2011), thus pushing up gold prices; meanwhile, US dollar depreciation pushes up oil prices (see, e.g., Reboredo, 2012a). These mechanisms all support the argument that gold and oil prices follow quite similar behaviour patterns.

This paper endeavours to shed light upon the gold–oil price relationship by studying the dependence structure between these two commodities. Despite the fact that the different channels described above establish a positive relationship between gold and oil prices, no study to date has analysed gold–oil market co-movement while paying specific attention to tail dependence. We try to fill this gap using copula functions, which measure both average movements across marginals and upper and lower tail dependence (joint extreme movements) and so will help us determine whether gold is a hedge or a safe haven against oil price movements. Knowledge of gold and oil price co-movement is useful for portfolio managers who want to maintain a diversified portfolio and who want investment protection against downside risk. It is also useful for designing policy strategies, given the association between oil and gold and macroeconomic variables such as interest rates and exchange rates (see Soytas et al., 2009). By studying the dependence structure between oil and gold we attempt to contribute to the existing literature in two ways. First, we assess the role played by gold as a hedge or safe haven with respect to oil prices—unlike previous studies, which have examined gold dependence on stock markets (see, e.g., Baur and McDermott, 2010) and on exchange rate markets (see, e.g., Joy, 2011). This dependence is especially relevant for countries with gold in their international reserve portfolio and, in particular, for oil-exporting countries that try to preserve or stabilise purchasing power by investing in gold. Second, we test gold–oil dependence using copulas, which model dependence structures with more flexibility than parametric bivariate distributions. More interestingly, perhaps, copulas enable us to determine whether markets are somewhat dependent or independent on average or in times of market stress; such information is crucial in determining gold's role as a hedge or an investment safe haven.

The rest of the paper is laid out as follows: Section 2 provides a brief overview of the existing empirical literature on the relationship between gold and oil prices. In Section 3, we outline the methodology and test our hypothesis. Sections 4 and 5 present data and results, respectively, and Section 6 concludes the paper.

Literature review

Studies that directly examine the relationship between oil and gold markets are few. In this section we briefly review six papers on this topic.

Baffes (2007), using annual data, examined the pass-through of crude oil price changes to the price of 35 internationally traded primary commodities. He found that the price of precious metals, in particular gold, responded strongly to the crude oil price.

Through three volatility models from the generalised autoregressive conditional heteroskedasticity (GARCH) family, Hammoudeh and Yuan (2008) studied the impact of oil prices and interest rate shocks on gold returns and the volatility of gold returns. For daily data and using an exponential general autoregressive conditional heteroskedastic (EGARCH) model, they found that oil price shocks had an insignificant effect on gold returns and reduced the volatility of gold returns.

Soytas et al. (2009) studied, for Turkey, the relationship between oil prices and gold, silver and other macroeconomic variables using a vector autoregressive model to examine the short-run and long-run relationships between metal prices and the oil price. Based on daily data, they reported that the world oil price had no predictive power over precious metal prices in the Turkish economy.

Using impulse response functions and forecast error variance decompositions, Sari et al. (2010) analysed the effect of oil price shocks on precious metal returns and the US dollar/euro exchange rate. Their empirical evidence for daily data revealed that precious metal markets responded positively and significantly to oil prices, but only in the short-run, with the effect dissipating over the long run.

Narayan et al. (2010) examined the long-term relationship between gold and oil prices (both spot and futures) at different maturities, finding that investors used gold as a hedge against inflation and that oil and gold could be used to mutually predict prices.

Using daily data, Zhang and Wei (2010) studied the co-integration relationship, linear and non-linear Granger causality and price discovery for crude oil–gold markets. Their evidence indicated that crude oil and gold markets shared similar price trends, that there was a long-term equilibrium relationship between the two markets, that there was linear Granger causality from the oil price to the gold price but not vice versa and, finally, that there was no evidence of non-linear Granger causality.

The main feature of these studies, which partially motivates our research, is that there was no analysis of the role of gold as a hedge in a commodity portfolio or as a safe haven with respect to crude oil price movements. Evidence of gold's hedging ability against the US dollar was provided by Capie et al. (2005). Joy (2011) similarly showed, using a model of dynamical conditional correlations, that gold behaved as a hedge against the US dollar, although it was a poor safe haven. The role of gold as a financial asset was studied by McCown and Zimmerman (2006), who showed that gold has inflation-hedging ability and the characteristics of a zero beta asset, with no market risk. Gold's role as a safe-haven asset with respect to stock market movements, meanwhile, was analysed by Baur and Lucey (2010), who showed that gold tended to hold its value in Germany, the UK and the USA when stock markets experienced extreme negative returns. Additionally, Baur and McDermott (2010) showed that gold was both a hedge and a safe haven for major European and US stock markets but not for stock markets in Australia, Canada, Japan and some emerging markets.

Our article contributes to this literature by examining the relationship between gold and oil markets using copulas. The aim was to determine whether these markets are somewhat dependent or independent on average or in times of market stress.

Average and tail dependence is not only crucial information for determining the role of gold as a hedge or investment safe haven; it is also of great importance for investors interested in resisting commodity market risk and particularly in reducing the risk of heavy losses in times of severe market stress. Below we describe the copula methodology and its usefulness in characterising average and tail dependence.

Methodology

To assess the role of gold as a hedge or safe haven against oil prices, we analysed the dependence structure between gold and oil. Knowledge of their joint distribution permits dependence to be measured in several ways, for example, in terms of average movements across marginals or joint extreme movements. We used copulas to flexibly model the joint distribution and we then linked dependence information to the hedge and safe-haven properties of gold.

A copula[2] is a flexible representation of the dependence structure between two random variables that does not constrain the choice of the marginal distributions. According to Sklar (1959) theorem, the joint distribution of two continuous random variables X and Y, $F_{XY}(x,y)$, with marginal functions $F_X(x)$ and $F_Y(y)$, is characterised by a copula function C such that

$$F_{XY}(x,y)=C(F_X(x),F_Y(y)) \tag{1}$$

Thus, copulas can be used to connect margins to a multivariate distribution function, which in turn can be decomposed into its univariate marginal distributions and a copula that captures the dependence structure between the two variables. In terms of construction, the copula is a multivariate distribution function that relates the quantiles of the marginal distributions rather than the original variables; it is thus unaffected by monotonically increasing transformation of the variables.

By relaxing the i.i.d. assumption in Sklar's theorem, Patton (2006) introduced the conditional copula function,

$$F_{XY|W}(x,y|w)=C(F_{X|W}(x|w),F_{Y|W}(y|w)|w), \tag{2}$$

where W is the conditioning variable, $F_{X|W}(x|w)$ is the conditional distribution of $X|W=w$, $F_{Y|W}(y|w)$ is the conditional distribution of $Y|W=w$ and $F_{XY|W}(x,y|w)$ is the joint conditional distribution of $(X,Y)|W=w$.

Copulas are a useful tool for modelling dependence, especially in cases where the joint distribution of two variables is far from the elliptical distribution. In those cases, the traditional dependence measure given by the linear correlation coefficient is insufficient to describe the dependence structure; Embrechts et al. (2003), for example, illustrate the drawbacks of using linear correlation to analyse dependency. Furthermore, some measures of concordance (Nelsen, 2006) between random variables, like Spearman's rho and Kendall's tau, are properties of the copula.

An appealing feature of the copula is tail dependence. Tail dependence measures the probability that two variables are in the lower or upper joint tails of their bivariate distribution. Intuitively, tail dependence is a measure of the propensity of two random variables to go up or down together. The coefficient of upper (right) and lower (left) tail dependence can be expressed in terms of the copula between X and Y as

$$\lambda_U=lim_{u\to 1}Pr\left[X\geq F_X^{-1}(u)\middle|Y\geq F_Y^{-1}(u)\right]=lim_{u\to 1}\frac{1-2u+C(u,u)}{1-u}, \tag{3}$$

$$\lambda_L=lim_{u\to 0}Pr\left[X\leq F_X^{-1}(u)\middle|Y\leq F_Y^{-1}(u)\right]=lim_{u\to 0}\frac{C(u,u)}{u}, \tag{4}$$

where F_X^{-1} and F_Y^{-1} are the marginal quantile functions and where $\lambda_U,\lambda_L\in[0,1]$. Two random variables exhibit lower (upper) tail dependence if $\lambda_L>0$ ($\lambda_U>0$), which indicates a non-zero probability of observing an extremely small (large) value for one series together with an extremely small (large) value for another series.

In order to capture different patterns of dependence and tail dependence, we consider different copula functions. The bivariate Gaussian copula is given by $C_N(u,v;\rho)=\Phi(\Phi^{-1}(u),\Phi^{-1}(v))$, where $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are standard normal quantile functions and where Φ is the bivariate standard normal cumulative distribution function with correlation ρ between X and Y. The Gaussian copula has zero tail dependence, $\lambda_U=\lambda_L=0$. The Student-t copula is defined by $C_{ST}(u,v;\rho,\upsilon)=T(t_\upsilon^{-1}(u),t_\upsilon^{-1}(v))$, where T is the bivariate Student-t cumulative distribution function, with degree-of-freedom parameter υ and correlation ρ, and where $t_\upsilon^{-1}(u)$ and $t_\upsilon^{-1}(v)$ are the quantile functions of the univariate Student-t distribution, with υ as the degree-of-freedom parameter. The Student-t copula allows for symmetric non-zero dependence in the tails (see Embrechts et al., 2003), where large joint positive or negative realisations have the same probability of occurrence, $\lambda_U=\lambda_L=2t_{\upsilon+1}(-\sqrt{\upsilon+1}\sqrt{1-\rho}/\sqrt{1+\rho})>0$. In considering asymmetric tail dependence, we used the Clayton and Gumbel copulas. The degree of dependence in the Clayton copula, given by $C_{CL}(u,v;\alpha)=max(u^{-\alpha}+v^{-\alpha}-1)^{-1/\alpha},0$, is higher in the lower tail than in the upper tail, where it is zero. In contrast, the Gumbel copula, given by $C_G(u,v;\delta)=exp(-((-log\ u)^{\delta}+(-log\ v)^{\delta})^{1/\delta})$, has higher dependence in the upper tail than in the lower tail, where it is zero. Finally, we consider the Clayton–Gumbel copula, defined by $C_{CG}(u,v;\delta,\eta)=\{[(u^{-\delta}-1)^{\eta}+(v^{-\delta}-1)^{\eta}]^{1/\eta}+1\}^{-1/\delta}$, where η determines the upper and lower tail dependence and δ determines only the latter; hence, as $\delta\to 0$, the Clayton–Gumbel copula converges to the Gumbel copula.

In addition, to admit time-varying dependence, we allowed the correlation parameter of the Gaussian and Student-t to vary according to an autoregressive (AR) moving average (MA), specifically, an ARMA(1,q)-type process (as in Patton, 2006):

$$\rho_t=\Lambda(\psi_0+\psi_1\rho_{t-1}+\psi_2\tfrac{1}{q}\textstyle\sum_{j=1}^{q}\Phi^{-1}(u_{t-j})\cdot\Phi^{-1}(v_{t-j})), \tag{5}$$

where $\Lambda(x)=(1-e^{-x})(1+e^{-x})^{-1}$ is the logistic transformation modified to maintain the value of ρ_t in $(-1,1)$. The dependence parameter is explained by a constant, ψ_0, by an AR term, ψ_1, and by the average product over the last q observations of the transformed variables, ψ_2. For the Student-t copula, $\Phi^{-1}(x)$ is substituted by $t_\upsilon^{-1}(x)$. In order to analyse the impact on the joint distribution, other variables, like stock or bond market returns and global risk perceptions, may be added to the dynamic specification of the dependence parameter in Eq. (5).

We can use the information provided by the copula to distinguish between the hedge and safe-haven features of an asset. Firstly, we need to define hedge and safe haven. In this respect, we followed the definitional approach adopted in Kaul and Sapp (2006), Baur and Lucey (2010) and Baur and McDermott (2010):

- Hedge: an asset is a hedge if it is uncorrelated or negatively correlated with another asset or portfolio on average.
- Safe haven: an asset is a safe haven if it is uncorrelated or negatively correlated with another asset or portfolio in times of extreme market movements.

The crucial distinction between these two features is that dependence is required to hold under extreme market movements for a safe haven, whereas, for a hedge, it must do so on average. Baur and McDermott (2010) draw a distinction between strong

[2] For an introduction to copulas, see Joe (1997) and Nelsen (2006).

and weak hedges and safe havens on the basis of the negative or null value of the correlation, respectively.

Both dependence on average and dependence in times of extreme market movements can be obtained from a copula. For dependence on average, the correlation measure (given by the linear correlation, Spearman's rho or Kendall's tau) can be obtained from the dependence parameter of the copula, whereas dependence in times of extreme market movements can be obtained through the copula tail dependence parameter. We can thus formulate two hypotheses in order to determine whether gold can serve as a hedge or as a safe haven against oil prices:

Hypothesis 1. $\rho_{G,O}>0$ (gold is not a hedge),

Hypothesis 2. $\lambda_L>0$ (gold is not a safe haven),

where $\rho_{G,O}$ is the measure of correlation between gold and crude oil prices. Note that gold can act as a hedge if we find evidence against Hypothesis 1. Similarly, gold can serve as a safe-haven asset against downward extreme market movements if Hypothesis 2 is rejected for λ_L. However, extreme upward market movements are also relevant for investors holding short positions; in this circumstance, if Hypothesis 2 is rejected, gold can act as a safe-haven asset against extreme upward market movements by considering λ_U instead of λ_L.

The copula parameters are estimated by maximum likelihood (ML) using a two-step procedure called inference for the margins (Joe and Xu, 1996). From Eqs. (1) and (2), the bivariate density function can be decomposed into the product of the marginal densities and the copula density. Thus, we first estimate the parameters of the marginal distributions separately by ML and then estimate the parameters of a parametric copula by solving the following problem:

$$\theta = \arg\ max_{\theta} \sum_{t=1}^{T} ln\ c(\hat{u}_t, \hat{v}_t; \theta), \tag{6}$$

where θ are the copula parameters, $\hat{u}_t = F_X(x_t; \hat{\alpha}_x)$ and $\hat{v}_t = F_Y(y_t; \hat{\alpha}_y)$ are pseudo-sample observations from the copula. Under standard regularity conditions, this two-step estimation is consistent and the parameter estimates are asymptotically efficient and normal (see Joe, 1997).

For the marginal densities, we considered the widely used threshold generalised autoregressive conditional heteroskedasticity (TGARCH) model introduced by Zakoian (1994) and Glosten et al. (1993). Thus, the crude oil spot price return or the gold return, r_t, can be specified as

$$r_t = \phi_0 + \sum_{j=1}^{p} \phi_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \tag{7}$$

where p and q are non-negative integers and where ϕ and θ are the AR and MA parameters, respectively. The white noise process ε_t follows a skewed Student-t distribution:

$$\sqrt{\frac{\upsilon}{\sigma_t^2(\upsilon-2)}}\, \varepsilon_t \sim i.i.d.t_{\upsilon}, \tag{8}$$

with υ degrees of freedom, where σ_t^2 is the conditional variance of ε_t evolving according to

$$\sigma_t^2 = \omega + \sum_{j=1}^{r} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{m} \alpha_j \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \gamma_j \varepsilon_{t-j} I_{t-j}, \tag{9}$$

where ω is a constant; σ_{t-j}^2 is the previous period's forecast error variance, the GARCH component; ε_{t-j} is news about volatility from previous periods, the ARCH component; $I_{t-j}=1$ if $\varepsilon_{t-j}<0$, otherwise 0; and where γ captures leverage effects. For $\gamma>0$, the future conditional variance will increase proportionally more following a negative shock than following a positive shock of the same magnitude. Leverage or inverse leverage effects have been found in some commodity prices (see, e.g., Mohammadi and Su (2010); Bowden and Payne (2008)). The number of p, q, r and m lags for each series was selected using the Akaike information criterion (AIC).

The performance of the different copula models was evaluated as follows: (a) using the AIC adjusted for small-sample bias, as in Breymann et al. (2001) and Rodriguez (2007); and (b) using a goodness-of-fit test of copulas, as per the pseudo-likelihood ratio test of Chen and Fan (2006), in order to compare the different dependence structures described above.

Data

We used weekly data consisting of a total of 613 price samples from 7 January 2000 to 30 September 2011, showing the trend displayed in Fig. 1. The use of weekly data was more appropriate in our case, given that we wished to characterise a dependence structure. Daily or high-frequency data may be affected by drifts and noise that could mask the dependence relationship and complicate modelling of the marginal distributions through non-stationary variances, long memory or sudden jumps. Our results were insensitive to the choice of a daily or weekly frequency.[3] Gold prices, measured in US dollars per ounce, were downloaded from the website of the Bank of England (http://www.bankofengland.co.uk). Crude oil prices, quoted in US dollars per barrel, were obtained for the WTI benchmark from the US Energy Information Agency (http://www.eia.doe.gov). We used WTI because it is a reference for determining the price of other light crudes in the USA and is closely related to other crude oil markers such as those for Brent, Maya, Dubai, etc (see Reboredo (2011)). Fig. 1 shows that the two markets exhibit consistent price trends, given that they are based on common information.

Table 1 reports descriptive statistics for gold and oil price return series computed on a continuous compounding basis. Average returns were very small relative to the standard deviations and there was no significant trend in the data. The negative values of the skewness statistic suggest a greater probability of large decreases in returns. The return distributions have fat tails, in accordance with the high values for the kurtosis statistic. In fact, the Jarque–Bera test strongly rejected the normality of the unconditional distribution for all the series. Likewise, the existence of serial correlation in the volatility of the returns series was indicated by the Ljung-Box statistic, and the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic suggested that ARCH effects were likely to be found in all the return series. The linear correlation coefficient indicated that oil and gold price returns were dependent; moreover, this dependence increased after the onset of the global financial crisis, even though there was no evidence of any structural change in the correlation coefficient throughout the sampling period.

The dependence structure between gold and oil prices was first examined by obtaining the empirical copula table for the returns in the following way. We ranked each gold–oil return series pairs in ascending order and separated each series uniformly into 10 bins such that bin 1 included the observations with the lowest values and bin 10 included the observations with the highest values. Next, for each series we assigned each observation at time t to its specific bin and counted the number of observations that shared each (i,j) compartment, for $i, j=1, 2,\ldots,10$ and $t=1, 2, \ldots,T$. The number of observations for each (i,j) compartment were included in a 10×10 matrix in such a way that the rows included

[3] The empirical results with data sampled for a daily frequency are available on request.

Table 1
Descriptive statistics for oil and gold price returns.

	Gold	WTI
Mean	0.0028	0.0018
Std. Dev.	0.0267	0.0581
Skewness	−0.3632	-0.6057
Kurtosis	6.5255	8.3014
Jarque–Bera	330.42*	754.12*
Q(20)	418.67*	366.37*
ARCH-LM	10.89*	13.45*
Pearson correlation		
Overall sample	0.2624	
After July 2008	0.3570	

Note: Weekly data for the period 7 January 2000 to 30 September 2011. Jarque-Bera is the χ^2 statistic for the test of normality. $Q(k)$ is the Ljung-Box statistics for serial correlation in the squared returns computed with k lags. ARCH-LM is Engle's LM test for heteroskedasticity, conducted using 20 lags. An asterisk (*) indicates rejection of the null hypothesis at the 5% level.

Table 2
Empirical copula for gold and oil returns.

Gold-WTI	15	17	7	5	2	7	3	3	2	1
	4	7	7	10	9	2	6	6	7	3
	4	2	9	8	5	11	3	6	6	7
	7	7	11	9	6	5	5	4	4	3
	6	8	8	5	3	4	3	11	6	7
	8	4	5	6	6	6	9	2	7	8
	5	5	3	7	7	8	5	6	7	8
	5	3	5	4	6	5	10	10	6	7
	5	5	1	3	9	9	8	5	6	10
	3	3	5	4	8	4	9	8	10	8

Note: For each series there are 612 observations. Gold returns are ranked along the horizontal axis in ascending order (from top to bottom) and oil returns are ranked along the vertical axis in ascending order (from left to right). Each box shows the number of observations belonging to the respective quantiles of the gold and oil series.

the bins of one series in ascending order (from top to bottom) and the columns included the bins of the other series in ascending order (from left to right). Thus, if the two series were perfectly positively (or negatively) correlated, we would see most observations lying on the diagonal connecting the upper-left with the lower-right corner (or the lower-left with the upper-right corner) of the 10×10 matrix; and if they were independent we would expect the numbers in each cell to be about the same. Furthermore, if there was lower tail dependence between the two series we would expect more observations in cell (1,1); and if there was upper tail dependence we would expect more observations in cell (10,10).

Table 2 presents the empirical copula table. There is no clear evidence of positive high dependence, as the number of observations along the upper-left/lower-right diagonal is not much greater than the number of observations in the other cells. Likewise, there are no significant differences in the joint extreme frequencies on comparing the lowest and highest 10th percentiles, thus providing no evidence of potential asymmetric tail dependence. Overall, the results in Table 2 and the dependence shown by the unconditional correlation analysis in Table 1 are entirely consistent.

Empirical results

Results for the marginal models

We estimated the marginal ARMA(p,q)–TGARCH(r,m) distribution model described in Eqs. (7)–(9) for gold and oil returns, considering different combinations of the parameters p, q, r and m for values ranging from zero (no lags) up to a maximum lag of 2, with the most suitable model selected according to AIC values. Results are shown in Table 3. The best model was an ARMA(0,0)–TGARCH(1,1) specification for gold and an ARMA(0,0)–TGARCH (1,0) specification for oil. In general, volatility was quite persistent for both series and the leverage and inverse leverage effects were significant for oil and gold returns, respectively. These results are consistent with previous empirical results for oil price dynamics (Mohammadi and Su, 2010; Reboredo, 2012a; Reboredo, 2012b) and for commodity prices (Bowden and Payne, 2008). The degrees of freedom for the Student-t distribution were relatively low, suggesting that the error terms were not normal; this is entirely consistent with the evidence reported in Table 1. Table 3 also shows that neither autocorrelation nor ARCH effects remained in the residuals.

For the construction of the copula model, the goodness-of-fit assessment of the marginal models is crucial: the copula will be mis-specified if the marginal distribution models are mis-specified, that is, if the probability transformations $\hat{u}_t = F_X(x_t; \hat{\alpha}_x)$ and $\hat{v}_t = F_Y(y_t; \hat{\alpha}_y)$ are not i.i.d. uniform (0,1). Therefore, we evaluated the goodness-of-fit of the marginal distributions following Diebold et al. (1998): if marginal distributions were correctly specified, then $\hat{u}_t$ and $\hat{v}_t$ should be i.i.d. uniform (0,1). We first checked for the i.i.d. assumption by studying the serial correlation of $(\hat{u}_t - \overline{u})^k$

Table 3
Parameter estimates for oil and gold return marginal distributions.

	Gold	WTI
Mean equation		
ϕ_0	0.0034 (3.90)*	0.0040 (1.99)*
Variance equation		
ω	0.0001 (1.89)	0.0003 (2.59)*
α_1	0.2178 (3.10)*	
β_1	0.8352 (16.72)*	0.7991 (13.16)*
λ	−0.1659 (−2.39)*	0.1457 (3.21)*
Tail	10.9645 (2.57)*	8.5968 (3.48)*
Log-Likelihood	1423.44	945.05
Q(20)	23.551 [0.263]	22.634 [0.307]
ARCH(20)	0.74 [0.781]	0.42 [0.987]

Note: This table shows the ML estimates and z statistic (in brackets) for the parameters of the marginal distribution model defined in Eqs. (7)–(9). The lags p, q, r and m were selected using the AIC for different combinations of values ranging from 0 to 2. Q(20) is the Ljung-Box statistic for serial correlation in the model residuals computed with 20 lags. ARCH(20) is Engle's LM test for the ARCH effect in the residuals up to the 10th order. P values (in square brackets) below 0.05 indicate a rejection of the null hypothesis. An asterisk (*) indicates significance at the 5% level.

Table 4
Test of the marginal distribution models for gold and oil returns.

	Gold	WTI
First moment	0.1103	0.2073
Second moment	0.5706	0.5222
Third moment	0.2585	0.7156
Fourth moment	0.3402	0.5615
K–S test	0.8136	0.3592
C–vM test	0.7209	0.2211
A–D test	0.7107	0.1203

Note: This table shows, for the marginal models presented in Table 4, the p values for the LM statistic for the null of no serial correlation of the first four moments of the variables u_t and v_t. For both variables for k=1,2,3,4, $(\hat{u}_t - \overline{u})^k$ and $(\hat{v}_t - \overline{v})^k$ were regressed on 20 lags. The test statistic was distributed as $\chi^2(20)$ under the null. P values below 0.05 indicate rejection of the null hypothesis that the model is correctly specified. Also shown are p values for the Kolmogorov-Smirnov (K–S), Cramer–von Mises (C–vM) and Anderson–Darling (A–D) tests for the adequacy of the distribution model.

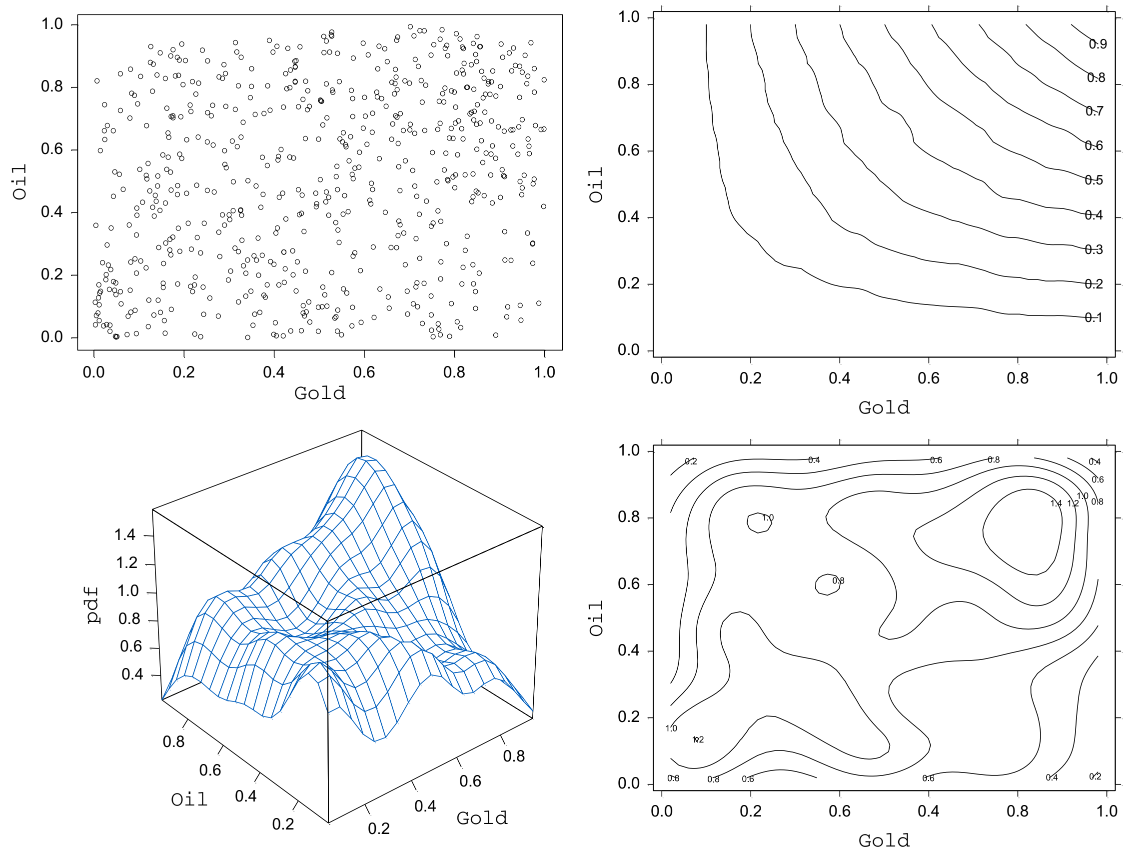

Fig. 2. Empirical non-parametric estimates for the gold–oil copula.

and $(\hat{v}_t - \overline{v})^k$ on h lags for both variables for $k=1,2,3,4$ and used the Lagrange multiplier (LM) statistic under the null of serial independence. The LM statistic, distributed as $\chi^2(h)$ under the null, is defined as $(T-h)R^2$, where R^2 is the coefficient of determination for the regression. Table 4 reports the results of this test for the two marginal distribution models; since they both passed at the 5% level, the i.i.d. assumption could not be rejected. Secondly, we tested whether $\hat{u}_t$ and $\hat{v}_t$ were uniform (0,1) by comparing the empirical distribution and the specified theoretical distribution function using the well-known Kolmogorov–Smirnov, Cramer–von Mises and Anderson–Darling tests. The last rows of Table 4 report the p values for all these tests; for both marginal models, the null of the correct specification for the distribution function could not be rejected at the 5% significance level. To summarise, the goodness-of-fit tests for our marginal distribution models indicated that these were not mis-specified; consequently, the copula model can correctly capture co-movement between gold and oil markets.

Results for the copula models

Before estimating the parametric copulas for the dependence relationship, we first obtained a non-parametric estimate of the copula. This estimate, proposed by Deheuvels (1978), at points $(i/T, j/T)$ is given by

$$\hat{C}\left(\frac{i}{T},\frac{j}{T}\right) = \frac{1}{T}\sum_{k=1}^{T} 1_{\{u_k \le u_{(i)}, v_k \le v_{(j)}\}}, \tag{10}$$

where $u_{(1)} \le u_{(2)} \le \ldots \le u_{(T)}$ and $v_{(1)} \le v_{(2)} \le \ldots \le v_{(T)}$ are the order statistics of the univariate samples and where 1 is the usual indicator function. Fig. 2 depicts a scatterplot for the gold–oil prices and the corresponding non-parametric density estimate. Consistent with the empirical copula results shown in Table 2, the non-parametric density estimates provide graphical evidence of positive dependence between gold and oil prices and no evidence of tail dependence. Interestingly, the bivariate empirical distribution for gold and oil returns—displayed in Fig. 2, an approximate graphical representation of the empirical copula table reported in Table 2—provides informal evidence of: (a) weak dependence of both series at the tails, so the two markets are not booming or crashing together, and (b) a low probability of disjoint extreme market movements, so extreme upward (downward) oil price movements are not in lock-step with extreme downward (upward) gold price movements. Obviously, this evidence has implications for the role of gold as a safe haven asset (discussed below).

Table 5 reports the results for the parametric copula models described above. Examining the symmetric copulas, the dependence parameter in the Gaussian and Student-t copulas was positive, significant and consistently close to the linear correlation coefficient for the data, given that both copulas belong to the elliptical copula family. The degrees of freedom for the Student-t copula were very large, so the Student-t converged to the normal copula. Parameter estimates for the Clayton and Gumbel copulas were significant and reflected positive dependence between gold and oil prices. Tail dependence was also different from zero, although lower tail dependence was quite near to zero for the Clayton copula. Similarly, the estimated parameter values for the Clayton–Gumbel copula, which admits different upper and lower tail dependence values, provided evidence of positive dependence —like the normal copula—and weak upper and lower tail dependence. Finally, time-varying dependence results are reported only for the normal copula, given that the Student-t converged to the normal. Fig. 3 shows the dynamics of the correlation coefficient for the Gaussian copula. Note that, for all sample moments, the correlation coefficient was positive and, ranging as it did between 0.12 and 0.38, was different from zero; the evidence of positive

Table 5
Estimates for the copula models.

		Copula parameters	λ_U	λ_L	Spearman	Kendall
Gaussian copula	ρ	0.253 (0.037)*	0	0	0.242	0.162
	AIC	−37.35				
Student-*t* copula	ρ	0.257 (0.038)*	0	0	0.242	0.162
	υ	100				
	AIC	−34.97				
Clayton copula	α	0.250 (0.050)*	0	0.062	0.166	0.111
	AIC	−30.11				
Gumbel copula	δ	1.175 (0.036)*	0.196	0	0.220	0.148
	AIC	-25.36				
Gumbel–Clayton	δ	0.168 (0.072)*	0.092	0.021	0.208	0.141
	η	1.073 (0.052)*				
	AIC	−30.18				
TVP Gaussian	ψ_0	0.005 (0.009)	0	0		
	ψ_2	0.033 (0.021)				
	ψ_1	2.044 (0.057)*				
	AIC	**−37.95**				

Note: The table reports the ML estimates for the different copula models based on weekly gold and crude oil price data for the period 7 January 2000 to 29 July 2011. Standard errors (in brackets) and the AIC values adjusted for small-sample bias are provided for the different copula models. In bold is the minimum AIC value indicating the best copula fit. For the TVP Gaussian copula, q in Eq. (5) was set to 8. Spearman and Kendall denote Spearman's rho and Kendall's tau, respectively. An asterisk (*) indicates significance at the 5% level.

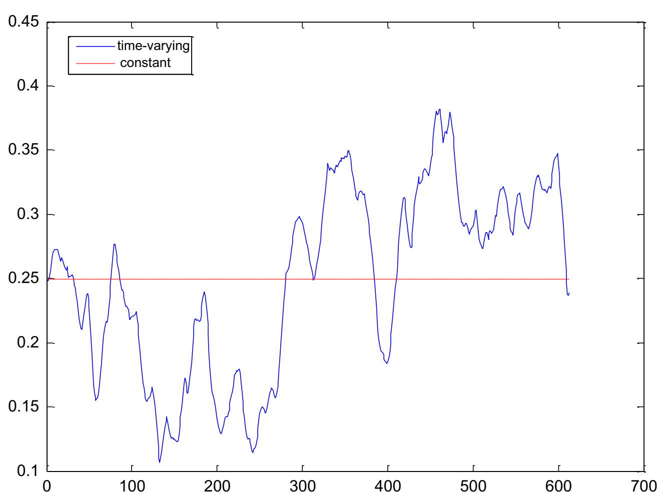

Fig. 3. Conditional correlation for the Gaussian copula.

dependence is thus time consistent. Moreover, the dynamics of the correlation coefficient indicated that dependence increased with the onset of the financial crisis, as this value was above the mean value of 0.25; this is consistent with the evidence regarding the change in the Pearson correlation coefficient reported in the last two rows of Table 1.

On the basis of the estimated copula models we were able to test the hypotheses proposed above regarding gold's hedge and gold's safe-haven status against oil prices. Given that different copula models have different average and tail dependence characteristics, we needed to select the copula that most adequately represented the dependence structure of gold and oil. For the AIC adjusted for small-sample bias, the time-varying normal copula offered the best performance. We also present a formal goodness-of-fit test of copulas based on the Chen and Fan (2006) pseudo-likelihood ratio test, whereby each copula model is compared with a benchmark copula—namely, the Gaussian copula with time-varying parameters (TVP Gaussian), given that this offers the best AIC value. Table 6 presents the results of this test; the TVP Gaussian copula was clearly preferable to any alternative copula

Table 6
Pseudo-likelihood ratio test for comparing dependence structures.

TVP Gaussian vs. Gaussian	−7.001
TVP Gaussian vs. Clayton	−3.935
TVP Gaussian vs. Gumbel	−7.021
TVP Gaussian vs. Clayton–Gumbel	−5.162

Note: Test statistics were obtained using the Chen and Fan (2006) pseudo-likelihood ratio test. An asterisk (*) indicates significance at the 5% level.

specification and so was the best model to represent the dependence structure between the gold and oil markets. Consequently, (a) Hypothesis 1 cannot be rejected since the correlation coefficient is significant and positive for the whole sample period, so gold is not a hedge against oil price movements; and (b) Hypothesis 2 is rejected for both λ_L and λ_U because the Gaussian copula exhibits zero upper and lower tail dependence, so gold is a safe haven against oil price movements. These results remain the same for the global financial crisis for the period July 2008 to September 2011: in re-estimating copula models, the normal copula model with a constant parameter was the best performing model, even though the positive value of the correlation coefficient increased to 0.38.

Our empirical evidence has several important policy and financial implications. First, in order to reduce market risk and maintain a portfolio's commodity value, some oil-exporting countries in the Middle East and North Africa increase their investment in gold as their oil dollar revenues grow. Our evidence against gold's role as a hedge against oil prices indicates that this policy is not a suitable strategy for spreading market risk. However, when oil markets experience extreme upward or downward movements, gold's safe-haven status suggests that these same countries can preserve, or even increase, revenues from extreme increases in oil prices by investing in gold; moreover, by not investing in gold they can protect their oil revenue purchasing power at times of extremely negative oil price movements.

Second, gold's ability to act as a safe haven and its inability to hedge against oil prices may have implications for the effective management of fiscal policy in oil-exporting countries that use sovereign wealth funds to try and isolate government spending from oil revenue volatility. Our results point to positive average dependence and tail independence, indicating that gold, as an asset, is unable to isolate government spending from oil revenues volatility, except in extreme market conditions when gold can represent a diversification mechanism.

Finally, our finding regarding the dependence structure between gold and oil price movements has important implications for asset pricing and risk management, as follows: (a) the existence of left (right) tail independence implies normal downside (upside) risk in investments, in contrast with the case of tail dependence; (b) the absence of extreme joint losses in gold–oil markets implies normal value-at-risk, an important and useful element in risk management; (c) tail independence is important for safety-first investors (Susmel, 2001), who minimise the chances of a loss that might drive them out of business; and finally, (d) as discussed in Poon et al. (2004), since tail dependence—as a true measure of systematic risk in times of extreme market events—has effects on the pricing of assets, investors should be compensated for such risk taking.

Conclusions

We contribute to findings regarding gold–oil market interaction by examining the role of gold as a hedge or an investment safe haven. The distinction is helpful for both portfolio managers with gold and oil in their portfolios and for designers of policy, given that oil and gold are linked to macroeconomic variables such as interest rates and exchange rates and that some oil-exporting countries hold gold in their international reserves portfolio. At the theoretical level, the link between the gold and oil markets is evident in the use that investors make of gold to hedge against inflation and by the fact that some countries include gold in their international asset portfolio; this is especially the case with oil-exporting countries, which use gold to preserve or stabilise the purchasing power of their oil revenues.

Our approach to testing whether gold can serve as a hedge or safe haven is based on using copulas to analyse the dependence structure between the gold and oil markets. We used average dependence and tail dependence information provided by copulas to specifically test for the role of gold. Different copula functions applied to weekly data for the period January 2000 to September 2011 reveal positive and significant dependence between gold and oil on average, implying that gold cannot hedge against oil prices. A different conclusion was drawn regarding gold's role as a safe haven, as we found evidence of tail independence, indicating that gold acts as an effective safe haven in periods of oil market stress. These results have implications for portfolio risk management, for the design of policies aimed at maintaining commodity values for oil-exporting countries and even for the smoothing of spending for governments dependent on oil revenues.

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