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Dynamics and causality in distribution between spot and future precious metals: A copula approach

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Abstract

This paper examines the dependence structure and the Granger causality in distribution (GCD) between spot and future returns of precious metals (gold, silver, and platinum) via copula modelling. This study considers the evidence on real precious metals returns from Jan 2, 2002 to Jan 13, 2017. Throughout literature, the use of copula in precious metals markets is still limited. Indeed, unlike linear methods, using a copula-based approach has several attractive advantages. Our empirical findings show the following: (1) Using static and dynamic copulas, we find that the dependence between the spot and the future returns of precious metals is relatively strong and time varying with a strong tail dependence for all pairs (3) Using independence test based on the empirical copula, we detect a unidirectional GCD from future to spot precious metals market during normal times. This results means that past information from the future returns improve forecasts of spot returns. However, the causal relationship seems to be bidirectional in the case of gold and platinum during crisis periods.

Our findings are important to investors for investigating hedging strategies since the efficacy of a hedging strategy is dependent on the price discovery mechanism. Hence, they should take the above findings into consideration to make optimal decisions, especially during periods of marked instability.

Keywords: Copula, Granger causality in distribution, nonparametric test based on the empirical copula, precious metals, future market, spot market

***JEL classification*:** C02; C58; G1

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Acknowledgment

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1. Introduction

Commodity futures markets are generally considered to perform two major economic functions including risk transfer and price discovery roles.

The futures contract prices transmit information to all economic agents. Indeed, producers may base their supply decisions on the futures contract prices to hedge against the undertaken risks, while physical traders might use futures contracts as a reference to price their commodities. Theoretically, under the market efficiency hypothesis, futures and spot prices must simultaneously reflect new information because they both reflect the same aggregate value of the underlying assets. However, in real word, commodity markets are imperfect; frictions including transaction costs and asynchronous trading drive one market to respond more quickly to new information flows than the other market and a lead–lag relationship occurs.

In particular, as far as the precious metals market is concerned, knowledge of precious metals' future price movements is quite important. Identifying the direction of information flows between spot and futures prices, then, appears to be essential in understanding how fast one market reacts to the new information relative to the other.

The causal relationship between spot and futures markets has been an area of extensive empirical research, as it can help investors during decision-making process and help in discovering potential arbitrage opportunities between spot and futures prices. Therefore, this topic still attracts noteworthy attention from the academic scene.

As might be expected, the empirical results of the literature are mixed. Evidence for a unidirectional causality from the futures market to the spot market is frequently found in the literature (e.g., Joseph et al., 2014; Jena, 2018). Nonetheless, unidirectional causality from spot to futures market (for instance, Srinivasan, 2012) and bidirectional causality were fully identified (e.g., Dash and Andrews, 2010 and Bhatia et al., 2018).

Regarding the methods used in the academic literature, the most conventional methods are Granger causality test, cointegration test, vector error correction model and GARCH models (see, e.g. Shihabudheen and Padhi, 2010; Srinivasan, 2012 and Mayer et al., 2017 among others).

Considering the stochastic properties of metals prices; such as nonlinearity, uncertainty and dynamics, non linear causality models; including causality via quantile approach (e.g. Bhatia et al., 2018; Jena et al., 2019) and causality via copula approach (e.g. Lee and Yang, 2014), has been growing.

In our study, we apply a copula-based approach to model the dependence and causality between spot-future pairs of precious metals. Fist, static and dynamic copulas are applied to analyse the dependence structure between spot-future precious metals pairs. Then, Granger causality in distribution test is applied, as in Lee and Yang (2014), to assess for the causal relationship between spot-future precious metals pairs.

Thus, our contribution to the literature on dynamics and causality between the spot and futures returns in precious metals market is two-fold. First, to the best of our knowledge, our paper being the first of its kind investigates the dynamic and causal relationship between the spot-futures pairs of precious metals returns namely; gold, silver, and platinum using causality copula based model. Second, seeking robustness, this is the first study considering the real prices of precious metals by taking into account inflation and the interest rate. We therefore consider deflated spot prices and deflated-implied spot prices (rather than future prices).

Therefore, the use of a copula-based model enables as to answer two main questions: (1) How do spot and future precious metal markets co-move? (2) What is the nature of the causal relationship between precious metals spot-future pairs?

Our results show a time varying dependence with strong tail dependence for all spot-future pairs. Also, a unidirectional causality from future to spot precious metals market was dected during normal times and the causal relationship seems to be bidirectional in the case of gold and platinum during crisis periods. These results have implications for producers, policy makers, hedgers and speculators.

The remainder of this paper is structured as follows: section 2 is a review of previous works. Section 3 describes the dataset used in this study. Section 4 details the methodology with a brief theoretical background of copula theory. Section 5 reports and discusses the empirical results of our analysis. Finally, section 6 concludes.

2. Literature Review

There exists a considerable body of literature on the dynamics of precious metals which can be divided into different topics. A First main area of interest has been investigating the relationship between precious metals and other market factors such as; exchange rates (e.g., Ciner et al., 2013 and Pierdzioch et al., 2016), inflation (e.g., Hoang et al., 2016 and Salisu et al., 2019), stock market uncertainty captured by the VIX (e.g., Jubinski and Lipton, 2013), oil prices (e.g., Rehman et al., 2018), stock market indices (e.g., Hood and Malik, 2013 and Klein

2017) and risk aversion (e.g., Qadan, 2019). These studies are of key importance regarding the information that they may give about hedging and diversification strategies for investors.

Second stand of literature highlights the stochastic properties of precious metals, their dynamic interlinkages and their volatility spillover. Arouri et al. (2012), find strong evidence of long range dependence in the conditional returns and volatility processes for the daily spot and future precious metals returns. Sensoy (2013) show that gold has a uni-directional volatility shift contagion effect on the other precious metals while silver has a similar effect on platinum and palladium. Lucey et al. (2014) study returns and volatility spillovers between gold cash market and gold futures. They find that returns spill over more strongly than do volatilities. Antonakakis and Kizys (2015) suggested that gold is the dominant commodity transmitter of return and volatility spillovers to the remaining assets under study conditional on time and event-specific patterns. Kang et al. (2017) reported that gold and silver may serve as sources of information transmission among the commodity futures markets and the spillover effects are particularly intensified during recent financial crises. More recently, Balcilar and Ozdemir (2019) examine the dynamic relationships between the price of spot precious metals and their volatility showing that volatility negatively affects the returns of precious metals and the changes in precious metal price returns have positive effects on volatility, meaning that periods with higher (lower) metal price returns are accompanied with higher (lower) return volatility.

Regarding the causality between precious metals spot and futures markets to assess price discovery mechanism; gold market has received the most attention from academic researches. Praveen and Sudhakar (2006) analysed causality between stock market and the commodity futures market. They considered Nifty futures traded on National Stock Exchange (NSE) and gold futures on Multi Commodity Exchange of India (MCX). Based on causality test in the commodity market, a unidirectional causal relationship from the gold futures market toward the spot gold market was detected meaning that gold futures price influenced the spot gold price, but the opposite was not true. Shihabudheen and Padhi (2010) examined the price discovery mechanism and volatility spillovers effect for six Indian commodity markets including gold and silver. For that end, Johansen cointegration test, Error Correction Model (ECM) and bivariate EGARCH model were used. The results for gold and silver supported that futures price acts as an efficient price discovery vehicle. They found that the volatility spillover exists from futures to spot market. Further, Dash and Andrews (2010) studied the causality with reference to many commodities among them gold and silver. Using Granger

causality techniques, they find that for most commodities under study there was bidirectional causality between futures and spot. Pavabutr and Chaihetphon (2010) studied price discovery for gold futures contracts in the Multi Commodity Exchange of India (MCX) over the period 2003 to 2007. By applying Vector Error Correction Model (VECM), results show that gold futures prices lead spot price.

Srinivasan (2012) examined the price discovery process and volatility spillover in Indian spot-future commodity markets including metal market (MCXMETAL) by applying Johansen cointegration test, VECM model and the EGARCH model. VECM model results show that the spot commodity markets play a dominant role and serve as an effective price discovery vehicle. Besides, the bivariate EGARCH model indicates that bidirectional volatility spillover persists and the volatility spillovers from spot to the futures market are dominant.

Arouri et al. (2013) also investigate the efficiency of energy and precious metal markets, by employing four linear and non-linear models based on structural breaks and long memory. Their findings confirm that futures prices do not constitute unbiased predictors of future spot prices although futures prices are found to be cointegrated with spot prices.

Chinn and Coibion (2014) examine whether futures prices are unbiased and/or accurate predictors of subsequent prices by analyzing four groups of commodities including gold. Results show that precious metals are poor predictors of subsequent prices changes, while energy futures fair much better. Using a frequency domain approach, Joseph et al. (2014), find a unidirectional causality from futures to spot market in eight different commodities including gold and silver.

Lakshmi et al. (2015) explore the nexus between spot and futures contracts for crude oil and gold. Results reveal that trading volume of gold futures respond faster to information in market and help to predict gold spot returns, which is not the case for crude oil. Nicolau and Palomba (2015) analyze the dynamic relationship and the direction of causality between spot and futures prices of crude oil, natural gas and gold. Using recursive bivariate VAR model, they find the existence of some interactions between spot and futures prices.

Mayer et al. (2017) looked at the causal relationship between trading activity and spot price volatility for metals; specifically, copper, gold, palladium, platinum, and silver over the period of January 1993 – December 2013. Using Granger causality tests and EGARCH model, they find that there is a strong evidence to suggest that spot prices and volatility drive changes in trading activity. Jena et al. (2018) examine time and frequency varying co-movements between gold LBMA spot market and gold futures traded in COMEX, SGE (Shanghai), and

MCX (India) using daily closing price from 2008 to 2013. Applying wavelet analysis, they find a strong interaction among gold futures and the spot market at different time scales, with the correlation being very high at lower frequencies.

Bhatia et al. (2018) examine the causal relationship among the spot prices of precious metals (gold, silver, platinum and palladium) from April 2000 to July 2016 using a quantile causality approach. Their results show an evidence of bidirectional causality in mean and variance among the prices of precious metals. More recently, Jena et al. (2019) investigate causality between spot and future commodities, including gold and silver, using nonparametric causality -in - quantiles tests. Their results reveal a strong predictability of the futures market in the normal market which declines into extreme bearish and bullish conditions.

Hence, to the best of our knowledge, although several studies investigate the dynamics and causality among precious metals, the causality among pairs of spot-futures precious metals, other than gold, has not been described in the existing literature, which serves as a motivation to undertake this study.

3. Data

3.1. Data description on precious metals

Our dataset consists of daily prices for gold, silver and platinum over the period from Jan 1, 2002 to Jan 13, 2017, making a total of 3924 observations.

Gold and silver bullion spot prices are provided by the London Bullion Market Association (LBMA), while platinum spot prices are collected from the London Platinum Free Market. Gold and silver future prices are from Commodity Exchange, Inc. (COMEX), while platinum future prices are from the New York Mercantile Exchange (NYMEX). With regard to precious metals future prices, the nearby contracts (front-month contracts)[2] were considered in this study, as they are mostly heavily traded as compared to next month and far month futures contracts. All data were extracted from Datastream, a division of Thomson Reuters, and prized in US dollars per troy ounce. These preliminary prices series will be transformed, as described here after, in order to obtain our final dataset.

[2] Futures front month contract refer to the contract month with an expiration date closest to the current date, which is often in the same month.

3.2. Data transformation

Precious metals are by tradition traded in U.S. dollars per troy ounce (oz). Since the dollar exchange rate is changing, it is possible that inflation and other monetary variables like interest rate have real effects on precious metals prices. Hence, considering the real prices is likely to be more important for precious metals.

For robustness, we therefore consider the spot and future prices deflated by the U.S. CPI and the future prices transformed to implied spot prices to take into account the effect of the interest rate. For that end, daily US three-month LIBOR rate and monthly U.S.CPI were derived from the Federal Reserve Bank.

3.2.1. Calculation of the deflated precious metals prices

The spot and future prices of precious metals are deflated by the US CPI. The choice of the US CPI as deflator is a fairly standard practice in the literature.[3]

The daily CPI values are computed from monthly CPI values using linear interpolation method as follows:

$$CPI_d = CPI_{M-1} + \left[\frac{(d-1)}{D-1}(CPI_M - CPI_{M-1})\right], \quad (1)$$

Where;

d: the date of settlement (day in a month),

M: the month in which d occurs,

D: the number of days in the month *M*,

CPI_d: The daily index on day *d*,

CPI_M: The CPI in the month M.

3.2.2. Calculation of the implied spot precious metals prices

The future pricing formula:

$$F(t) = S(t) - Kexp\big(-r(t)\ (T-t)\big), \quad (2)$$

Where; F(t) is the price of future contract, S(t) is the spot price of the underlying asset, r(t) the US interest rate at date t, (T-t) is the time until maturity of the contract and K is the strike price.

[3] Deaton and Laroque (1996) in their celebrated paper deflated commodity prices by the U.S. Consumer Price Index and the literature has followed their lead.

In order to eliminate the interest rate effect, the implied spot prices for each corresponding underlying asset are calculated by inverting the theoretical future pricing formula as follows:

$$S^*(t) = F(t) + Kexp(r(t)\,(T-t)), \tag{3}$$

where; $S^*(t)$ is the implied spot price.

As usual, we consider logarithmic returns, which are defined as the first difference in the natural logarithm of the transformed daily prices such that: $R_t = \ln(P_t) - \ln(P_{t-1})$,

where R_t are returns at time t, P_t and P_{t-1} are current and one-period lagged spot/future prices of precious metals respectively. After eliminating the mismatching transaction days, we finally obtain 3882 log-returns for each series.

Figure 1 shows that spot and future returns exhibit periods of high and low volatility. We can clearly see that all of precious metals returns have similar patterns and display volatility clustering. For each market, the frequency of large and negative price movements is more frequent than that of large and positive price movements reflecting that returns are negatively skewed.

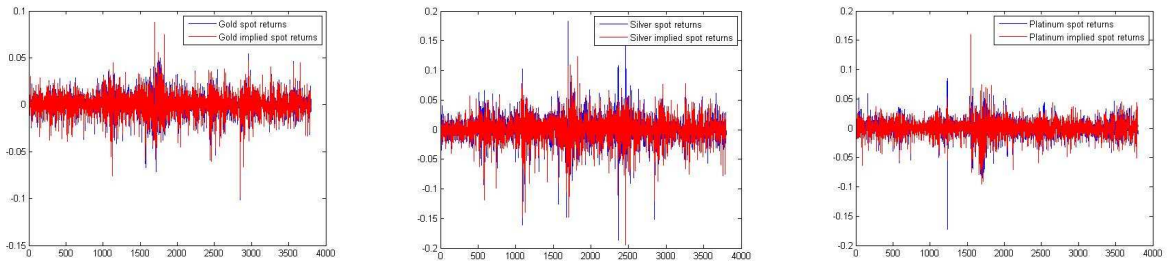

Figure 1 : Precious metals spot and future returns dynamics

4. Methodology

4.1. Copula and dependence

The copula expresses the joint distributions of two or more random variables. Its biggest advantage is, it separates marginal distribution modelling from modelling the copula that combines these marginal into a joint distribution and therefore provides the flexibility to consider the clustering effect of return series and the complexity of the dependence structure at the same time. The cornerstone of the copula theory is the Sklar's theorem which states that a joint distribution $F_{XY}(x, y)$ of two continuous random variables X and Y can be expressed in

terms of a copula function $C(u,v)$ and the marginal distribution functions of the random variables, $F_X(x)$, $F_Y(y)$, as:

$$F_{XY}(x,y) = C(u,v), \tag{4}$$

where $u = F_X(x)$ and $v = F_Y(y)$. Hence, a bivariate copula $C(u,v)$ is a multivariate distribution function in $[0,1]^2$ with uniform marginal distribution in the interval [0,1].[4]

The joint probability density of the variables X and Y can be obtained as follows:

$$f_{XY}(x,y) = c(u,v)f_X(x)f_Y(y)\,, \tag{5}$$

where $f_X(x)$ and $f_Y(y)$ denote the marginal densities of the variables X and Y, respectively and $c(u,v)$ is the copula density which given by $\frac{\partial^2 C(u,v)}{\partial u \partial v}$.

An appealing feature of a copula is that it provides information on average dependence and on tail dependence.

On one hand, the dependence on average is given by dependence measures such as Kendall's tau which measure the dependence as the difference between probability of concordance and probability of discordance which is defined as follows: $\tau(X,Y) = \Pr[(X_1 - X_2)(Y_1 - Y_2) > 0] - \Pr[(X_1 - X_2)(Y_1 - Y_2) < 0]$. And it can be written as a function of the copula as follow: $\tau(X,Y) = 4\int_0^1 \int_0^1 C(u,v)\, d(u,v) - 1 = 4E[C(U,V)] - 1$,where U,V∼U(0,1) with joint distribution function *C*. On the other hand, the dependence structure during periods of extreme market conditions is given by upper (right) and lower (left) tail dependence measures, respectively, as follows:

$$\lambda_U = \lim_{u\to 1} \Pr[X \geq F_X^{-1}(u) \mid Y \geq F_Y^{-1}(u)] = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u}\,, \tag{6}$$

$$\lambda_L = \lim_{u\to 0} \Pr[X \leq F_X^{-1}(u) \mid Y \leq F_Y^{-1}(u)] = \lim_{u\to 0} \frac{C(u,u)}{u}\,, \tag{7}$$

where λ_U, $\lambda_L \in [0,1]$ and X and Y are random variables with distribution functions, respectively F_X and F_Y.

Our study uses a diverse range of copulas with different dependence structures and time-invariant and time-varying parameters to capture the nexus between spot and future precious metal markets.

The symmetric copulas include the Gaussian copula (with tail independence) and Student-*t* copula (with equal lower and upper tail dependence). The asymmetric copulas include the Gumbel copula (with strong upper tail dependence), the Clayton copula (with strong lower tail dependence) and the symmetrised Joe-Clayton copula (SJC), which can be either

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

symmetric or asymmetric and captures the lower and the upper tail dependence at the same time. The main characteristics of copulas functions used in this study are summarized in Table 1 bellow.

Table 1. Bivariate copula functions

Copula	Function	Parameter	Tail dependence
Gaussian	$C(u,v\|\rho) = \Phi(\Phi^{-1}(u), \Phi^{-1}(v))$	$\rho \in [-1,1]$	No tail dependence
t-copula	$C(u,v;\rho,\vartheta) = T(t^{-1}{}_{\vartheta}(u), t^{-1}{}_{\vartheta}(v))$	$\rho \in [-1,1]$	Symmetric tail dependence
Clayton	$C^{C}(u,v;\theta) = \left(u^{\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}}$	$\theta \in (0,\infty)$	Lower tail dependence
Gumbel	$\boldsymbol{C^{G}(u,v;\theta) = exp(-(\,(-ln(u))^{\frac{1}{\theta}} + (-ln(v))^{\frac{1}{\theta}})^{\theta})}$	$\theta \in [1,\infty)$	Upper tail dependence
Joe-Clayton	$C^{JC}(u,v\|\tau^{U},\tau^{L}) = 1 - (1 - \{[1-(1-u)^{k}]^{-\gamma} + [1-(1-v)^{k}]^{-\gamma} - 1\}^{-1/\gamma})^{1/k}$	$\tau^{U} \in (0,1)$ $\tau^{L} \in (0,1)$	$\tau^{U} = \Lambda\left(\omega_{U}^{SJC} + \beta_{U}^{SJC}\tau_{t-1}^{U} + \alpha_{U}^{SJC}\frac{1}{q}\sum_{i=1}^{q}\lvert u_{t-i} - v_{t-i}\rvert\right)$ $\tau^{L} = \Lambda\left(\omega_{L}^{SJC} + \beta_{L}^{SJC}\tau_{t-1}^{L} + \alpha_{L}^{SJC}\frac{1}{q}\sum_{i=1}^{q}\lvert u_{t-i} - v_{t-i}\rvert\right)$
SJC	$\boldsymbol{C^{SJC}(u,v\|\tau^{U},\tau^{L}) = 0,5(C^{JC}(u,v\|\tau^{U},\tau^{L}) + C^{JC}(1-u,1-v\|\tau^{U},\tau^{L}) + u + v - 1)}$	$\tau^{U} \in (0,1)$ $\tau^{L} \in (0,1)$	$\tau^{U} = \tau^{L}$

Notes: λ_U and λ_L denote the lower and upper tail dependence, respectively. For the Gaussian copula $\Phi^{-1}(u)$ et $\Phi^{-1}(v)$ are the standard normal quantile functions and Φ is the bivariate standard normal cumulative distribution function with correlation parameter ρ. For the t-copula $t^{-1}{}_{\vartheta}(u)$ and $t^{-1}{}_{\vartheta}(v)$ are the quantile functions of the univariate Student-t distribution and T is the bivariate Student-t cumulative distribution function with ϑ the degree-of-freedom and ρ the correlation parameter. For the SJC copula, $k = \frac{1}{\log(2-\tau^{U})}$ and $= \frac{-1}{log\tau^{L}}$. τ^{U} and τ^{L}denote the upper and lower tails of the SJC and the Joe-Clayton copulas.

Furthermore, in our study, we consider several time-varying copulas that capture different patterns of time-varying dependence, namely, time-varying Normal, time-varying Student, time-varying Clayton and time-varying SJC copulas.

The time-varying, dynamic or conditional copulas have been introduced by Patton (2006) who extended Sklar's theorem to the conditional case as follow: Given some information set ω, let $F(x,y|w)$ be the bivariate conditional distribution of (X,Y)|W with continuous conditional marginals $F(x|w)$ and $F(y|w)$. Then there is a unique conditional copula function C such that; $F(x,y|w) = C(F(x|w), F(y|w))$.

In this paper, we assume that the dependence parameter is allowed to vary over time following an ARMA(1,10) process.

For the time-varying Gaussian copula, the parameter ?? is defined by Patton (2006) as follow:

$$\rho_t = \widetilde{\Lambda}\left(\omega + \beta\rho_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{10}\Phi^{-1}(u_{t-i})\Phi^{-1}(v_{t-i})\right), \quad (8)$$

where Φ^{-1} is the inverse of the standard normal cumulative density function, $\widetilde{\Lambda}(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is the modified logistic transformation used to keep ρ within the interval

[-1,1], $\beta\rho_{t-1}$ is the autoregressive term that captures the persistence effect and the mean of the product of the last 10 observations of the transformed variables $\Phi^{-1}(u_{t-i})$ and $\Phi^{-1}(v_{t-i})$ captures the variation effect in dependence. For the Student-t copula, the parameter dynamics are also given by Eq. (8) by substituting Φ^{-1} by $t^{-1}{}_{\vartheta}$.

The time-varying dependence processes for the Clayton copula is described as:

$$\theta_t = \left(\omega + \beta\theta_{t-1} + \alpha\frac{1}{10}\sum_{i=1}^{q}|u_{t-i} - v_{t-i}|\right). \quad (9)$$

Finally, for the SJC copula, we specify that the tail dependence parameters τ^U and τ^L vary overtime according to:

$$\tau_t^U = \Lambda\left(\omega_U^{SJC} + \beta_U^{SJC}\tau_{t-1}^U + \alpha_U^{SJC}\frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|\right), \quad (10)$$

$$\tau_t^L = \Lambda\left(\omega_L^{SJC} + \beta_L^{SJC}\tau_{t-1}^L + \alpha_L^{SJC}\frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|\right), \quad (11)$$

where $\Lambda(x) \equiv (1 + e^{-x})^{-1}$ is a logistic transformation used to retain τ_t^U and τ_t^L in (0,1) all the time, $\beta_U^{SJC}\tau_{t-1}^U$and $\beta_L^{SJC}\tau_{t-1}^L$ are the autoregressive terms that capture the persistence effect and the forcing variables represented by the mean absolute difference between u_t and v_t over the previous 10 observations captures the variation effect in dependence.

4.2. Copula based GJR-GARCH model

The copula based-GARCH-type model is a combination between GARCH and copula theory, where the random variables X and Y in the marginal distributions are assumed to follow some time series models, such as the ARMA model for the conditional mean and GARCH type model for the conditional volatility. Therefore, it is able to model simultaneously the volatility dynamics by GJR-GARCH model and the conditional dependence structure by copula functions.

In this study, an AR (1)-GJR-GARCH(1,1)[5] model is adopted for the marginal distributions according to the AIC and BIC information criterion for possible values ranging from zero to four. It should be noted that due to market efficiency, the dependence in mean should be very small, even nil. Thus an AR(1) specification is much more enough to capture this dependence.

[5] The GJR-GARCH (Glosten-Jagannathan-Runkl GARCH) model is an asymmetric variation of GARCH model which captures the stylized fact that negative and positive shocks in stock returns tend to have different impacts on volatility. Hence, the model adds an asymmetric term on the variance equation in order to take into account the leverage effect (prices movements are negatively correlated with volatility).

Moreover, the GARCH type models are flexible, and (1,1) orders are in general enough to model most of the financial series of the literature.[6] The model can be written as:

$$r_t = \mu + \emptyset_1 r_{t-1} + \varepsilon_t \,, \tag{12}$$

$$h_t = \omega + (\alpha_1 + \gamma_1 I_{t-1})\varepsilon_{t-1}^2 + \beta_1 \, h_{t-1}^2 \,, \tag{13}$$

where $\varepsilon_t = z_t \sqrt{h_t}$ such that the innovation z_t is a zero mean and unit variance i.i.d. random variable that follows a Student-t density distribution and h_t is the conditional variance; where ω >0, $\alpha_1, \beta_1 \geq 0$, γ_1 are the asymmetric effect coefficient or the leverage effect and $\boldsymbol{I_{t-1}}$ is an indicator function that takes on the unit value when $\varepsilon_{t-1} < 0$ and zero otherwise. To ensure the stationary of GJR-GARCH model, two conditions are imposed respectively: $\alpha_1 + \gamma_1 \geq 0$ and $\alpha_1 + \gamma_1 + \beta_1 < 1$.

The GJR-GARCH-Copula model is implemented in two steps. The first step consist in estimating GJR-GARCH specifications to capture the dynamic volatility and the stylized facts of our data. In the second step, the standardized residuals obtained from the previously estimated GJR-GARCH models are transformed into uniform variables by means of their empirical cumulative distribution functions to be used as an input in copula parameters estimation. The copula functions are then estimated using a semi parametric two-step estimation method, namely the Canonical Maximum Likelihood, or CML (Cherubini et al., 2004).[7] This method uses empirical probability integral transform in order to obtain the uniform marginals needed to estimate the copula parameter, as a first step. In the second step, copula parameters can then be estimated by maximizing the log likelihood function of the copula density using the uniform variables by solving the following problem:

$$\hat{\theta} = argmax_\theta \sum_{t=1}^{T} \ln c \, (\hat{u}_t \, , \hat{v}_t ; \theta), \tag{14}$$

where $\hat{\theta}$ are the estimated copula parameters and c denotes the copula density.

The performance of the different copula functions is evaluated by using the log likelihood values and the AIC and BIC information criteria.

[6] The order of AR terms and the lag orders of the GARCH model are all specified to be 1, which is in line with Brooks, 2008 who stated that a GARCH-family model with lag order of 1 can sufficiently describe volatility clustering in the data, and higher-order models are rarely used in financial literature.

[7] Using simulation techniques Kim et al. (2007) show that the CML performs better than FML and IFM methods when the marginal distributions are unknown, which is almost always the case in practice.

4.3. Copula-based Granger causality model

In this section, we will briefly present the Granger causality in distribution (GCD) method used in our study. As it's known, Granger causality is a statistical measure of directional influences between two time series. Throughout literature, Granger-causality in mean and in volatility has been widely investigated whereas these tests assume that series are normally distributed and do not detect causality in higher moments. Thus, it is more informative to test GCD to explore a causal relationship between two financial time series.

To explore causality between two time series we use $\{X_t\}$ to denote the preceding variable and $\{Y_t\}$ as the trailing variable. We assume that information set before market X closes is denoted as G_t, and the information set after market X closes but before market Y closes is denoted as Z_t ($Z_t = G_t \cup \{X_t\}$).

Following Lee and Yang 2014, $\{X_t\}$ Granger-cause $\{Y_t\}$ in distribution (in short $\{X_t\}$ GCD $\{Y_t\}$) if $F_Y(y|Z_t) \neq F_Y(y|G_t)$, where $F_Y(y|Z_t) = P(Y_t < y|Z_t)$ and $F_Y(y|G_t) = P(Y_t < y|G_t)$.

There is no Granger-cause in distribution (in short $\{X_t\}$ NGCD $\{Y_t\}$) if $F_Y(y|Z_t) = F_Y(y|G_t)$ a.s. for $\{Y_t\}$.

The above implies that testing NGCD can be based on the following null hypothesis:

$$H_0^1: f_Y(y|Z_t) = f_Y(y|G_t), \tag{15}$$

Where; $f_Y(y|Z_t)$ and $f_Y(y|G_t)$denote densities of conditional distributions respectively $F_Y(y|Z_t)$ and $F_Y(y|G_t)$. Using the fact that joint density function is the product of the conditional density and the marginal density:

$$f_{X,Y}(x, y|G_t) = f_Y(y|Z_t).f_X(x|G_t), \tag{16}$$

and with the assumption that :

$$f_{X,Y}(x, y|G_t) = f_X(x|G_t).f_Y(y|G_t). \tag{17}$$

Hence, the null hypothesis of NGCD in equation (1) can be stated as the null hypothesis that conditional marginal distributions are independent:

$$H_0^2: F_{XY}(x, y|G_t) = F_X(x|G_t).F_Y(y|G_t). \tag{18}$$

Conditional distributions $F_X(x|G_t)$ and $F_Y(y|G_t)$ are modelled using two univariate AR-GARCH(1,1) model and the null hypothesis in eq. (18) is verified using multivariate independence test based on the empirical copula process, following the suggestion of Genest and Rémillard (2004) and Genest et al. (2006, 2007) for standardized residuals.

The test consists in comparing a distance between the empirical copula $\boldsymbol{C}_n$and the independent copula, which is based on the empirical process:

$$\mathbb{C}_n(u) = \sqrt{n}\left(C_n(u) - \prod_{j=1}^{d} u_j\right), \tag{19}$$

where C_n is the empirical copula, which is defined by:

$$C_n(u) = \frac{1}{n}\sum_{i=1}^{n} 1_{\{U_{i1} \le u_1, \ldots, U_{id} \le u_d\}}, \tag{20}$$

With $u = (u_1, \ldots, u_d) \in [0,1]^d, u_1 \ldots u_d$ are the pseudo-observations.

As it is shown by Genest et al. (2007), this test is applied in two steps. Firstly, we simulate the distribution of the test statistics under independence for the sample size under consideration. Secondly, we compute the value of the global Cramér-Von Mises statistic derived directly from the independence empirical copula process.

5. Empirical results and discussion

5.1. Preliminary descriptive statistics of precious metals returns

The descriptive statistics for the spot and implied spot daily returns of precious metals are reported in Table 2. The results show that the mean average returns of the spot and implied spot returns are positive with gold having the highest positive returns. In addition, the silver spot and future markets are the most volatile while the gold spot and future markets are the least volatile. All markets are negatively skewed and have high kurtosis, which means that asymmetry and fat tails in the spot and future returns were evidently rejecting the normality of the series. Moreover, the Jarque–Bera (JB) test reinforce the rejection of the normality hypothesis while, the Ljung-Box (LB) statistic confirm the presence of autocorrelations in the data. Likewise, the ARCH effect test indicates the presence of ARCH effects in all series.

Table 2. Statistical properties for precious metal log-returns.

	Gold		Silver		Platinum	
	Spot	Implied Spot	Spot	Implied Spot	Spot	Implied Spot
Mean (10^{-3})	0.3019	0.2999	0.2600	0.2610	0.1040	0.1076
Std. Dev.	0.0119	0.0120	0.0220	0.0210	0.0146	0.0145
Maximum	0.0686	0.0879	0.1825	0.1229	0.0847	0.1602
Minimum	-0.1014	-0.0980	-0.1871	-0.1953	-0.1726	-0.0957
Skewness	-0.4449	-0.3314	-0.5638	-0.8854	-0.7101	-0.1158
Kurtosis	7.7140	7.7490	11.7176	9.9642	11.8647	10.0699
JB Stat.	3641.85	3638.44	12227.7	8171.39	12755.04	7918.28
Q (20) stat.	31.109	44.20	22.345	19.4641	30.0141	22.996
$Q^2(20)$ stat.	709.71	561.639	834.75	580.83	1030.57	860.94
ARCH LM (10) stat	40.347	70.85	296.71	118.33	153.70	44.68

Notes: The Sdt. Dev. denotes the standard deviation, JB denotes the Jarque–Bera statistic for normality testing, (*) indicates rejection of the null hypothesis at the 5% level. Q^2 (20) denotes the Ljung-Box statistic on the squared residual series for aucorrelation testing. The ARCH LM stat denotes Engle's LM test statistic for heteroskedasticity testing and the P-values are reported in brackets.

Table 3 reports the linear and rank correlation coefficients between pairs of spot-implied spot precious metals returns. The results show that the correlation between all pairs is positive with higher correlation in the gold market and lower correlation in the silver market. This result is associated with the fact that the silver market is a bit liquid and the total trading volume is low compared to gold and platinum markets.

The high correlation between spot and futures markets may be explained by the fact that the futures contract is a good hedge device for the corresponding spot asset since futures prices contain information that can help to predict spot prices. Nevertheless, this does not mean that the two markets move in the same direction or have a symmetric relation, regardless the increase or decrease in price. Therefore, we estimated a range of copulas to take into account the possible asymmetric tail dependence and the possible asymmetric co-movements between precious metals spot and future markets.

Table 3. Linear and rank correlation between spot -implied spot returns pairs of precious metals

		Linear correlation	**Rank correlation**	
		Pearson	**Kendall**	**Spearman**
Spot -Implied spot returns	Gold	0.8194	0.6040	0.7772
	Silver	0.4010	0.2324	0.3347
	Platinum	0.7126	0.5009	0.6759

To have a general insight of the dependence structure, as a preliminary step, we establish the scatter plot of each spot-implied spot pair. Figure 2 shows positive correlation between spot – implied spot pairs of precious metals returns.

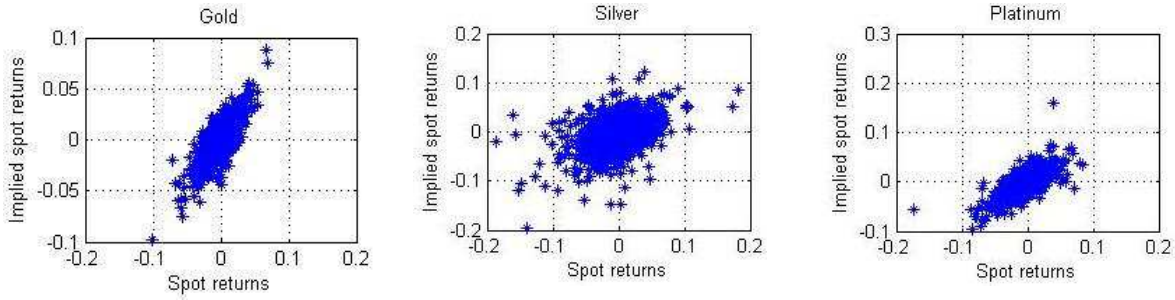

Figure 2 : Scatter plots of spot vs implied spot returns of precious metals

5.2. Marginal models results

To identify the most adequate model among the models of the GARCH family, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) have been used. In this work, daily returns are modelled via an AR (1)-GJR-GARCH (1.1)-*t* model.

Table 4 reports the empirical estimates of the marginal model for returns given by equations (12) and (13). The alpha coefficients which measure the adjustment to past shocks are low and significant for all series. Interestingly, the returns of the gold and silver are characterized by an asymmetric negative impact of shocks on their volatility due to the significance of the gamma coefficient. Moreover, the beta coefficients which measure the volatility persistence of the process are significant for all series which indicates that the conditional volatility is persistent over time and past-dependent.

Table 4. Estimates of AR(1)-GJR-GARCH (1, 1) model parameters

	Gold		Silver		Platinum	
	Spot	Implied spot	Spot	Implied spot	Spot	Implied spot
Panel A: ***Mean equation***						
μ	0.000390	0.000400	0.000313	0.000325	0.000250	0.000205
	(2.411)	(2.419)	(1.222)	(1.175)	(1.325)	(1.031)
ϕ_1	-0.043547	-0.055797	-0.100035	-0.043522	-0.013825	-0.006900
	(-2.904)	(-3.805)	(-6.019)	(-2.900)	(-0.8443)	(-0.4125)
Panel B: ***Variance equation***						
ω (10^4)	0.010199	0.009474	0.023428	0.019412	0.025225	0.016275
	(3.197)	(2.913)	(2.957)	(2.221)	(2.834)	(2.560)
α_1	0.052402	0.045813	0.058868	0.057188	0.071050	0.043488
	(6.657)	(6.511)	(6.830)	(5.638)	(5.863)	(3.937)
β_1	0.956737	0.960466	0.958085	0.95949	0.924873	0.949827
	(194.7)	(205.7)	(148.2)	(145.5)	(70.65)	(92.17)
γ_1	-0.028825	-0.022015	-0.040471	-0.031329	-0.014340	-0.001841
	(-3.097)	(-2.552)	(-4.878)	(-3.177)	(-1.268)	(-0.1780)
ϑ	5.108566	4.908707	5.148647	3.922898	6.400495	6.580866
	(11.37)	(11.94)	(12.20)	(14.65)	(9.933)	(8.393)
Panel C: ***Diagnostic tests***						
LL	11897.4	11829.4	9734.36	9875.31	11215.3	11139.5
Q(20)	13.9438	16.58	9.9895	18.6158	12.5901	17.1231
	[0.8333]	[0.6801]	[0.9684]	[0.5469]	[0.8943]	[0.6450]
Q^2(20)	12.9446	17.2375	14.1205	25.5592	50.5871	32.0751
	[0.8797]	[0.6375]	[0.8243]	[0.1809]	[1.8210^{-4}]	[0.0425]
ARCH LM(10) stat	38.0616	7.9217	2.2010	19.5413	33.0888	1.3411
	[6.8510^{-10}]	[0.0049]	[0.1379]	[9.8410^{-6}]	[8.8010^{-9}]	[0.2468]

Notes: This table reports the ML estimates and t-statistic (in brackets) for the parameters of the marginal distribution model defined in Eqs. (12)-(13). LL denotes log-likelihood values. The $Q(20)$ and $Q^2(20)$ are the Ljung-Box statistics for serial correlation in the model's standardized residuals and standardized squared residuals, respectively, using 20 lags. ARCH is Engle's LM test for the ARCH effect in the standardized residuals up to 10th order. K-S denotes the Kolmogorov-Smirnov test. The reported p values (in square brackets) above 0.05 indicate the acceptance of the null hypothesis that the model distribution is correctly specified.

Indeed, all series are described by significant GARCH effects**.** The results for the diagnostic tests of our marginal models are reported in the Panel *C* of Table 4. The Ljung-Box (Q statistic) and ARCH (LM statistic) statistics indicate that neither autocorrelation nor ARCH effects remained in the residuals of the marginal models.

5.3. Copula based GJR-GARCH model results

In this section, we investigate the estimation results of the static and dynamic copulas. Then, based on the AIC and BIC criteria, we select the best-fit copula model that describes the best the linkage between precious metals spot and futures markets.

Table A in appendix reports the parameter estimates for static copulas. For all pairs, the parameter dependencies of copulas are positive and significant. Regarding the Gaussian and Student copulas, the Spot-Implied spot pairs of Gold and Platinum have higher correlation than the Silver. This means that the spot returns are positive and generally strong in relation with the future returns. The degrees of freedom for the Student-t copula indicate the existence of tail dependence. In considering asymmetric tail dependence, the parameter estimates for Clayton, Gumbel, BB1 and SJC copulas are positively significant which means that the dependence between the spot returns and the future returns vary under different conditions of the market.

Looking to the LL, AIC and BIC values[8], among the static copulas, the Student copula is the best copula to describe the most adequately the dependence structure between pairs of GoldS-GC1 and PlatinumS-PL1 while the dependence between silvers-Sl1 pair is represented by the SJC copula. Regarding the tail dependencies, results from selected copulas show that the pairs GoldS-GC1 and PlatinumS-PL1 exhibit symmetric tail dependence signifying the possibility that the values of spot price and futures prices crashing (booming) together at the same time. The tail dependence of returns between gold spot and future markets ($\hat{\lambda}_L = \hat{\lambda}_U = 0.6$)[9] is highest, while the tail dependence in platinum market is equal to 0.31 ($\hat{\lambda}_L = \hat{\lambda}_U = 0.31$). For the SilverS-Sl1 pair the tail dependence is asymmetric in the upper (τ^{U}) and lower (τ^{L}) tail. ($\hat{\tau}^U = 0.25$, $\hat{\tau}^L = 0.021$).

Finally, for each pair, we estimate the time-varying (tv) Gaussian, Student, Clayton and SJC copulas. The obtained results are reported in Table B in appendix. Based on the LL, AIC and BIC values, we find that the time varying Student copula improves the performance of all the other copula specifications for the Spot-Implied spot pairs of Gold and Platinum. Likewise, the time-varying SJC copula improves the performance of all the other copula specifications for the pairs SilverS-Sl1. These results show a symmetric dynamic dependence between the spot and future market of gold and platinum whereas, the dynamic dependence between spot and future markets of silver is asymmetric.

The estimation results of the time-varying SJC copula for the SilverS-Sl1 pair, show that the parameters β_U^{SJC} and β_L^{SJC}(which represent the degree of persistence) and $\alpha_U^{SJC}$and α_L^{SJC}(which capture the adjustment in the dependence process) are negative and significant. This result indicates a high persistence in the dependence level and confirms that the dependence varies

[8] We choose the copula which maximizes the LL values and minimizes the AIC and BIC criterion.
[9] Source : Author calculation

in time. Also, the conditional tail dependencies estimation shows that the conditional upper tail dependence ω_U^{SJC} is positively no significant and the conditional lower tail dependence ω_L^{SJC} is positively significant implying that there is a higher possibility of joint extreme events during bear markets rather than bull markets.

Overall, our empirical results on the dependence structure between precious metals spot and future markets can be summarized as follows:

(1) The linkage between all spot-future pairs is characterized by time varying dependence structure. This dependence is generally strong on average.

(2) The dependence between all spot-future pairs is characterized by tail dependence which is relatively strong.

5.4. Copula- based Granger causality test results

In order to further justify the use of the Grange causality in distribution test, the behavior in terms of nonlinearity of the variables under consideration was examined. To assess the existence of nonlinearity, the BDS test of serial independence proposed by Broock et al. (1996) was employed on the residuals of the AR (1)-GJR-GARCH (1,1) model for spot and future precious metals returns. The test statistics for the BDS test are presented in Table 5. The results clearly reject the null hypothesis that the variables of interest are independently and identically distributed (*iid*) (across various dimensions (from 2 to 6) and at 1% level of significance). Hence, the phenomenon of nonlinearity is strongly evident in not only precious metals spot and future returns, but also in their relationship.

Table 5: BDS Test results

	Dimension				
	2	3	4	5	6
Spot returns					
Gold	8.407***	8.557***	6.887***	3.743***	1.133
Silver	5.409***	4.894***	4.867***	1.206	4.293***
Platinum	2.535***	4.029***	5.222***	3.286***	9.675***
Implied Spot returns					
Gold	4.106***	4.461***	2.562***	4.616***	2.431***
Silver	8.521***	8.213***	7.334***	7.087***	6.057***
Platinum	4.329***	4.630***	6.768***	4.922***	6.352***

Notes: This table reports the test statistics for the BDS test.
*** Indicates the rejection of the BDS null hypothesis at the 1% level of significance.

Therefore, the linear Granger causality tests may lead to misspecification. (Babalos and Balcilar, 2016; Bekiros et al., 2016). In light of the nonlinearity BDS test results, we proceed with the nonparametric causality in distribution test, which can relied upon to deal with the above mentioned econometric problem.

Our study period covers several periods of instabilities (e.g. the energy cisis (2000-2003), the global financial crisis (2007 - 2008), the great recession (2008 - 2009) and the European debt crisis (2010-2013)). During this period the number of transactions in the commodity market increased rapidly. To conduct the causality over time, we split the period of study into 12 subsamples of 5 years each and the subsample shifts forward by 1 year. Details on the subsamples are listed in Table 6 below.

Table 6: Description of data sets and subsamples

Subsample	Period	Obs.	Subsample	Period	Obs.
1	Jan 02- Dec 06	1263	7	Jan 08- Dec 12	1263
2	Jan 03- Dec 07	1264	8	Jan 09- Dec 13	1262
3	Jan 04- Dec 08	1265	9	Jan 10- Dec 14	1262
4	Jan 05- Dec 09	1264	10	Jan 11- Dec 15	1262
5	Jan 06- Dec 10	1265	11	Jan 12- Dec 16	1263
6	Jan 07- Dec 11	1264	12	Jan 13- Jan 17	1020

The GCD analysis is conducted for each sub-sample from Table, assuming that a preceding variable is a logarithmic rate of return lagged by 1.

For each spot-future pair, each sub-sample and each conditional lag, distribution was modelled with the use of univariate AR(1)-GARCH(1,1), in which standardized residuals follow Student's t-distribution.[10]Causality between pairs is tested using a multivariate independence test based on the empirical copula. Obtained values of Cramér-Von Mises statistic for GCD are presented in Table 7 and Table 8 for all analysed sub-periods.

a) Is there a causal impact of spot precious metals returns on their future returns?

The results of GCD based on the Cramér Von Mises statistic are presented in Table 7. As we can see, gold spot returns do not Granger cause gold future returns in all sub-periods except for the first and second sub-periods (the p-value of the Cramér-Von Mises statistic is below the 5% significance level). For platinum, spot returns Granger cause future returns only in the

[10] The order of AR terms and the lag orders of the GARCH model are all specified to be 1, as (Brooks, 2002) stated that a GARCH-family model with lag order of 1 can sufficiently describe volatility clustering in asset returns, and higher-order models are rarely used in financial literature.

first five sub-periods (from 2002 to 2010). Meanwhile, silver spot returns do not Granger cause the silver future returns in all sub-periods.

These results indicate that past information from the spot returns does not improve forecasts of future returns.

Table 7: GCD testing results (S→F)

	Gold		**Silver**		**Platinum**	
	S→F		S→F		S→F	
Subsample	CM	P-value	CM	P-value	CM	P-value
1	0.0715	**0.0154**	0.0283	0.3361	0.1074	**0.0024**
2	0.0631	**0.0354**	0.0312	0.2842	0.1653	**0.0005**
3	0.0501	0.0894	0.0402	0.1523	0.1013	**0.0094**
4	0.0437	0.1113	0.0374	0.1713	0.0907	**0.0064**
5	0.0493	0.0914	0.0356	0.2122	0.0638	**0.0334**
6	0.0421	0.1283	0.0293	0.3011	0.0260	0.3921
7	0.0334	0.2542	0.0280	0.3691	0.0192	0.6838
8	0.0341	0.2152	0.0194	0.6438	0.0189	0.6698
9	0.0211	0.5759	0.0233	0.4890	0.0182	0.7117
10	0.0277	0.3361	0.0169	0.7617	0.0156	0.8356
11	0.0392	0.1533	0.0259	0.3991	0.0203	0.6258
12	0.0387	0.1663	0.0327	0.2642	0.0195	0.6338

Notes: S and F refer, respectively, to spot returns and future returns.

b) Is there a causal impact of future precious metals returns on their spot returns?

The results of GCD for testing causality from precious metals future returns to spot returns are presented in Table 8. The results show that in all sub-periods precious metals future returns Granger-cause spot returns (the p-value of the Cramér-Von Mises statistic is below the 5% significance level). Thus, this implies that information is first disseminated in the future market and then later reflected in the spot market. This result is mainly due to the higher liquidity and lower transaction costs of the future market. Such advantages attract traders and make the futures market react first to market information. Hence, the future prices lead the spot market prices.

Table 8: GCD testing results (F→S)

	Gold		Silver		Platinum	
	F→S		F→S		F→S	
Subsample	CM	P-value	CM	P-value	CM	P-value
1	0.3742	**0.0005**	6.6240	**0.0005**	0.4004	**0.0005**
2	0.2387	**0.0005**	6.2864	**0.0005**	0.2836	**0.0005**
3	0.1889	**0.0005**	5.7153	**0.0005**	0.3971	**0.0005**
4	0.4106	**0.0005**	5.1615	**0.0005**	0.6165	**0.0005**
5	0.3741	**0.0005**	4.9677	**0.0005**	0.7883	**0.0005**
6	0.4129	**0.0005**	4.3598	**0.0005**	1.1114	**0.0005**
7	0.4955	**0.0005**	4.2037	**0.0005**	1.430	**0.0005**
8	0.4520	**0.0005**	3.7569	**0.0005**	1.4047	**0.0005**
9	0.2195	**0.0005**	3.2684	**0.0005**	1.3396	**0.0005**
10	0.1983	**0.0005**	2.7189	**0.0005**	1.3910	**0.0005**
11	0.1195	**0.0015**	2.6716	**0.0005**	1.3019	**0.0005**
12	0.0735	**0.0284**	1.8993	**0.0005**	0.9200	**0.0005**

Notes: S and F refer, respectively, to spot returns and future returns.

5.5. Discussion and policy implications

By leading this study, additional contributions are made to the literature debate on the causality between spot and futures markets, focusing on the dynamic and the nonlinear causal relationship between precious metals futures and spot returns. This relationship was characterized by a time-varying dependence structure on average and tail dependence during extreme market conditions.

On one hand, by examining the dependence structure between spot-future pairs of precious metals returns, evidence of a strong dependence between all pairs are found. This close relationship between spot and futures precious metals markets makes the information transmission faster between the two markets. This is due to the absence of arbitrage opportunity (AAO) hypothesis implying that if there is a price shift in a market, there is a price shift in the other market to preserve the AAO. This is classical in derivative markets. For instance, in option market, it corresponds also to arbitrager activities, but also to covering covered warrants, making synthetic options etc. Efficient markets should display such a strong dependence.

On the other hand, our results reveal a causal relationship from future to spot market for all pairs and all subsamples which tend to be bidirectional for gold and platinum during some subsamples that refer to crisis periods.

The unilateral causality form derivatives to spot can be explained by the fact that the derivative markets are more professional, and react more instantaneously to shocks from spot markets, whereas spot market investors look less at what's going on in the derivatives markets. Thus a shock in the derivatives market needs time to impact the spot market, making a (temporal) causality. During crisis periods, the markets seem to be less efficient since even shocks in spot markets take time to impact the derivatives markets.

Most empirical studies of the price discovery mechanism support the hypothesis that changes in futures prices lead those in spot prices. However, this is not always the case, and our study confirms this stylized fact. Our results are somehow in line with previous researches and suggest that futures markets dominate spot markets. Although in some subsample periods, our GCD test reveals bi-directional causality between spot-future pairs of gold and platinum. These subsamples cover the energy crises and the global financial crisis.

In general, for all spot-future precious metals pairs, futures returns lead changes in spot returns across all sample sub-periods. Indeed, financial markets are imperfect; frictions including transaction costs and asynchronous trading create a lead–lag relationship between the future market and its underlying spot market so one market responds more quickly to new information than the other market. In reality, the spot market is imperfect; frictions including transaction costs, cash constraints, as well as storage costs for the physical metal create a lead–lag relationship between the future market and its underlying spot market so the spot market responds slowly to new information. In contrast, transactions in the futures market can be implemented immediately by hedgers and speculators who react more swiftly to new information due to lower transaction costs, greater liquidity and flexibility.

Additionally, the spot market is influenced by the speculation, hedging and arbitrage activities in the futures market. Indeed, speculators are interested in earning profit from variations in the market value so they opt for futures contract rather than physical precious metals.

Meanwhile, hedgers who haven't capacity to store physical metals will opt for futures contracts for hedging purposes. As a matter of fact, both speculators and hedgers will respond to news by operating in the futures markets instead of spot markets.

During the first and second sub-samples, we find bidirectional causality between pairs of spot-futures gold returns, which means that both spot and futures prices react simultaneously to new information. This period spans from Jan 2002 to Dec 2007 including the energy crisis and the beginning of the global financial crisis, when we recorded the highest and sharpest gold price increase. During crisis periods, on one hand the large shocks are more correlated,

and on the hand these shocks are not completely transmitted instantaneously to the other market, probably because of the uncertainty of the prediction, and perhaps because of psychological behavior.

6. Conclusion

The study attempts to evaluate the dependence structure and the Granger causality in distribution between spot-future returns pairs of precious metals namely gold, silver, and platinum. There are two main findings in this study.

First, the static and time varying copulas estimation results show a strong dynamic dependence between spot and future returns of precious metals. Regarding the dependence during extreme market conditions, we find strong symmetric tail dependence described by the *t*-copula for gold and platinum spot-future pairs and the SJC copula for silver spot-future pair.

Second, the assessment of Granger causality in distribution was carried out with the use of the non-parametric independence test based on the empirical copula. Our results reveal a unidirectional causality in distribution from future precious metal returns to spot precious metal returns during normal periods. So, we can say that during normal times spot returns of precious metals depend on past values of future returns, which means that the future market leads the spot market. However, the causal effect seems to be bi-directional in times of crises for gold (from 2002 to 2007) and platinum (from 2002 to 2010) due to the high demand in the physical market in such periods. Hence, during time of instabilities the precious metals future and spot returns show the cause and effect relationship.

Our findings are important to traders and investors since understanding market conditions is a central issue as it will help to provide an idea about trading strategies.

In this study, we only focused on an in-sample analysis between the spot and futures precious metals markets by using a non-linear and nonparametric causality test based on empirical copula. Further research might analyze the out-of-sample forecasting of spot and futures precious metals markets.

Appendix

Table A. Static copula estimation

	Gold	Silver	Platinum
Gaussian			
ρ	0.8181729	0.383397	0.7050
	(0.0041)	(0.006)	(0.002)
AIC	-4190.27	-598.13	-2598.39
BIC	-4184.03	-591.88	-2592.15
LL	2096.14	300.06	1300.2
Student			
ρ	**0.8240**	0.3800	**0.7085**
	(0.005)	(0.014)	**(0.008)**
ϑ	**3.1745**	10.3346	**6.1495**
	(0.25)	(1.99)	**(0.735)**
AIC	**-4532.76**	-630.08	**-2712.81**
BIC	**-4520.28**	-617.59	**-2700.32**
LL	**2268.38**	317.04	**1358.4**
Clayton			
θ	0.5328	0.2055	0.4086
	(0.007)	(0.009)	(0.008)
AIC	-3653.2562	-541.0745	-2153.8714
BIC	-3647.0139	-534.8323	-2147.6292
LL	1827.628	271.537	1077.936
Gumbel			
θ	2.5012	1.2834	1.9110
	(0.041)	(0.014)	(0.02)
AIC	-4125.13	-508.36	-2476.18
BIC	-4118.89	-502.11	-2469.94
LL	2063.57	255.18	1239.09
Clayton-Gumbel (BB1)			
θ_1	0.4333	**0.1458**	0.3759
	(0.037)	**(0.028)**	(0.035)
θ_2	2.1654	**1.2324**	1.6668
	(0.043)	**(0.019)**	(0.031)
AIC	-4486.1	**-643.41**	-2696.12
BIC	-4473.61	**-630.93**	-2683.64
LL	2245.05	**323.71**	1350.06
SJC			
τ^U	0.6325	0.1417	00.4917
	(0.008)	(0.022)	(0.017)
τ^L	0.6850	0.2455	0.5324
	(0.010)	(0.010)	(0.014)
AIC	-4402.2437	-638.3618	-2644.5951
BIC	-4389.7593	-625.8773	-2632.1106
LL	2203.122	321.181	1324.298

Notes: (.) contains the corresponding Standard Error. Bold denotes the minimum AIC and BIC values.

Table B. Time varying copula estimates of spot-future pairs

	Gold	Silver	Platinum
DCC-G			
$\boldsymbol{\alpha}$	0.0294	0.0081	0.0147
	(0.007)	(0.002)	(0.009)
$\boldsymbol{\beta}$	0.9616	0.9870	0.9795
	(0.010)	(0.004)	(0.019)
AIC	-4575.7280	-630.8277	-2650.7560
BIC	-4563.2436	-618.3433	-2638.2715
LL	2289.864	317.414	1327.378
DCC-t			
$\boldsymbol{\vartheta}$	**5.3047**	10.7340	**6.5655**
		(2.071)	**(0.780)**
$\boldsymbol{\alpha}$	**0.0240**	0.0084	**0.0140**
		(0.002)	**(0.012)**
$\boldsymbol{\beta}$	**0.9760**	0.9878	**0.9795**
		(0.004)	**(0.025)**
AIC	**-4767.9912**	-663.4257	**-2750.5081**
BIC	**-4749.2645**	-644.6990	**-2731.7814**
LL	**2386.996**	334.713	**1378.254**
tvClayton			
$\boldsymbol{\omega}$	0.1346	-0.3053	0.4302
	(0.042)	(0.151)	(0.057)
$\boldsymbol{\alpha}$	-0.6833	-1.8060	-1.7699
	(0.202)	(0.305)	(0.232)
$\boldsymbol{\beta}$	0.9524	0.2057	0.4070
	(0.017)	(0.141)	(0.098)
AIC	-3941.9980	-588.6755	-2236.4757
BIC	-3923.2713	-569.9488	-2217.7490
LL	1973.999	297.338	1121.238
tvSJC			
$\boldsymbol{\omega_U^{SJC}}$	1.2187	**-0.0930**	2.9010
	(1.891)	**(0.447)**	(0.485)
$\boldsymbol{\alpha_U^{SJC}}$	-0.2331	**-8.5676**	-9.9962
	(0.197)	**(3.001)**	(2.613)
$\boldsymbol{\beta_U^{SJC}}$	-4.0124	**-0.5252**	-0.6934
	(0.763)	**(0.238)**	(0.130)
$\boldsymbol{\omega_L^{SJC}}$	1.3336	**0.8014**	3.3111
	(2.644)	**(0.993)**	(0.573)
$\boldsymbol{\alpha_L^{SJC}}$	-0.2226	**-7.9071**	-9.9986
	(0.837)	**(3.879)**	(3.136)
$\boldsymbol{\beta_L^{SJC}}$	-4.2186	**-0.7081**	-0.7770
	(1.323)	**(0.146)**	(0.135)
AIC	-2208.4831	**-652.9044**	-2690.7123
BIC	-2171.0297	**-615.4511**	-2653.2589
LL	1110.242	**332.452**	1351.356

Note: (.) contains the corresponding Standard Error. The parameters$\boldsymbol{\omega}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are given by Eq.(10). The parameters$\boldsymbol{\omega_U^{SJC}}$, $\boldsymbol{\alpha_U^{SJC}}$and $\boldsymbol{\beta_U^{SJC}}$ are given by Eq.(13). The parameters$\boldsymbol{\omega_L^{SJC}}$, $\boldsymbol{\alpha_L^{SJC}}$and $\boldsymbol{\beta_L^{SJC}}$ are given by Eq.(14). Bold denotes the minimum AIC and BIC values.

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