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## Is the role of precious metals as precious as they are? A vine copula and BiVaR approaches

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### Abstract

This paper revisits the international evidence on hedge, safe haven, and diversification properties of precious metals—namely gold, silver, and platinum—for the G-7 stock markets. Therefore, this study proposes a multivariate vine copula-based GARCH model to assess the hedge and safe haven properties of precious metals and a Bivariate Value at Risk-based copula (BiVaR) measure to analyse the diversification potential of precious metals. Our empirical results suggest that; (1) gold is the strongest hedge and safe haven asset in almost all the G-7 stock markets, (2) silver and platinum results show that they may act as weak hedge assets, (3) silver bears the potential of a strong safe haven role only for Germany's and Italy's stock markets; however, platinum provides a weak safe haven role for most developed stock markets, (4) precious metals appear as interesting assets for diversifying a portfolio for G-7 stock markets investors. Overall, our findings provide noteworthy practical implication for investors.

**Keywords:** Precious metals, G-7 stock markets, hedge, safe haven, diversification, vine copula, BiVaR.

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

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## 1. Introduction

In the aftermath of the Global Financial Crisis, the interest in holding precious metals has been increased, triggering a rise in their prices. This interest is due to the role of precious metals, practically gold, as important stores of value and in diversifying risk (Adrangi et al., 2003; Lucey and Tully, 2006). The literature on the hedging and safe haven potentials of precious metals, especially gold, is among the faster growing fields of the financial literature since the turmoil period of the last decade. Therefore, the aim of this study is to move forward the academic debate on the precious metals-stock markets nexus by examining the hedge, safe haven and diversification properties of precious metals, namely gold, silver, and platinum for the G-7 countries <sup>1</sup> using more flexible copula-based models, named vine copula, that allows a finer analysis. We also deepen the analysis of our results using the BiVaR method.

The existing literature provides evidence that gold may serve as a hedge asset against stock market in normal periods and as a safe haven during turmoil periods (e.g., Baur and Lucey, 2010; Baur and McDermott, 2010; Ciner et al., 2013; Reboredo, 2013; Beckmann et al., 2015, among others). Recently, attention has been shifted from gold in favour of other precious metals, which have often similar properties to gold. Precious metals may serve as hedge assets against various market risks such as exchange rates (e.g., Ciner et al., 2013; Reboredo, 2013b; Bedoui et al., 2019; Nguyen et al., 2020), inflation (e.g., Hoang et al., 2016; Salisu et al., 2019), oil prices (e.g., Rehman et al., 2018) and stock market indices (e.g., Hood and Malik, 2013; Mensi et al., 2015; Ali et al., 2020). Some other studies have documented the stochastic properties of precious metals, their dynamic interlinkages, and their volatility spillover (e.g., Lucey and Li, 2015; Balcilar and Ozdemir, 2019; Talbi et al., 2020). These studies are of key importance regarding information about hedging strategies for investors.

Prior studies on the hedge and safe-haven properties of precious metals for stock markets highlights a heterogeneous role of precious metals against equity movement. A number of papers including Baur and Lucey (2010), Baur and McDermott (2010), Hood and Malik (2013), Ciner et al. (2013), Bredin et al. (2015) and Shahzad et al. (2017) has particularly focused on gold which is traditionally accepted as hedge and safe haven asset. While recent studies have expanded the set of potential hedges and safe havens to other precious metals (e.g., Lucey and Li 2015; Low et al., 2016; Li and Lucey 2017; Ali et al., 2020). On the whole, although the literature has documented the role of precious metals, the results are quite mixed for different markets. This is somewhat to be expected, given the use of different

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<sup>1</sup> The G-7 countries are Canada, France, Germany, Italy, Japan, U.K and U.S

market variables, different countries, different time periods and different methods. Therefore, this incites us to further explore this topic.

To examine the interactions between precious metals and stock markets, various econometric methods have been used, which can be divided into generalized autoregressive conditional heteroskedasticity (GARCH)-type models (e.g., Hood and Malik 2013; Low et al. 2016; Li and Lucey 2017 and Wu and Chiu 2017), vector autoregression (VAR)-type models (e.g., Wan and Kao 2015), wavelet models (e.g., Bredin et al. 2015), bivariate copulas ( e.g., Nguyen et al. 2016) and quantile regression methods ( e.g., Shahzad et al. 2017 and Ali et al. 2020).

In particular, the contribution of this present research consists of three main aspects. Firstly, we extend the analysis of precious metals hedging and safe haven properties by modeling the multivariate dependence using vine copula- based GARCH model to study whether precious metals are strong or weak safe haven and/or hedge for the stock markets. The use of copula in higher dimensions is challenging, where standard multivariate copulas, such as the multivariate Gaussian or Student-t copulas, suffer from inflexibility in modelling the dependence structure among larger numbers of variables and exhibit a problem of parameters restriction so they do not allow for different dependency structures between pairs of variables. Hence, the use of vine copulas overcomes the restrictive characteristics of the bivariate copulas by providing flexible and conditional dependence structure between the variables (Brechmann and Czado 2013; Ji et al. 2018). Therefore, the vine copula approach has been widely used in the context of time series models, risk management and so on (see the review about the financial applications of vine copulas provided by Aas (2016)). Nevertheless, in this paper we use the information of dependence on average and in times of extreme market conditions provided by the vine copula to assess, respectively, for the hedge and safe haven properties of precious metals. Secondly, we propose a new definition of “strong safe haven” property. In fact, the copula can test only for weak safe haven since it provides a non-zero probability of extreme price movements to test for uncorrelated series. So, to overcome this limitation, we propose to use simulated data from the best-fitting copula model to compute the tail correlation to rigorously test for strong safe haven property of precious metals. Finally, a BiVaR novel method proposed by Bedoui et al. (2018), will be employed to check for the diversification potential of precious metals for G-7 investors. As far as we know, we are the first to apply the BiVaR based copula method. The importance of this measure remains in combining the copula and the VaR techniques. In fact, the use of copulas allows to construct a level graph of two-dimensional Value at Risk and examine for a risk level, the marginal rate

of substitution (TMS) between the Value at Risk of precious metal and the stock index. So, this method illustrates the level graph of a two-dimensional Value at Risk in a graphical way which enable us to have a clearer vision on the dependence structure between variable and their positioning with regard to the independence, comonotonicity and anti- monotonicity cases which enable as to analyse the diversification property.

The remainder of this paper is structured as follows: Section 2 presents the state of the art. Section 3 develops the data and the methodology. Section 4 reports and discusses the empirical results of our analysis. Finally, Section 5 concludes.

## **2. Literature review**

In the recent literature, a stream of research emerges focusing on the role of gold and other precious metals as hedges, safe haven and diversifier assets for stock markets. Notwithstanding the vast existing literature on precious metal markets, the gold market has received the most extensive study.

As defined in Baur and Lucey (2010) who provide the first operational definition of hedge and safe haven, an asset is considered to be a strong (weak) hedge instrument when it is negatively correlated (uncorrelated) on average with another asset. For safe haven property, an asset is considered to be a strong (weak) safe haven instrument when it is negatively correlated (uncorrelated) during the extreme market conditions. However, these hypotheses are based on linear models which generally look at linear correlation and cannot capture rare events on the tails of distributions.

In their paper, they examine the static and time-varying relations between United States (US), United Kingdom (UK), and German stock return and gold return using daily data from 1995 to 2005 to evaluate gold as a hedge and a safe haven. They find that gold serves as an effective hedging tool for stocks and has a role as a safe haven in extreme stock market conditions. As an extension of Baur and Lucey (2010)'s work, Baur and McDermott (2010) study the relationship between gold and stock markets in developed and developing countries using multiple-frequency data from 1979 until 2009. They apply rolling window regression to analyse the time-varying relationship between gold return and the world portfolio index. They find that gold serves as a hedge and safe haven only in European and US markets but not in the BRICs markets (Australia, Canada and Japan). Adopting the same methodology, Hood and Malik (2013) study the role of precious metals (gold, silver, and platinum) relative to the Volatility Index (VIX) as a hedge and safe haven against the US stock market; and they find

that, unlike gold, platinum and silver serve neither as a hedge nor as a safe haven for the US stock market. Similarly, Arouri et al. (2015) use a bivariate VAR-GARCH model to study return and volatility spillovers between world gold prices and the Chinese stock market over the period from 22 March 2004, through 31 March 2011. They find significant return and volatility cross effects between the variables, and gold may serve as a safe haven for the Chinese stock market.

Shen et al. (2013) investigate the dependence structure among gold price, stock price index of gold mining companies, and the Shanghai Composite Index in China using bivariate copula based GARCH models and find that the gold return price has positive correlation with stock market returns, which differs from the findings of other research (gold price typically has negative correlation with stock market returns).

Kumar (2014) investigates the mean and volatility transmission between gold and Indian industrial sectors. Using a generalised VAR-ADCC-BVGARCH model, he finds unidirectional and significant return spillover from gold to stock sectors and claims that gold can be considered a valuable asset class that can improve the risk-adjusted performance of a well-diversified portfolio of stocks and acts as a hedge against different markets.

Applying the Dynamic Conditional Correlation (DCC) Multivariate GARCH Model, Lucey and Li (2015) study the safe haven properties of four precious metals (gold, silver, platinum, and palladium) using daily data from 1989 to 2013. They find evidence that in some periods of time, silver and platinum can act as safe haven when gold does not, and the effect can sometimes be stronger.

Nguyen et al. (2016) investigate the role of gold as a safe haven in seven countries: UK, US, Indonesia, Japan, Malaysia, Philippines, Singapore, and Thailand. Using bivariate copulas, they find that gold may be a safe haven asset during a market crash for the cases of Malaysia, Singapore, Thailand, the UK and US markets but not for the Indonesian, Japanese, and the Philippine markets.

Expanding the work of Lucey and Li (2015), Li and Lucey (2017) examine the safe haven properties of precious metals versus equity market movements across a wide variety of countries using daily data from January 1994 to July 2016. Applying the standard approach as outlined in Baur and Lucey (2010) and Baur and McDermott (2010), they find that each metal may play a safe haven role against the stock market during tail events.

Klein (2017) examines the connection of developed markets and precious metal prices using daily data from Jan 2000 to Dec 2016. Applying DCC-GARCH model, he finds that gold and

silver act as safe haven assets while platinum serves as a temporal surrogate safe haven in extreme market conditions.

He et al. (2018) re-examines whether gold is a safe haven asset for UK and US investors. Applying a Markov-switching CAPM (Capital asset pricing model) approach, they find that gold is consistently a hedge but that no distinct safe haven state exists between gold and UK or US stock markets.

Junttila et al. (2018) study the hedging property of gold and oil against stock market risk in times of financial crisis. They find that stock and gold markets become negatively correlated during times of financial crises. Thus, the gold market provides a better hedge than the oil market against stock market risks.

Recently, Ali et al. (2020) re-examine the safe haven, hedge, and diversification potentials of 21 commodities (including precious metals) for 49 international stock markets. Using the cross-quantilogram approach (the quantile dependence across the whole range of quantiles), they find that precious metals in general and gold in particular provide strong safe havens for developed and frontier stock markets.

Table 1 summarises leading works, covering the period 2010 to 2020, that dealt with the hedge, safe haven, and diversification properties of precious metals. In the existing literature, linear models, GARCH-type models, and quantile regressions are frequently used methods. Our contribution to the literature is two-fold. First, we apply a vine copula to analyse the hedge and safe haven properties. Then, we propose a novel method, the BiVaR measure, to examine the diversification potential of precious metals.

**Table 1. Literature review summary**

<b>Authors</b>	<b>Precious metal</b>	<b>Stock markets data</b>	<b>Examined Property</b>	<b>Model</b>	<b>Findings</b>
<b>Baur and Lucey (2010)</b>	Gold	Germany, US and UK	Hedge and safe haven	Asymmetric GARCH	Gold is a hedge and a safe haven
<b>Baur and McDermott (2010)</b>	Gold	Developed and emerging markets	Hedge and Safe haven	Quantile regression approach	Gold is a hedge and a safe haven in Europe and the US and strong safe haven in developed countries
<b>Ibrahim and Baharom (2011)</b>	Gold	Malaysia	Diversifier, Hedge and safe haven	EGARCH model	Gold is a diversifier
<b>Ciner et al. (2013)</b>	Gold	US and UK	Safe haven	DCC model	Gold is a safe haven
<b>Hood and Malik (2013)</b>	Gold, silver and platinum	US	Hedge and safe haven	GARCH model	Gold serves as hedge and weak safe haven
<b>Flavin et al. (2014)</b>	Gold	US	Safe haven	Regime-switching Model	Gold is a safe haven
<b>Bredin et al. (2015)</b>	Gold	Germany, US and UK	Hedge and safe haven	Wavelet analysis	Gold is a hedge and a safe haven
<b>Arouri et al. (2015)</b>	Gold	China	Diversifier, hedge and safe haven	VAR-GARCH	Gold is a hedge and a safe haven
<b>Lucey and Li (2015)</b>	Precious metals	US	Safe haven	DCC model	Silver, platinum and palladium serve as safe haven assets
<b>Chkili (2016)</b>	Gold	BRICS	Hedge and safe haven	Asymmetric DCC model	Gold is a hedge and a safe haven
<b>Mensi et al. (2016)</b>	Gold	Gulf	Hedge and safe haven	Quantile regression and wavelet decomposition	Gold is a strong hedge and safe haven at various investment horizons.
<b>Low et al. (2016)</b>	Gold, silver, platinum and palladium	Brazil, Australia, China, Germany, France, UK and US	Hedge and safe haven	GJR-GARCH model	Gold, silver, platinum and palladium serve as hedges and safe haven assets

**Table 1. (Continued)**



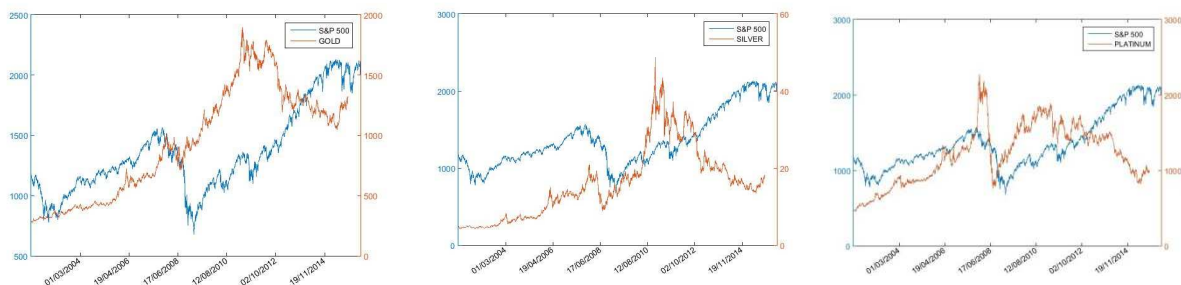
<b>Authors</b>	<b>Precious metals data</b>	<b>Stock markets data</b>	<b>Examined Property</b>	<b>Model</b>	<b>Findings</b>
<b>Nguyen et al. (2016)</b>	Gold	Japan, Singapore, Malaysia, Thailand, Philippines, US and UK	Hedge and safe haven	Copula	Gold serve as a safe haven asset for US, UK, Singapore and Thailand
<b>Li and Lucey (2017)</b>	Gold, silver, platinum and palladium	Developed and emerging markets	Safe haven	Asymmetric GARCH	Precious metals serve as safe haven assets for all countries under study clustered during some periods.
<b>Shahzad et al. (2017)</b>	Gold	Developed and Eurozone peripheral	Diversifier, hedge and safe haven	Quantile-on-quantile method	Gold is a strong hedge and a diversifier asset
<b>Bekiros et al. (2017)</b>	Gold	BRICS	Diversifier, hedge and safe haven	Multi-scale wavelet copula-GARCH	Gold is a diversifier asset
<b>Wu and Chiu (2017)</b>	Gold	US	Diversifier and safe haven	Asymmetric GARCH model	Gold is a safe haven
<b>Wen and Cheng (2018)</b>	Gold	BRICS, Chechnya, Malaysia, and Thailand	Safe haven	Copula	Gold is a safe haven for emerging markets
<b>Raza et al. (2019)</b>	Gold	Developed, emerging markets Europe, Asia Pacific and Islamic stock markets	Hedge and diversifier	DCC model	Gold serves as a hedge and diversifier asset
<b>Ali et al. (2020)</b>	Gold, silver, platinum and palladium	49 international stock markets	Safe haven, hedge, and diversification	Cross-quantilogram approach	Precious metals and gold in particular provide strong safe havens for developed and frontier stock markets.

### 3. Data and methodology

#### 3.1. Data description

This study considers daily prices data for precious metals and stock indices. The precious metals include PM fixing of London of the US\$/Troy ounce for gold,<sup>2</sup> the PM fixing of London Platinum price in US\$/Troy ounce, and the silver price in US\$/kilogram fixed by the London Bullion Market (LBMA). We consider the following G-7 stock market indices: S&P/TSX Composite (Canada), CAC 40 (France), DAX (Germany), FTSE MIB (Italy), Nikkei 225 (Japan), FTSE 100 (UK) and the S&P 500 (US). The study period runs from 01 January 2002 through 05 February 2018, which covers several turbulent periods and crises, including the energy price instability period and 2008–2009 GFC. All data were extracted from DataStream, a division of Thomson Reuters, and priced in US dollars. All variables are transformed into logarithmic returns, which are defined as the first difference in the natural logarithm of the daily prices, such that  $R_t = \ln(P_t) - \ln(P_{t-1})$ , where  $R_t$  are returns at time  $t$ , and  $P_t$  and  $P_{t-1}$  are the current price and one-period lagged price, respectively.

Fig 1 displays the dynamics between precious metals and the S&P 500 index prices during the sampling period.<sup>3</sup> It reflects that precious metals and the US stock market are poorly correlated. The same is true for the other markets shown in Fig. A 1 in the Appendix. For almost all countries, a falling stock market results in a rise in precious metals demand.



**Fig 1. Precious metals and S&P500 dynamics**

<sup>2</sup> The fixing occurs twice a day, except for silver, which is fixed at noon each day. The price fixing done in the morning is called the AM Fix, while the afternoon fixing is called the PM Fix.

<sup>3</sup> Plots of precious metals and other stock market indexes are reported in Appendix A, **Error! Reference source not found.**

### 3.2. Vine copula model

Copulas have found many successful applications in a various empirical works to model joint distributions of random variables.<sup>4</sup> In his theorem, Sklar (1959) states that any  $n$ -dimensional multivariate distribution can be decomposed into  $n$  marginal distributions and a unique copula. More formally:

$$F(x_1, x_2, \dots, x_d) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \quad (1)$$

where  $F$  is a joint distribution of  $x_1, x_2, \dots, x_n$  with marginal distributions  $F_i = F_i(x_i)$  for  $i = 1, 2, \dots, n$ , and  $C: [0,1]^n \rightarrow [0,1]$  is a copula function. Suppose that  $F_i$  and  $C$  are differentiable. Then, the joint density function is defined as:

$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n f_i(x_i) c(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \quad (2)$$

where  $f_i = f_i(x_i)$  is the (unconditional) density of  $F_i$  and  $c$  is the density of the copula.

Hence, the copula function separates the joint distribution into two contributions: the marginal distributions of each variable and the copula that combines these marginal distributions into a joint distribution.

Given the rich variety of bivariate copulas, they are limited to only one or two parameters to describe the dependence structure among variables. Hence, even though it is simple to generate multivariate Elliptical or Archimedean copulas, they cannot adequately capture the dependence in the multivariate scale.<sup>5</sup> Therefore, we may go beyond these standard multivariate copulas by using vine copula approach, which is a more flexible alternative measure to capture the dependence structure among assets. (Joe, 1997; Bedford and Cooke, 2001, 2002; Kurowicka and Cooke, 2006; Aas et al., 2009)

Technically, a vine copula consists of building a multivariate joint distribution from a cascade of unconditional and conditional bivariate copulas. It is well known that any multivariate density function can be represented as a product of unconditional and conditional densities:

$$f(x_1, \dots, x_n) = f(x_1) \cdot f(x_2|x_1) \cdot f(x_3|x_1, x_2) \dots f(x_n|x_1, \dots, x_{n-1}) \quad (3)$$

Bedford and Cooke (2002) introduced two types of vine copulas: canonical vine copulas (C-vine) and drawable vine copulas (D-vine).

In the C-Vine copula one variable plays a pivotal role. The general  $n$ -dimensional C-vine copula can be written as:

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<sup>4</sup> We refer the reader to Joe (1997) and Nelson (2006) for more details about copulas.

<sup>5</sup> The main characteristics of copula functions used in this study are summarised in Appendix A, Table A 1.

$$c(x_1, \dots, x_n) = \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{i,i+j|1,\dots,i-1} \left( F(x_i|x_1, \dots, x_{i-1}), F(x_{i+j}|x_1, \dots, x_{i-1}) \right) \quad (4)$$

For instance, a 4-dimensional C-vine density decomposition and its hierarchical tree structure are represented as follows:

$$\begin{aligned} f(x_1, x_2, x_3, x_4) &= f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \cdot f_4(x_4) \\ &\cdot c_{1,2}(F_1(x_1), F_2(x_2)) \cdot c_{1,3}(F_1(x_1), F_3(x_3)) \cdot c_{1,4}(F_1(x_1), F_4(x_4)) \\ &\cdot c_{2,3|1}(F_{2|1}(x_2 | x_1), F_{3|1}(x_3 | x_1)) \cdot c_{2,4|1}(F_{2|1}(x_2 | x_1), F_{4|1}(x_4 | x_1)) \\ &\cdot c_{3,4|1,2}(F_{3|1,2}(x_3 | x_1, x_2), F_{4|1,2}(x_4 | x_1, x_2)). \end{aligned} \quad (5)$$

Similarly, D-vine copulas are also constructed by choosing a specific order for the variables in which variables are connected in a symmetric way. The general  $n$ -dimensional D-vine copula can be written as:

$$c(x_1, \dots, x_n) = \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{j,j+i|j+1,\dots,j+i-1} \left( F(x_j|x_{j+1}, \dots, x_{j+i-1}), F(x_{j+i}|x_{j+1}, \dots, x_{j+i-1}) \right). \quad (6)$$

We illustrate an example of 4-dimensional D-vine density decomposition and its hierarchical tree structure as follows:

$$\begin{aligned} f(x_1, x_2, x_3, x_4) &= f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \cdot f_4(x_4) \\ &\cdot c_{1,2}(F_1(x_1), F_2(x_2)) \cdot c_{2,3}(F_2(x_2), F_3(x_3)) \cdot c_{3,4}(F_3(x_3), F_4(x_4)) \\ &\cdot c_{1,3|2}(F_{1|2}(x_1 | x_2), F_{3|2}(x_3 | x_2)) \cdot c_{2,4|3}(F_{2|3}(x_2 | x_3), F_{4|3}(x_4 | x_3)) \\ &\cdot c_{1,4|2,3}(F_{1|2,3}(x_1 | x_2, x_3), F_{4|2,3}(x_4 | x_2, x_3)). \end{aligned} \quad (7)$$

For the selection of the appropriate vine tree structure, pair-copula families and their parameter values, we follow the sequential procedure proposed by Dissmann et al. (2013), which is summarised in Table 2.

**Table 2. Sequential method to select a vine copula model**

Algorithm. Sequential method to select a vine copula model
1- Calculate the empirical Kendall's $\tau$ for all possible variable pairs.
2- Select the tree that maximises the sum of absolute values of Kendall's $\tau$ .
3- Select a copula for each pair and fit the corresponding parameters.
4- Transform the observations using the copula and parameters from Step 3. To obtain the transformed values.
5- Use transformed observations to calculate empirical Kendall's $\tau$ 's for all possible pairs.
6- Proceed with Step 2. Repeat until the vine copula is fully specified.

The estimation of vine copulas is a two-step separation procedure which is called the inference functions for the margin method (IFM). It implies that the joint log-likelihood is

simply the sum of univariate log-likelihoods, and the copula log-likelihood is given as follows:

$$l(x) = \sum_{i=1}^n \ln(f_i(x_i)) + \ln\left(c(F_1(x_1), \dots, F_n(x_n))\right). \quad (8)$$

To full fill the aim of our study, we investigated the conditional dependence structure. As a first step, we filtered the returns using AR(1)-GARCH (1,1) processes.<sup>6</sup> Then, we applied the empirical cumulative distribution function (ECDF) for the standardized residuals. As a final step, we estimated the parameters of the vine copula, mainly the C-vine and D-vine copulas, using the sequential maximum likelihood estimation procedure described in Table 2 in order to examine the multivariate dependence and analysis of the hedge and safe haven properties of precious metals against stock markets.

### 3.3. Testing for hedge and safe haven properties

The use of copulas is crucial since it gives us information about both the average dependence and the dependence in times of extreme market movements (independent from how the marginal distributions are modelled). On one hand, the average dependence is given by correlation measures (Kendall's tau or Spearman's rho) which are obtained from the dependence parameter of the copula. On the other hand, the dependence in terms of extreme market movements is obtained from the copula tail dependence coefficients.

On the basis of copula dependence information, we can formulate the conditions under which a precious metal is characterised as a strong (weak) hedge and/or strong (weak) safe haven for the stock indexes under study as in Table 3.

**Table 3. Hypothesis testing**

Conditions	Conclusion
$\rho_{PM,I} < 0$	Precious metal is a strong hedge
$\rho_{PM,I} = 0$ or strongly near to 0	Precious metal is a weak hedge
$\lambda_L = 0$	Precious metal is a weak safe haven
$\lambda_L = 0$ and $\rho(PM, I I < I_q) < 0$	Precious metal is a strong safe haven

Notes:  $\rho_{PM,I}$  is the average dependence measure (given by the copula parameter or the Kendall tau) between precious metals (PM) and stock market indexes (I) and  $\lambda_L$  is the lower tail dependence coefficient for the joint

<sup>6</sup> We refer readers to see Table A2, in Appendix A

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distribution of precious metals and stock market indexes. We define  $\rho(PM, I|I < I_q)$  as the correlation between precious metals (PM) and stock market indexes (I) at the lower tail of stock returns distribution, where  $I_q$  denotes the  $q^{\text{th}}$  percentile of I.

Based on the values of Kendall's tau, the precious metal serves as a strong hedge when the value of Kendall's tau is negative or equal to zero. Meanwhile, if Kendall's tau is positive and near to zero, the precious metal is considered as a weak hedge. Then, based on the lower tail dependence coefficient  $\lambda_L$ , the precious metal is a weak safe haven asset when it shows zero lower tail dependence ( $\lambda_L = 0$ ) with the stock market index. This means that in this case investors will not experience a loss in their precious metal holdings when the stock market crashes. And, if  $\lambda_L > 0$ , this implies that there is a positive probability of concurrent losses in precious metal and stock market indexes during periods of turmoil. However, positive lower tail dependence does not strictly signify a null probability of positive precious metal returns during the time of significant equity downturns since  $\lambda_L$  is only a conditional probability measure rather than a tail correlation. The reason is that it is more reasonable to compute the value of correlation between stock market (I) and precious metal (PM) returns at the lower tail of the stock returns distribution. Hence, the precious metal is a strong safe haven asset for the stock market if  $\lambda_L = 0$  and  $\rho(PM, I|I < I) < 0$  at the same time.

### 3.4. BiVaR based copula model

Based on the dependence structure computed using copulas, the bivariate Value at Risk (BiVaR) risk measure is implemented to examine the diversification benefits of precious metals. Copulas allow us to draw the level curves of the two-dimensional Value at Risk and examine, for a given threshold level ( $\alpha=5\%$ ), the marginal rate of substitution (TMS) between the VaR of the two univariate risks. Hence, for a given marginal distribution of precious metals and stock returns, it is possible to draw the contours corresponding to the minimum copula (anti-monotonicity case), maximum copula (comonotonicity case), and the independence copula.

Let  $r_X$  and  $r_Y$  be the precious metal and stock market index return series with univariate distribution functions,  $F_X$  and  $F_Y$ , respectively. Hence,  $\forall$  the threshold  $\alpha \in [0,1]$ , we have:

$$\{(r_X, r_Y); F_X(r_X) \cdot F_Y(r_Y) = \alpha\}, \text{ independence case} \quad (9)$$

$$\{(r_X, r_Y); \max(F_X(r_X) + F_Y(r_Y) - 1, 0) = \alpha\}, \text{ anti-monotonicity case} \quad (10)$$

$$\{(r_X, r_Y); \min(F_X(r_X), F_Y(r_Y)) = \alpha\}, \text{ comonotonicity case} \quad (11)$$

The level curves from the empirical copula are given by:

$$\{(r_X, r_Y); \mathbf{C}(F_X(r_X), F_Y(r_Y)) = \alpha\}. \quad (12)$$

The level curves are used to determine the TMS between the two univariate VaR. The higher the level of the empirical curves (approaching the anti-monotonicity case), the more that dependence between the precious metals and stock market indices returns is negative. Hence, there is the presence of a compensation effect. However, the closer the curves are to their lower limit, corresponding to the case of comonotonicity (positive dependence) where the returns tend to move in the same direction, the more the correlation between losses is therefore extremely high. Regarding the curves of multiplication, they correspond to the diversification case (see Cherubini and Luciano, 2001; Bedoui and Ben Dbabis, 2009).

#### 4. Empirical results and discussions

This section discusses the empirical results of this study. The preliminary analyses results are firstly presented. Then, we discuss our main results about the hedge, safe haven and diversification potentials of precious metals for the G-7 stock markets.

##### 4.1. Preliminary analyses results

The descriptive statistics for the daily returns of precious metals and equity indexes are reported in Table 4. Results show that all the means are close to zero, and the standard deviations are small, which means that all series are around the mean. Likewise, among the precious metals, silver has the highest standard deviation, while gold has the lowest, which implies that silver is the most volatile. Moreover, asymmetry and fat tails in the returns were evident for all series. Thus, the results for the skewness and the excess of kurtosis reinforce the rejection of normality. The Jarque–Bera (JB) test rejects the normality hypothesis, while the Ljung-Box (LB) statistic confirmed the absence of serial correlation, except for the Nikkei 225, gold, and platinum. Likewise, the ARCH effect test indicates the presence of ARCH effects in all series.

**Table 4. Descriptive statistics for log-returns**

	CAC40	DAX	FTSE 100	FTSE MIB	NIKKEI 225	S&P\ TSX	S&P500	Gold	Silver	Platinum
Mean( $10^{-2}$ )	0.0102	0.0255	0.0054	-0.0016	0.0211	-0.1195	0.0232	0.0370	0.0270	0.0178
Std. Dev	0.0155	0.0156	0.0134	0.0167	0.0140	0.0983	0.0115	0.0110	0.0200	0.0148
Max	0.1214	0.1236	0.1221	0.1238	0.1164	0.0992	0.1095	0.0684	0.1828	0.0843
Min	-0.117	-0.0960	-0.1150	-0.1542	-0.1211	-6.6025	-0.0947	-0.0960	-0.3535	-0.1728
Skewness	0.0926	0.0573	-0.0203	-0.1592	-0.4742	-0.5417	-0.2356	-0.3902	-1.7524	-0.9114
Kurtosis	8.8223	8.2855	10.7229	9.1053	9.6310	11.2394	11.3305	7.5531	31.2669	12.1964
JB stat	4757,6*	3918,7*	8362,7*	5240,3*	6291,1*	9682,9*	9761,1*	2992*	113751*	12323,7*
Q(20)	63.41*	40.09*	81.20*	46.17*	22.31	68.80*	73.77*	26.53	84.10*	20.89
LM stat	198.79*	171.45*	354.85*	114.19*	243.51*	345.60*	365.35*	40.81*	117.90*	155.82*

Notes: Std. Dev denotes the standard deviation, JB denotes the Jarque–Bera statistic for normality testing. Q (20) denotes the Ljung-Box statistic for autocorrelation testing, LM stat denotes Engle’s LM test statistic for heteroskedasticity testing. (\*) indicates rejection of the null hypothesis at the 5% level.

## 4.2. Main results

In the first step, we filter the returns using GARCH model, aiming to obtain the residuals since copula model request independent and identically distributed (i.i.d) uniform data (the results of AR-GARCH model are presented in Appendix A, Table A 2). Parameter estimates for marginal models of precious metals and stock market returns). Then, we filter the standard innovation by t- distribution. Thereafter, we apply the vine copula to the transformed standardised residuals of each asset returns, mainly the C-vine and D-vine copulas.<sup>7</sup>

Table 5 presents the best vine copula model that fits our data using the Log Likelihood (LL) values, AIC, and BIC criteria. The results show that the D-vine structure for Canada, Japan, UK, and US markets is more appropriate than the C-vine, whereas the latter is more suitable for France, Germany, and Italy than the former.

**Table 5. Vine copula model selection**

Country	Criteria	C-vine	D-vine	Choice
France	LL	<b>1774.82</b>	1773.219	C-vine
	AIC	<b>-3529.64</b>	-3526.438	
	BIC	<b>-3468.428</b>	-3465.226	
UK	LL	1788.083	<b>1791.184</b>	D-vine
	AIC	-3554.167	<b>-3559.85</b>	
	BIC	-3486.834	<b>-3491.96</b>	
Italy	LL	<b>1772.113</b>	1737.825	C-vine
	AIC	<b>-3524.61</b>	-3513.65	
	BIC	<b>-3463.015</b>	-3446.317	
Germany	LL	<b>1773.678</b>	1774.566	C-vine
	AIC	<b>-3527.356</b>	-3459.798	
	BIC	<b>-3466.144</b>	-3459.798	
Japan	LL	1763.845	<b>1766.714</b>	D-vine
	AIC	-3505.69	<b>-3511.429</b>	
	BIC	-3438.357	<b>-3444.096</b>	
Canada	LL	1698.796	<b>1699.391</b>	D-vine
	AIC	-3375.592	<b>-3378.782</b>	
	BIC	-3308.259	<b>-3317.57</b>	
US	LL	1631.687	<b>1741.68</b>	D-vine
	AIC	<b>-3461.136</b>	-3459.617	
	BIC	-3393.803	<b>-3398.405</b>	

Notes: The LL denotes the Log Likelihoods. Bolds denote maximum of LL values and minimum of AIC and BIC values.

<sup>7</sup> Before estimating copula models, we calculate the empirical Kendall’s  $\tau$  for all possible pairs of variables to select the tree that maximises the sum of absolute values of Kendall’s  $\tau$ . (Appendix A, Table A 3) The results shows that platinum has the strongest dependency in terms of the empirical value of pairwise Kendall’s  $\tau$ ; hence, we consider platinum as the first root node. Thereby, the order of variables is as follows. For France, Canada, and US, the order of variables should be the following: Platinum (order 1), Gold (order 2), Silver (order 3), and the Stock Index (order 4). And for the rest of countries, the order is: Platinum (order 1), Silver (order 2), Gold (order 3), and the Stock Index (order 4).



Tables 6-7 represent results of the parameter estimation of the selected C-vine and D-vine copulas for each of the G-7 stock markets.

For France, Germany, and Italy, the first tree of Table 6 shows symmetric upper and lower tail dependence between all pairs, indicating similar dependence during upward and downward periods and an average dependence near to zero, particularly, between platinum and the stock market indexes. This result indicates that platinum may serve as a weak hedge for French, German, and Italian investors. Taking the second tree, results show that gold may serve as both hedge and safe haven on the stock market of France, and silver may have the role of a hedge and a safe haven asset in the stock markets of Germany and Italy. Finally, the third tree shows zero upper tail for France, Germany, and Italy, a weak dependence on average for France, and negative dependence on average for Germany and Italy. This result reveals that silver is a weak hedge and safe haven asset for French investors, and gold serves as a strong hedge and a safe haven asset for German and Italian investors.

**Table 6. Results of estimated parameters for C-vine copulas**

France							
#Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,G}$	t-Student	0.4	0.5938	9.1616	0.1381	0.1381
	$C_{P,S}$	t-Student	0.39	0.5804	8.6912	0.1408	0.1408
	$C_{P,I}$	t-Student	0.09	0.1344	14.7521	0.0032	0.0032
2	$C_{G,SIIP}$	t-Student	0.24	0.3655	12.2644	0.0272	0.0272
	$C_{G,IIP}$	Rotated Gumbel	-0.08	-1.0926	0	0	0
3	$C_{S,IIP,G}$	Clayton	0.02	0.0308	0	0.0168e-8	0
Germany							
#Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,S}$	t-Student	0.39	0.5814	8.7670	0.1397	0.1397
	$C_{P,G}$	t-Student	0.4	0.5932	9.0857	0.1394	0.1394
	$C_{P,I}$	t-Student	0.08	0.1288	15.7353	0.0023	0.0023
2	$C_{S,GIIP}$	t-Student	0.24	0.3637	12.2559	0.0269	0.0269
	$C_{S,IIP}$	Rotated Joe	-0.01	-1.0212	0	0	0
3	$C_{G,IIP,S}$	Rotated Gumbel	-0.09	-1.0968	0	0	0
Italy							
#Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,S}$	t-Student	0.39	0.5812	8.8180	0.1385	0.1385
	$C_{P,G}$	t-Student	0.41	0.5951	9.5462	0.1313	0.1313
	$C_{P,I}$	t-Student	0.08	0.1290	12.071	0.0073	0.0073
2	$C_{S,GIIP}$	t-Student	0.24	0.3637	12.276	0.0268	0.0268
	$C_{S,IIP}$	Rotated Joe	-0.02	-1.0297	0	0	0
3	$C_{G,IIP,S}$	Rotated Gumbel	-0.08	-1.0851	0	0	0

Notes: P= platinum, G=gold, S=silver and I= stock index for each country.  $C_{P,G}$  denotes copula between platinum and gold.  $C_{G,S|P}$  denotes copula between gold and silver given platinum.  $\tau$  is the Kendall's tau of the specified copulas,  $\theta$  is the copula parameter and  $\vartheta$  is the degree of freedom.

In the first tree of Table 7, we observe symmetric upper and lower tail dependence given by the t-copula. We also observe a dependence on average strongly near to zero between silver and stock market indexes for Canada and US and between gold and stock market indexes for UK and Japan, indicating that silver (gold) is only a weak hedge asset for Canadian and American (UK and Japanese) investors. In the second tree, results indicate that gold may serve as a strong hedge and a safe haven asset ( $\lambda_L = 0$ ) against the stock markets of Canada and US. However, silver is only a weak hedge for Japan and UK. Finally, the third tree shows weak dependence on average between platinum and stock market indexes, confirming the role of platinum as a weak hedge for the Canada, US, UK, and Japan stock markets. Regarding lower tail dependence, results indicate zero tail dependence for Canada and US, arguing that platinum is a safe haven for Canadian and American investors.

**Table 7. Results of estimated parameters for D-vine copulas**

Canada							
Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,G}$	t-Student	0.41	0.5955	8.5439	0.1523	0.1523
	$C_{G,S}$	t-Student	0.4	0.5859	10.732	0.1062	0.1062
	$C_{S,I}$	t-Student	0.01	0.0163	14.714	0.0013	0.0013
2	$C_{P,S G}$	t-Student	0.23	0.3575	12.055	0.0272	0.0272
	$C_{G,I S}$	Rotated Joe	-0.01	-1.0234	0	0	0
3	$C_{P,I G,S}$	Survival Clayton	0.01	0.0176	0	0	7.87e-18
UK							
Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,S}$	t-Student	0.39	0.5806	8.5573	0.1438	0.1438
	$C_{S,G}$	t-Student	0.4	0.5865	10.788	0.1056	0.1056
	$C_{G,I}$	t-Student	0.02	0.0319	7.4344	0.0216	0.0216
2	$C_{P,G S}$	t-Student	0.25	0.3889	11.811	0.0339	0.0339
	$C_{S,I G}$	Survival Gumbel	0.06	1.0609	0	0.0780	0
3	$C_{P,I S,G}$	t-Student	0.11	0.1704	20.132	0.0008	0.0008
US							
Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,G}$	t-Student	0.41	0.5951	8.5441	0.1521	0.1521
	$C_{G,S}$	t-Student	0.4	0.5851	10.732	0.1058	0.1058
	$C_{S,I}$	t-Student	0.02	0.0314	10.334	0.0073	0.0073
2	$C_{P,S G}$	t-Student	0.23	0.3579	12.055	0.0273	0.0273
	$C_{G,I S}$	Rotated Joe	-0.02	-1.0354	0	0	0
3	$C_{P,I G,S}$	Gaussian	0.09	0.1342	0	0	0
Japan							

Tree	Blocks	Family	$\tau$	Parameter		$\lambda_L$	$\lambda_U$
				$\theta$	$\vartheta$		
1	$C_{P,S}$	t-Student	0.39	0.5805	8.1081	0.1540	0.1540
	$C_{S,G}$	t-Student	0.4	0.5842	10.601	0.1074	0.1074
	$C_{G,I}$	t-Student	0.02	0.0379	8.7998	0.0133	0.0133
2	$C_{P,G S}$	t-Student	0.25	0.3883	11.645	0.0350	0.0350
	$C_{S,I G}$	Survival Gumbel	0.06	1.0617	0	0.0789	0
3	$C_{P,I S,G}$	t-Student	0.09	0.1433	19.984	0.0007	0.0007

Notes: P= platinum, G=gold, S=silver and I= stock index for each country.  $C_{P,G}$  denotes copula between platinum and gold.  $C_{P,S|G}$  denotes copula between platinum and silver given gold.  $\tau$  is the Kendall's tau of the specified copulas,  $\theta$  is the copula parameter and  $\vartheta$  is the degree of freedom.

In the next step, we estimate the tail correlation between precious metals and stock market index returns to find out if precious metals are strong safe haven assets or just weak safe haven assets for the stock markets under study. For that end, we performed a Monte Carlo simulation with  $N = 10^5$  simulations from the joint distributions characterised by the best fitting copula functions for each country where precious metals are shown to be weak safe haven assets. Then, we compute the correlation between precious metals and stock market index returns at the 1% tail of stock market returns.

**Table 8. Correlation between stock and precious metals returns at 1% tail of stock returns**

		Copula	Tail correlation	Conclusions
<b>France</b>	Gold	Clayton	-0.0005	Strong safe haven
<b>Germany</b>	Gold	Rotated Gumbel	-0.0001	Strong safe haven
	Silver	Rotated Joe	-0.0003	Strong safe haven
<b>Italy</b>	Gold	Rotated Gumbel	-0.0021	Strong safe haven
	Silver	Rotated Joe	-0.0014	Strong safe haven
	Platinum	Student-t	0.0021	Weak safe haven
<b>Canada</b>	Gold	Rotated Joe	-0.0010	Strong safe haven
	Platinum	Survival Clayton	0.0002	Weak safe haven
<b>US</b>	Gold	Gaussian	-0.0001	Strong safe haven
	Platinum	Rotated Joe	0.0042	Weak safe haven

As shown in Table 8, the tail correlation is negative only for gold and silver. Hence, based on our definition of a strong safe haven asset, we conclude that gold may act as a strong safe haven instrument against extreme losses in France, Germany, Italy, Canada, and US stock markets. Silver is a strong safe haven asset in Germany and Italy. However, platinum is a weak safe haven asset against extreme losses in Canada and US stock markets.

Table 9 summarises our empirical findings regarding hedge and safe haven properties of precious metals.

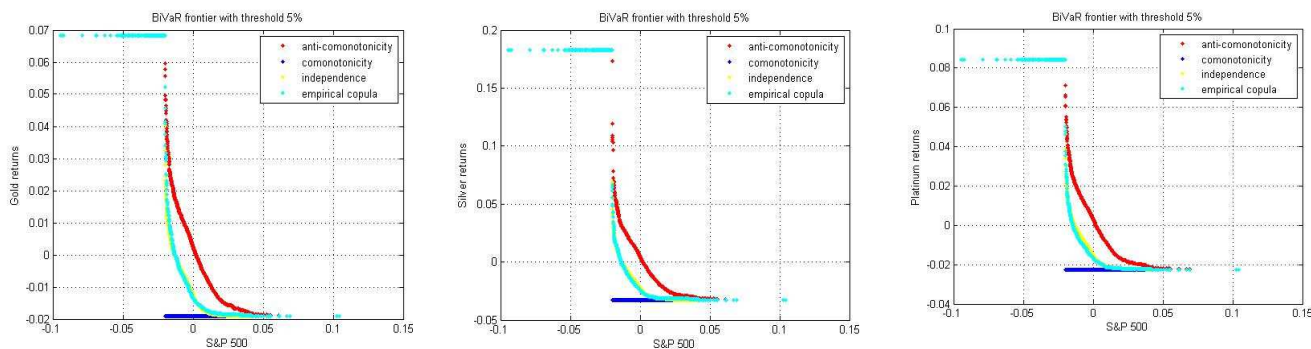
**Table 9. Hedge and safe haven analysis results summary**

		Copula	Hedge	Safe haven
France	Gold	Rotated Gumbel	Strong	Strong
	Silver	Clayton	Weak	No
	Platinum	Student-t	Weak	No
Germany	Gold	Rotated Gumbel	Strong	Strong
	Silver	Rotated Joe	Strong	Strong
	Platinum	Student-t	Weak	No
Italy	Gold	Rotated Gumbel	Strong	Strong
	Silver	Rotated Joe	Strong	Strong
	Platinum	Student-t	Weak	No
UK	Gold	Student-t	Weak	No
	Silver	Survival Gumbel	Weak	No
	Platinum	Student-t	Weak	No
Japan	Gold	Student-t	Weak	No
	Silver	Survival Gumbel	Weak	No
	Platinum	Student-t	Weak	Weak
Canada	Gold	Rotated Joe	Strong	Strong
	Silver	Student-t	Weak	No
	Platinum	Survival Clayton	Weak	Weak
US	Gold	Gaussian	Strong	Strong
	Silver	Student-t	Weak	No
	Platinum	Rotated Joe	Weak	Weak

In Fig 2 we present the 95% level curves of the BiVaR between precious metals and the S&P500 index. As we can see, the 95% level curve of the empirical copula is closer to the level curve of multiplication or independence, which means that the losses for precious metals and the stock market are uncorrelated.

As we expected before, the low correlations between the precious metals and equity market indices support the diversification properties of metals. Thus, in order to guarantee benefit from diversification, it is preferred to put precious metal and equity indexes in the same portfolio. This result is similar for the other stock markets.<sup>8</sup>

<sup>8</sup> The others level curves of the BiVaR are contained in Appendix A, **Error! Reference source not found.**



**Fig 2. BiVaR level curves between S&P 500 and Precious metals**

### 4.3. Discussion

By leading this study, additional insights are made regarding the literature debate on the interaction between precious metals and stock markets with a special concern on the valuable roles of precious metals; namely gold, silver and platinum as hedge, safe haven and diversification assets. Indeed, this study adopts the combination of copulas and VaR techniques. On one hand, we apply vine copulas to assess for the hedge and safe haven properties of precious metals for the G-7 stock markets and propose a new definition of “strong safe haven” asset by computing the tail correlation using simulated data from the best-fitting copula model. Our estimation results show that gold serves as a strong hedge and safe haven for European countries as well as the US and Canada, but only weak hedge for UK and Japan. These findings are in line with previous studies Baur and McDermott, 2010 and Bredin et al., 2015.

Gold is considered as safe haven asset for several reasons. To start with, gold served historically as a currency and still remains a monetary asset. Second, it is the most liquid precious metal and easiest to trade. Also, our results confirm that gold does not comove with stocks during extreme market conditions. Last but not least, it is an international asset, and its value is independent of the decision of a particular State.

Regarding silver, our results reveal that it may acts as strong hedge and safe haven asset in German and Italian stock markets, which means that it may be suitable and affordable alternative safe haven since it is cheaper than gold. However, silver is not considered as a safe haven asset for the rest of G-7 stock markets since it is more thinly traded, making it more volatile and illiquid. For the case of platinum, it is a weak hedge for all G-7 stock markets and only a weak safe haven for American, Canadian, and Japanese stock markets. As we know, an

asset is considered to be a safe haven when its market is extremely liquid, and platinum is relatively illiquid. This can explain the fact that platinum cannot be a safe haven for most of the G-7 stock markets. However, it is a cheap alternative to gold and may be profitable for investors if the price of gold continues to rise. On the other hand, we apply a novel method—the BiVaR based copula method—to analyse the diversification potential of precious metals. Our findings confirm that precious metals provide a useful means of diversification for G-7 investors.

Overall, our results suggest that there is some degree of heterogeneity regarding the role of precious metals between the G7 countries, which is due to the fact that each country has its own financial risk exposure.

To sum up, even though gold acts as a better hedge and safe haven for the G-7 stock markets, investors can find a valuable investment benefit in silver and platinum with different degrees (weak or strong).

## **5. Conclusions**

In this study, we analyse the hedge, safe haven, and diversification potential of precious metals—namely gold, silver, and platinum—for the G-7 stock markets. Indeed, the vine copula method is used to test the hedge and safe haven hypotheses and the BiVaR is applied to assess the diversification benefits of precious metals. Our empirical results show that precious metal hedge and safe haven behaviors vary by country.

First, gold provides the strongest safe haven property for all G-7 countries, which is consistent with previous literature. This result means that gold may be used to offset losses in equity markets during turmoil periods. Also, silver bears the potential of a strong safe haven role for German and Italian stock markets. However, platinum provides a weak safe haven role for most developed markets. Furthermore, in line with existing studies, our study suggests that gold has a strong hedging property in developed stock markets. For silver and platinum, results show that they may act as weak hedge assets. Finally, the results of the BiVaR analysis argue that all precious metals exhibit diversification benefits for G-7 stock markets investors.

Our findings provide a noteworthy practical implication for investors in the G-7 countries in building their investment strategies. We suggest that investors may hedge their equity investments in normal times by investing in these precious metals and ensure their portfolios from losses during periods of turbulence by investing in gold.

Further research might analyze the out-of-sample forecasting of expected returns in precious metals and how precious metals investment should fit into a diversified portfolio.

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## Appendix A.

**Table A 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	$C(u, v; \rho, \vartheta) = T(t^{-1}(u), t^{-1}(v))$	$\rho \in [-1, 1]$	Symmetric tail dependence
Clayton	$C^c(u, v; \theta) = (u^\theta + v^\theta - 1)^{-\frac{1}{\theta}}$	$\theta \in (0, \infty)$	Lower tail dependence
Gumbel	$C^G(u, v; \theta) = \exp(-((- \ln(u))^{\frac{1}{\theta}} + (- \ln(v))^{\frac{1}{\theta}})^\theta)$	$\theta \in [1, \infty)$	Upper tail dependence
Joe-Clayton	$C^{JC}(u, v   \tau^U, \tau^L) = 1 - (1 - \{[1 - (1 - u)^k]^{-\gamma} + [1 - (1 - v)^k]^{-\gamma} - 1\})^{1/k}$	$\tau^U \in (0, 1)$ $\tau^L \in (0, 1)$	$\tau^U = \wedge \left( \omega_U^{SJC} + \beta_U^{SJC} \tau_{t-1}^U + \alpha_U^{SJC} \frac{1}{q} \sum_{i=1}^q  u_{t-i} - v_{t-i}  \right)$ $\tau^L = \wedge \left( \omega_L^{SJC} + \beta_L^{SJC} \tau_{t-1}^L + \alpha_L^{SJC} \frac{1}{q} \sum_{i=1}^q  u_{t-i} - v_{t-i}  \right)$
<b>Rotated version of copula</b>			
There are three rotated forms, with angles 90 degrees, 180 degrees, and 270 degrees, defined as follows: $C_{90}(u, v) = v - C(1 - u, v)$ $C_{180}(u, v) = u + v - 1 + C(1 - u, v)$ $C_{270}(u, v) = u - C(u, 1 - v)$			
<b>Survival version of copula</b>			
$\bar{C}(u, v) = u + v - 1 + C(1 - u, 1 - v)$			
<b>Dependence measures</b>			
The Kendall's tau can be written as a function of the copula as follows: $\theta_\tau = 4 \int_0^1 \int_0^1 C(u, v) d(u, v) - 1$ , The upper (right) and lower (left) tail dependence measures are, respectively, $\lambda_U = \lim_{u \rightarrow 1} \Pr[X \geq F_X^{-1}(u)   Y \geq F_Y^{-1}(u)] = \lim_{u \rightarrow 1} \frac{1 - 2u + C(u, u)}{1 - u}$ and $\lambda_L = \lim_{u \rightarrow 0} \Pr[X \leq F_X^{-1}(u)   Y \leq F_Y^{-1}(u)] = \lim_{u \rightarrow 0} \frac{C(u, u)}{u}$			
Notes: $\lambda_U$ and $\lambda_L$ 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 $\Phi$ is the bivariate standard normal cumulative distribution function with correlation parameter $\rho$ . For the t-copula $t^{-1}(u)$ and $t^{-1}(v)$ are the quantile functions of the univariate Student-t distribution and $T$ is the bivariate Student-t cumulative distribution function with $\vartheta$ the degree-of-freedom and $\rho$ the correlation parameter. For the SJC copula, $k = \frac{1}{\log(2 - \tau^U)}$ and $\gamma = \frac{-1}{\log \tau^L} \cdot \tau^U$ and $\tau^L$ denote the upper and lower tails of the SJC and the Joe-Clayton copulas.			

**Table A 2. Parameter estimates for marginal models of precious metals and stock market returns**

The AR (1)-GARCH (1,1) model can be written as:  
 $R_t = \mu + \phi_1 R_{t-1} + \varepsilon_t$ ,  
 $\varepsilon_t = Z_t \sqrt{\sigma_t}, Z_t \sim Student - t(\vartheta)$ ,  
 $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ ,  
 where  $\omega > 0$ ,  $\alpha_1, \beta_1 \geq 0$ , and  $R_t$  are the logarithmic returns at time t,  $\mu$  is a constant term of the return equation,  $\varepsilon_t$  represents the return residuals, and  $Z_t$  are the standardised residuals which have a student-t distribution with  $\vartheta$  degrees of freedom.

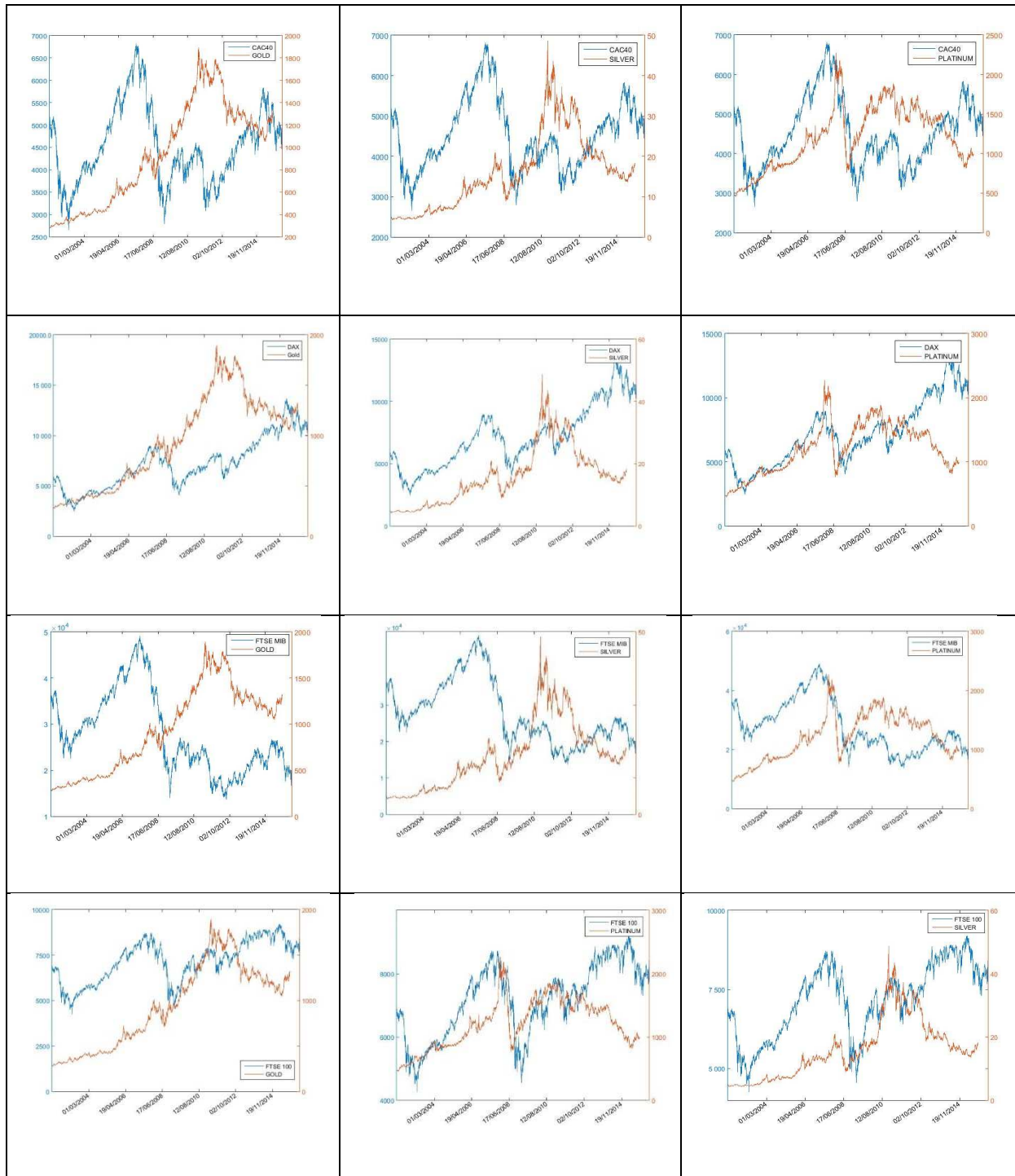
	CAC40	DAX	FTSE100	FTSE MIB	NIKKEI 225	S&P\TSX	S&P500	Gold	Silver	Platinum
<b>Mean equation</b>										
$\mu (10^{-4})$	7.1327 (3.76)	9.9147 (5.19)	5.0729 (3.47)	6.6756 (3.53)	7.5689 (3.57)	7.1591 (5.49)	7.9312 (5.57)	6.3487 (3.79)	5.8014 (2.04)	4.9329 (2.51)
$\phi_1$	-0.041 (-2.25)	-0.013 (-0.71)	-0.0350 (-1.89)	-0.056 (-2.27)	-0.0411 (-2.39)	0.0202 (1.13)	-0.0562 (-3.01)	-0.0079 (-0.458)	-0.0906 (-5.58)	-0.02073 (-1.186)
<b>Variance equation</b>										
$\omega (10^{-6})$	2.0475 (3.44)	1.7323 (3.25)	1.7199 (3.96)	8.4475 (2.60)	3.8797 (3.84)	9.6567 (3.38)	1.5845 (3.78)	1.3191 (3.15)	0.0406 (3.59)	3.3138 (3.83)
$\alpha_1$	0.0887 (8.58)	0.0870 (8.59)	0.1101 (9.11)	0.0712 (8.58)	0.0977 (8.73)	0.0818 (7.89)	0.101 (8.43)	0.0398 (6.11)	0.0406 (6.64)	0.0705 (7.48)
$\beta_1$	0.9055 (87.28)	0.9092 (89.48)	0.8813 (73.29)	0.9288 (118.5)	0.8889 (70.76)	0.9121 (88.99)	0.8919 (74.90)	0.9517 (123.33)	0.9510 (141.88)	0.9153 (84.41)
$\vartheta$	7.9602	8.0630	9.1590	7.3602	9.3696	6.5160	6.3356	5.5135	4.9273	5.9475
LL	9861.6	9810.3	10692.9	9709.3	9648.3	11145.8	10764.01	10440.4	8523.7	9855.2
Q(20)	19.55 [0.486]	23.98 [0.243]	16.87 [0.66]	18.50 [0.55]	8.326 [0.989]	13.768 [0.84]	23.39 [0.27]	23.53 [0.2635]	11.171 [0.941]	14.18 [0.821]
Q(20) <sup>2</sup>	18.30 [0.567]	30.41 [0.063]	6.47 [0.998]	15.12 [0.769]	17.67 [0.609]	15.19 [0.765]	24.13 [0.236]	7.96 [0.99]	7.99 [0.99]	23.29 [0.274]
ARCH- LM stat	0.55 [0.456]	0.02 [0.883]	1.7510 <sup>-5</sup> [0.996]	0.004 [0.944]	2.50 [0.113]	0.44 [0.505]	1.44 [0.229]	0.62 [0.430]	4.69 [0.030]	5.58 [0.018]
<b>Goodness of fit of the marginal distribution model</b>										
K-S test	[0.58]	[0.108]	[0.68]	[0.27]	[0.206]	[0.15]	[0.07]	[0.29]	[0.35]	[0.15]

Notes. This table reports the ML estimates and z-statistic (in brackets) for the AR (1)-GARCH (1,1) parameters of the marginal distribution model defined above. The  $Q(20)$  and  $Q(20)^2$  are the Ljung-Box statistics for serial correlation in the model's standardised residuals and standardised squared residuals, respectively, using 20 lags. ARCH is Engle's LM test for the ARCH effect in the standardised residuals up to 10th order. K-S denotes the Kolmogorov-Smirnov test. The reported  $p$  values (in square brackets) below 0.05 indicate the rejection of the null hypothesis that the model distribution is correctly specified.

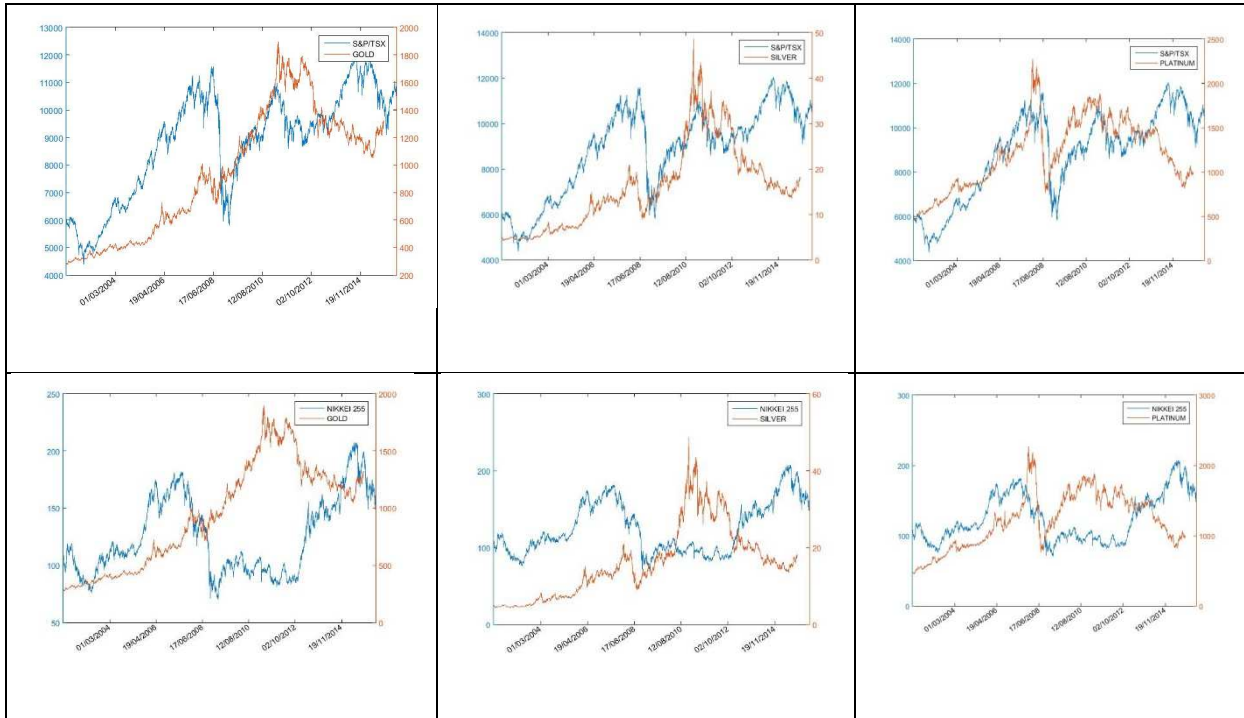
Table A 2 reports the empirical estimates of the marginal model for returns. The results of the volatility estimates show that the  $\alpha_1$  coefficients, which measure the adjustment to past shocks, and the  $\beta_1$  coefficients, which measure the volatility persistence of the process, are significant for all series, which indicates that the conditional volatility is persistent over time and is past-dependent. As usual, all series are described by significant GARCH effects. 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. We also checked the adequacy of the Student-t distribution model, testing the null hypothesis that the standardised model residuals were uniform (0,1) by comparing the empirical and theoretical distribution functions using the Kolmogorov-Smirnov test. The  $p$ -values for those tests indicate that the null hypothesis could not be rejected at the 5% significance level for either of the marginal models. Hence, the marginal models are correctly specified, and the copula model can correctly capture dependence between precious metals and equity markets.

**Table A 3. Empirical Kendall's tau matrices for G-7 countries**

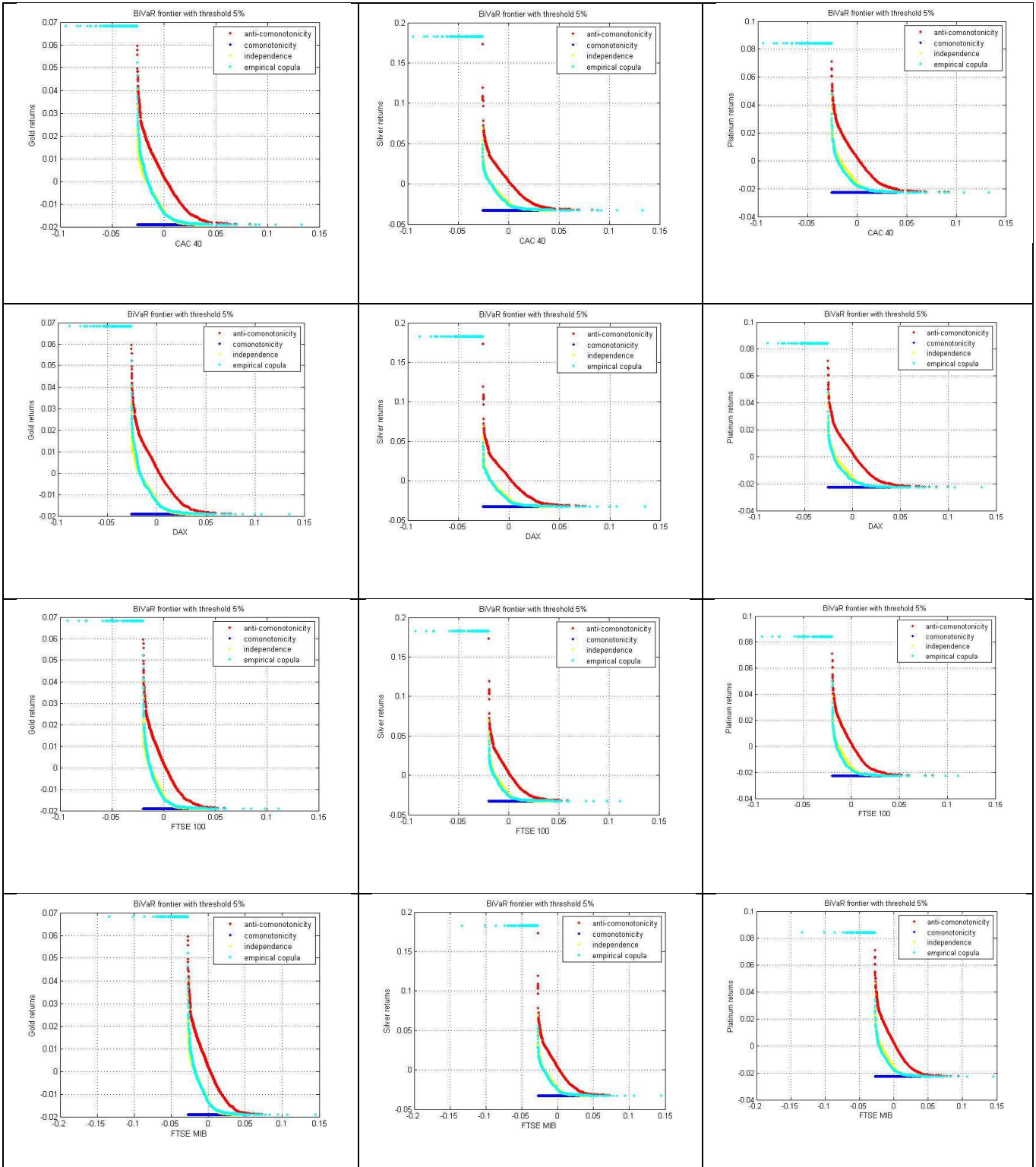
<b>France</b>				
	CAC 40	Gold	Silver	Platinum
CAC 40	1	-0.02249074	0.03375731	0.08429327
Gold	-0.02249074	1	0.39800740	0.41186940
Silver	0.03375731	0.39800740	1	0.39854344
Platinum	0.08429327	0.41186940	0.39854344	1
<b>Sum</b>	1,14054132	1,83236754	1,830308	1,89470611
<b>Germany</b>				
	DAX	Gold	Silver	Platinum
DAX	1	-0.02068612	0.04223904	0.08117698
Gold	-0.02068612	1	0.39800740	0.41186940
Silver	0.04223904	0.39800740	1	0.39854344
Platinum	0.08117698	0.41186940	0.39854344	1
<b>Sum</b>	1,14410214	1,8305629	1,83878988	1,89158982
<b>UK</b>				
	FTSE100	Gold	Silver	Platinum
FTSE100	1	0.01770941	0.06112196	0.1128933
Gold	0.01770941	1	0.39800740	0.4118694
Silver	0.06112196	0.39800740	1	0.3985434
Platinum	0.11289327	0.41186940	0.39854344	1
<b>Sum</b>	1,19172464	1,827586	1,8576728	1,923306
<b>Italy</b>				
	FTSE MIB	Gold	Silver	Platinum
FTSE MIB	1	-0.01972463	0.03392975	0.08201692
Gold	-0.01972463	1	0.39800740	0.41186940
Silver	0.03392975	0.39800740	1	0.39854344
Platinum	0.08201692	0.41186940	0.39854344	1
<b>Sum</b>	1,135671	1,829601	1,83048059	1,89242976
<b>Japan</b>				
	NIKKEI225	Gold	Silver	Platinum
NIKKEI225	1	0.02487169	0.05709541	0.09598458
Gold	0.02487169	1	0.39800740	0.41186940
Silver	0.05709541	0.39800740	1	0.39854344
Platinum	0.09598458	0.41186940	0.39854344	1
<b>Sum</b>	1,17795168	1,83474849	1,85364625	1,90639742
<b>Canada</b>				
	S&P/TSX	Gold	Silver	Platinum
S&P/TSX	1	-0.002292608	0.005024797	0.008544629
Gold	-0.002292608	1	0.398007396	0.411869405
Silver	0.005024797	0.398007396	1	0.398543445
Platinum	0.008544629	0.411869405	0.398543445	1
<b>Sum</b>	1,015862034	1,812169409	1,801575638	1,818957479
<b>US</b>				
	S&P500	Gold	Silver	Platinum
S&P500	1	-0.006665807	0.01759668	0.06968461
Gold	-0.006665807	1	0.39800740	0.41186940
Silver	0.017596684	0.398007396	1	0.39854344
Platinum	0.069684607	0.411869405	0.39854344	1
<b>Sum</b>	1,093947098	1,816542608	1,81414752	1,88009745



**Fig.A 1 Precious metals and stock market indexes dynamics**

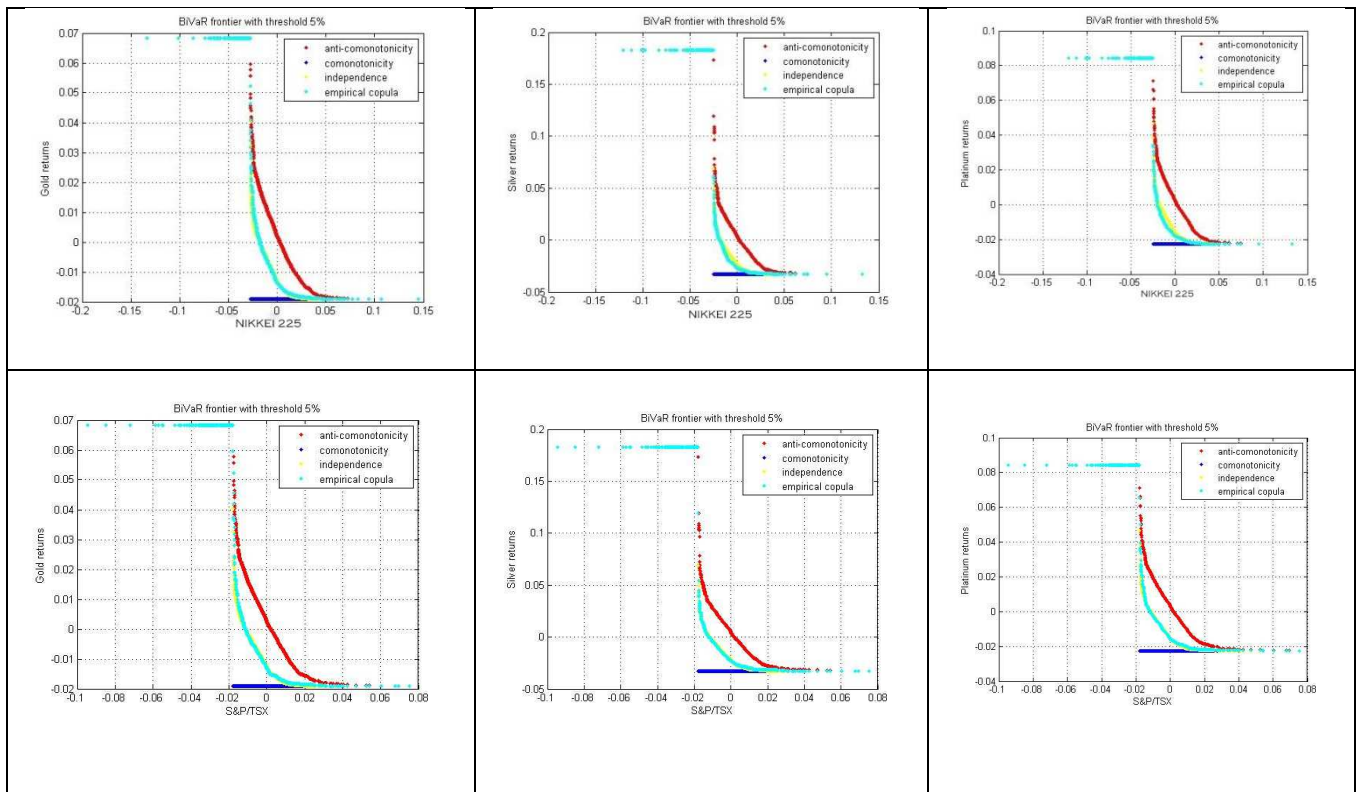


**FigA.1 (Continued)**



**Fig.A 2 BiVaR level curves between Precious between G-7 stock market-Precious metals**





**Fig.A 2 (Continued)**