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Tail dependence between gold and sectorial stocks in China: Perspectives for portfolio diversification*

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Abstract

This article analyzes the relationship between gold quoted on the Shanghai Gold Exchange and Chinese sectorial stocks from 2009 to 2015. Using different copulas, our results show that there is weak but significant tail dependence between gold and Chinese sectorial stock returns. This means that the dependence between extreme movements of the two assets is not pronounced and confirms the role of gold as a safe haven asset. Based on analyzing the efficient frontier, CCC-GARCH optimal weights, hedge ratios and hedging effectiveness, we further show that adding gold into Chinese stock portfolios can help to reduce their risk. Gold appears to be the most efficient diversifier for stocks of the materials sector and the less efficient for the utilities sector. As a robustness check, we also compare gold to oil and indicate that gold is more efficient than oil in the diversification of Chinese stock portfolios.

Keywords: Shanghai Gold Exchange, Chinese sectorial stocks, oil, copulas, portfolio implications

JEL classification: G11, C58

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1 Introduction

China has been the largest gold producer in 2014, contributing to 15% of the world production, and one of the largest gold consumers worldwide. Following the World Gold Council, China and India account for 54% of the world gold demand in 2014.[1] However, since Chinese investors cannot trade gold abroad without authorization, the Shanghai Gold Exchange (SGE) is the main trading platform for their gold investments (Cheng, 2014). The SGE is still a relatively novel market which was opened on October 30, 2002 and Chinese institutional and individual investors have been able to invest in gold through the SGE only since 2004 and 2007, respectively (Cheng, 2014). Despite this recent opening, its development has been noticed in numerous analyzes of specialists.[2] The "GFMS Gold Survey 2014" reported that the turnover of the SGE was just behind London, New York (Comex) and Tokyo (Tocom) over the 2007-2013 period. According to Wang (2011), the previous Chairman of the SGE, from October 2002 to April 2011, the transaction volume of gold on the SGE reached more than 20,000 tons. In 2013, it was 10,701 tons,[3] of which 1,132 tons were private demand (Cheng, 2014). Wang (2011) indicated that commercial banks accounted for 58% of the transaction volume, individual investors for 19% and institutional members for 23% in 2010. In 2014, Mr. Luode, the current Chairman of the SGE, announced its fully opening to international investors, for the first time, and this officially happened on September 18, 2014.[4]

Taking into account the leading role of China in the global gold market, the growing development and internationalization of the SGE has attracted interest among researchers and investors. However, the number of studies on the SGE remains quite small compared to the huge literature on the financial economics of gold.[5] To the best of our knowledge, there are only two published studies dealing with the SGE. First, Lucey *et al.* (2014) study the relationship between gold markets around the world and find that the SGE does not have significant interactions with other international gold markets.[6] Second, Hoang *et al.* (2015) find that including gold quoted at the SGE in Chinese stock and bond

[1] According to the World Gold Council, the total global demand for gold in 2014 was 3,924 tons, with India's consumer demand accounting for 843 tons and China's for 814 tons. See World Gold Council, "Gold Demand Trends", `http://www.gold.org/supply-and-demand/gold-demand-trends/back-issues/gold-demand-trends-full-year-2014`.

[2] China also joined the World Gold Council as a full member on September 22, 2015.

[3] Following the GFMS 2014 survey, the SGE was behind London, New York and Tokyo with transaction volumes of 570,000 tons, 147,093 tons, and 12,225 tons, respectively.

[4] The announcement took place at the LBMA Bullion Market Forum 2014 in Singapore. For more information see `http://www.en.sge.com.cn/about-us/sge-overview/sgei-intro/`.

[5] O'Connor *et al.* (2015) present a detailed survey of this literature strand and show that the number of papers published on gold has increased significantly in the last years and peaked in 2010 with almost 30 published papers.

[6] We notice that this pattern might change in the future due to the implications of the SGE opening to international members.

portfolios is more preferable to risk-seeking investors than to risk-averse ones. Other studies also focus on the analysis of the relationship between Chinese stocks and gold, such as Anand and Madhogaria (2012), Ziaei (2012), Thuraisamy *et al.* (2013), Gürgün and Ünalmis (2014) and Arouri *et al.* (2015). However, they do not take into account gold prices from the SGE but those from the London Bullion Market (LBM) converted into Chinese currency. Indeed, this choice can be appropriate only to foreign investors but not to Chinese ones who are unable to freely trade gold abroad as mentioned above. Thus, looking at gold prices on the SGE is much more appropriate for Chinese investors whose demand for gold investments has increased strongly and it is estimated that the private demand will potentially reach 1,350 tons in 2017 (Cheng, 2014).

In this twofold context, i.e. the rapid development of the SGE and the lack of studies on it, the objective of this study is to analyze the relationship between Chinese stocks and gold quoted at the SGE. We provide a new perspective on gold investments in general and on the Chinese market in particular for several reasons. First, we use gold prices quoted at the SGE and not those from the LBM converted into Chinese currency. As mentioned above, this is more suitable to Chinese investors and also bears some interesting implications for international investors, who trade gold on the SGE using the local currency, i.e., the Renminbi.[7] Second, we pay particular attention to extreme returns and the probability of joint extreme movements between Chinese stock and gold returns. Therefore, we take stylized facts of financial asset returns into account and model the tails of GARCH filtered return distributions through the generalized Pareto distribution. In doing so, we assess different patterns of tail dependence (i.e. probability of joint extreme movements) between Chinese stock and gold returns by applying competing copula approaches. Considering the recent high volatility of both gold and stock markets, investigating the tail dependence of returns can be useful for investors and also extends the literature on gold investments. Third, we analyze the impact of the sector of Chinese stocks on its relationship with gold. To the best of our knowledge, this issue has not been tackled for the SGE before, although it is of particular importance considering the specificity of each sector. Fourth, we further investigate if the tail (in)dependence of returns between gold on the SGE and Chinese sectorial stocks could be profitable in the context of portfolio diversification.

Based on a 2009-2015 daily dataset, we find that there is weak and mostly symmetric tail dependence between gold and Chinese sectorial stock returns. This implies that extreme returns of gold and stocks

[7] Following Mr. Luode, the current Chairman of the SGE, the objective of gold pricing in Renminbi (RMB) is to internationalize the Chinese currency. See Bénassy-Quéré and Forouheshfar (2015) for more information on the internationalization of the RMB.

in China are weakly correlated and confirms the role of gold as a safe haven asset claimed by Baur and Lucey (2010) among others. Based on this result, we further investigate whether this relationship bears potential to be profitable for the diversification of stock-gold portfolios in China. Using the efficient frontier, CCC-GARCH optimal weights, hedge ratios and hedging effectiveness measures, we find that adding gold into Chinese stock portfolios can help to reduce the risk. Gold appears to be the best diversifier for stocks of the energy, information, and materials sectors but the less efficient for the utilities sector. As a robustness check, gold is compared to oil and the results show that gold is more efficient than oil in the diversification of Chinese stock portfolios.

The rest of the paper is organized as follows. The second section reviews the literature related to the role of gold in the diversification of portfolios. Section 3 presents our empirical approach while Section 4 focuses on the dataset. In Section 5 our results are discussed. Section 6 presents a robustness check based on oil prices and Section 7 concludes.

2 Literature review: Gold in the diversification of portfolios

Gold investments and its relationship with stocks have been analyzed by numerous authors. The first study investigating gold investments was provided by McDonald and Solnik (1977), shortly after the abolition of the Bretton Woods system in August 1971 (Wood, 1988). It was followed by Sherman (1982), Jaffe (1989), Chua *et al.* (1990), Blose and Shieh (1995), Blose (1996), Davidson *et al.* (2003) and Lucey *et al.* (2006). All these studies reveal the significant relationship between gold and stocks, and the important role of gold in the diversification of portfolios. In 2010, Baur and Lucey (2010) and Baur and McDermott (2010) investigated the role of gold as a safe haven asset. Following these two studies, many others, for example Hood and Malik (2013) and Beckmann *et al.* (2015a), examined this role of gold in stock and bond portfolios for different economies based on different frameworks.

To provide more detailed results of some recent studies, we focus on the post 2010 period. Baur (2011) used US data from 1979 to 2011 and concludes that gold evolved as a safe haven only recently. Ciner *et al.* (2013) show that stocks, bonds, gold, and oil can be used as a safe havens for each other in the US and UK. Hood and Malik (2013) show that unlike other precious metals, gold can serve as a hedge and weak safe haven for the US stock market. Soucek (2013) finds that in unstable periods, the correlation between gold and equity returns tends to be weak or even negative. Gold can thus serve as a safe haven as well as for the diversification of portfolios. However, Beckmann *et al.* (2015a) find that the role of gold as a hedge and safe haven may be market-specific while proposing a more flexible approach that takes nonlinearity into account. The market-specific character of the safe haven status of gold has also been confirmed by Nguyen *et al.* (2016) while applying a mixed-copula approach and also by Beckmann *et al.* (2017) while highlighting the role of uncertainty. Sadorsky (2014) reveals that gold and oil can also be used as a hedge and safe haven for socially responsible stocks, in a similar way as for conventional stocks. In comparing gold to bonds, Flavin *et al.* (2014) find that both gold and longer-dated bonds can be considered as safe haven assets. Applying a wavelet approach on daily data from 1980 to 2013, Bredin *et al.* (2015) conclude that gold acts as a safe haven for stocks and bonds only for horizons up to one year, except for the period of the early 1980s. Overall, the above-mentioned studies show that gold acts as a safe haven for stocks and bonds. However, this role of gold is time-varying and market-specific.

Other studies go beyond analyzing the role of gold as a safe haven and focus on its impact in the diversification of portfolios. For example, Hammoudeh *et al.* (2013) find a significant relationship between gold and stocks and conclude that gold can play an important role in the diversification of stock portfolios. Kumar (2014) shows that stock-gold portfolios perform better than those with only stocks. Based on a wavelet analysis, Michis (2014) concludes that gold provides the lowest contribution to the portfolios' risk at medium- and long-term investment horizons. Baur and Löffler (2015), Choudhry *et al.* (2015), and Malliaris and Malliaris (2015) confirm the previous studies' finding of a significant impact of gold in the diversification of portfolios.

So far, the literature is silent on the relationship between gold prices from the SGE and Chinese sectorial stocks. The existent articles dealing with the Chinese market only use gold prices from the LBM converted into Chinese currency (except for Lucey *et al.* (2014) and Hoang *et al.* (2015), as mentioned in the Introduction). For example, Arouri *et al.* (2015) examine the relationship between world gold prices and Chinese stocks using a VAR-GARCH framework for the 2004-2011 period. Anand and Madhogaria (2012) assess the correlation and causality between gold prices and stocks in six countries (including China) using daily data from the LBM converted into local currencies. Thuraisamy *et al.* (2013) study the relationship between 14 Asian (including Chinese) equity and commodity futures markets based on gold prices from London. In the same vein, Gürgün and Ünalmis (2014) use daily data from MSCI and Bloomberg to analyze the safe haven characteristic of gold against the equity markets in emerging and developing countries, including China. However, as already discussed in the previous section, using LBM gold prices converted into Chinese currency is not appropriate for Chinese investors for whom gold investments abroad are still under the control of the government. Thus, our study extends the above-mentioned literature in using Chinese gold prices from the SGE and analyzing its relationship to Chinese stocks by taking into account the specificities of each sector. The next section details our empirical approach to address these issues.

3 Methodology

Our methodology can be divided into two different parts. As a first step, we explore the occurrence of joint extreme movements, i.e. the tail dependence, between gold and sectorial stock returns in China using several copula approaches. In doing so, we take asset specific properties into account and apply both a GJR-GARCH approach and the generalized Pareto distribution (GPD). A weak tail dependence between gold and stock returns would confirm the often mentioned hedge and/or safe haven function of gold. To examine this issue more closely we will also investigate the hedging efficiency of gold in Chinese sectorial stock portfolios based on four different portfolio scenarios as a second step. In order to check for robustness, the whole analysis will also be applied while replacing gold by oil.

3.1 GJR-GARCH

Before applying different copula measures to investigate the tail dependence, we first focus on the heteroscedasticity and serial correlation of the second moments of the distribution of returns. As conventional in the literature (see, for instance, Aloui *et al.* (2011) and Beckmann *et al.* (2015b)), we apply an ARCH filter since we deal with daily return series that can be characterized by serial correlation and conditional heteroscedasticity. Moreover, to account for the potential that shocks tend to impact the conditional volatility asymmetrically, we apply a GJR-GARCH filter as defined by Glosten *et al.* (1993):

$$r_t = \varphi_0 + \sum_{j=1}^{p} \varphi_j r_{t-j} + \lambda \sigma_t^2 + \varepsilon_t, \tag{1}$$

$$\sigma_t^2 = \Omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma I(\varepsilon_{t-1} < 0) \varepsilon_{t-1}^2, \tag{2}$$

where r_t denotes the return series and σ_t^2 represents the variance of its error terms ε_t. In this setup, Ω represents a constant, α measures the impact of shocks on the variance of errors and thus the GARCH effect, β indicates the persistence of the process. Moreover, γ captures the asymmetric impact of shocks on the volatility, where $I(\varepsilon_{t-1} < 0)$ is a Heaviside indicator function that takes a value of unity if the shock is negative and 0 otherwise. Through this model, we can test for the existence of the GARCH effect in analyzing the significance of the α-coefficient. If the GARCH effect exists, we will then apply a GJR-GARCH filter to neutralize this effect before calculating copulas by using the residuals from the model stated in Eq. (1).

3.2 Generalized Pareto Distribution

As we deal with different assets and thus with different asset specific properties, we use a flexible return distribution that adjusts to each asset individually to calculate copulas. More precisely, we rely on Longin and Solnik (2001) to apply the generalized Pareto distribution (GPD). The GPD models the tails of each distribution individually whereas its "interior part" is described by the empirical distribution. In order to model both tails of the marginal return distribution individually, we need to define the amount of observations that should be considered in the tails. Therefore, according to Aloui *et al.* (2011), we set a predefined threshold of $\alpha = 10\%$, so that the lowest 10% and highest 10% values of the time series are modeled via the GPD. The benefit of this procedure is that the i.i.d. assumption of the extreme value theory is less likely violated by the filtered series than the actual returns. These two extreme parts will be considered as the two tails of the distribution of returns that we investigate.

Based on the GJR-GARCH filtered return series, let x be the exceedances of the predefined threshold, then the cumulative distribution function (CDF) of the GPD is given by

$$F(x)_{\xi;\delta} = 1 - \left(1 + \xi \frac{x}{\delta}\right)^{\frac{-1}{\xi}} \tag{3}$$

with $x \geq 0$, $\delta > 0$ and $\xi > -0.5$. In this setup, ξ determines the shape and δ the scale of the respective tail. The parameters are maximized via the log-likelihood function as defined by Longin and Solnik (2001). Based on the 10% tails of the return series modeled using the GPD, we can now calculate different copulas as follows.

3.3 Copulas

Due to the fact that the linear correlation coefficient does not capture non-linear transformations of the margins and tail dependence, we use the copula approach to separate the modeling of the marginal distribution from that of the tail dependence. Generally, the copula approach goes back to Sklar's theorem (1959). Based on the GPD tail returns calculated above, we fit different copulas to assess different patterns of the tail dependence. These copulas are briefly introduced in the following paragraphs. For an in-depth discussion, we refer to Joe (1997).

Gaussian copula

The Gaussian copula is directly derived from the multivariate normal distribution:

$$C^{\text{Gauss}}(x_1, \ldots, x_n) = \Phi_\rho(\Phi^{-1}(x_1), \ldots, \Phi^{-1}(x_n))$$

$$= \int_{-\infty}^{\Phi^{-1}(x_1)} \cdots \int_{-\infty}^{\Phi^{-1}(x_n)} \frac{1}{2(\pi)^{\frac{n}{2}} |\rho|^{\frac{1}{2}}} exp\left(-\frac{1}{2} z^T \rho^{-1} z\right) dz_1 \ldots dz_n. \quad (4)$$

Φ_ρ stands for the multivariate normal distribution. If all margins are normally distributed, this copula equals the multivariate normal distribution. The Gaussian copula does not capture tail dependence between the analyzed time series. Therefore, joint extreme movements cannot be adequately captured. To account for this feature we consider the t copula.

t copula

Analogous to the Gaussian copula, the t copula is directly derived from the multivariate t distribution and is given as follows

$$C^t(x_1, \ldots, x_n) = t_{\rho,v}(t_v^{-1}(x_1), \ldots, t_v^{-1}(x_n))$$

$$= \int_{-\infty}^{t^{-1}(x_1)} \cdots \int_{-\infty}^{t^{-1}(x_n)} \frac{\Gamma\left(\frac{v+n}{2}\right)}{\Gamma\left(\frac{v}{2}\right) (v\pi)^{\frac{n}{2}} |\rho|^{\frac{1}{2}}} \left(1 + \frac{1}{v} z^T \rho^{-1} z\right)^{-\frac{v+n}{2}} dz_1 \ldots dz_n. \quad (5)$$

$t_{\rho,v}$ stands for the multivariate t distribution. Due to its degrees of freedom, the t copula captures joint extreme movements and is therefore characterized by symmetric tail dependence. For the degrees of freedom $v \to \infty$, the t copula approximates a Gaussian copula. Both the Gaussian and the t copula belong to the class of elliptical copulas.

Gumbel copula

In contrast, the Gumbel copula belongs to the family of Archimedean copulas and is widely used as it captures asymmetric joint movements. The setup of the Gumbel copula is given below:

$$C^{\text{Gumbel}}(x_1, x_2) = exp\left(-[(-\ln x_1)^\theta + (-\ln x_2)^\theta]^{\frac{1}{\theta}}\right) \tag{6}$$

with $\theta \in [1, \infty) \setminus \{0\}$. Positive tail dependence is characterized by $\theta \to \infty$.

Clayton copula

Another Archimedean copula is given by the Clayton copula. In contradiction with the setup of the Gumbel copula, the Clayton copula captures joint negative shocks, so-called negative tail dependence:

$$C^{\text{Clayton}}(x_1, x_2) = \left(max\{x_1^\theta + x_2^\theta - 1, 0\}\right)^{\frac{1}{\theta}} \tag{7}$$

with $\theta \in [1, \infty) \setminus \{0\}$. Negative tail dependence is given by $\theta \to \infty$.

Frank copula

The Frank copula also belongs to the family of Archimedean copulas, whereas it accounts for symmetric tail dependence:

$$C^{\text{Frank}}(x_1, x_2) = -\frac{1}{\theta} \ln\left(1 + \frac{(e^{-\theta x_1} - 1)(e^{-\theta x_2} - 1)}{e^{-\theta} - 1}\right) \tag{8}$$

for $\theta \in \mathbb{R} \setminus \{0\}$.

All copula parameters are estimated via the log-likelihood based on a two-step mechanism (see Joe and Xu, 1996). This setup is often referred to as Inference to the Margins (IFM) and allows us to estimate the GARCH parameters in the first step and the copula parameters in the second step.

3.4 Efficient frontier

The classical mean-variance portfolio optimization (MVPO) model introduced by Markowitz (1952) can be used to determine the asset allocation for a given amount of capital through the efficient frontier. To present the MVPO model formally, we assume that there are n assets and let x_i ($i =$

$1, \ldots, n$) be the fraction of the capital invested in asset i of portfolio P in which the average return R_P is maximized, subject to a given level of its variance σ_P^2. We denote R_i to be the expected return of asset i and σ_{ij} the covariance of returns between assets i and j, for any $i, j = \ldots, n$. The general MVPO model is presented as follows: $\max R_P = \sum_{i=1}^{n} R_i x_i$, subject to $\sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} x_i x_j = \sigma_P^2$ and $\sum_{i=1}^{n} x_i = 1$. If short sale is not used, we add one more condition: $x_i \geq 0, i = 1, \ldots, n$.

3.5 Optimal weight and hedging effectiveness

To assess the hedging and diversification potential of portfolios including gold, we determine the optimal weight of gold in Chinese sectorial stock portfolios in referring to the method proposed by Kroner and Ng (1998) as follows

$$w_t^G = \frac{h_t^S - h_t^{SG}}{h_t^G - 2h_t^{SG} + h_t^S} \tag{9}$$

with w_t^G as the optimal weight of gold in the portfolio, h_t^S as the conditional variance of the stock portfolio P, h_t^{SG} as the conditional covariance between the stock portfolio and gold, and h_t^G as the conditional variance of gold. The optimal weight $w_t^{G'}$ is thus calculated for each date under the condition that $w_t^{G'} = 0$ if $w_t^G < 0$, $w_t^{G'} = w_t^G$ if $0 \leq w_t^G \leq 1$, and $w_t^{G'} = 1$ if $w_t^G > 1$. We use the average value over the study period which is the average of all optimal weights of gold for each date to minimize the conditional variance of returns of the portfolio.

In this study, we rely on the bivariate CCC-GARCH(1,1) model of Bollerslev (1990) to estimate the conditional variances and covariance. We use the CCC representation as it provides more economic significance in estimating conditional correlation rather than the conditional covariance (like in the BEKK-GARCH model of Engle and Kroner (1995) for example). In general, for each pair of stock-only portfolio and gold returns, the bivariate VAR(1)-GARCH(1,1) has the following specification:

$$R_t = \mu + \Theta R_{t-1} + \varepsilon_t, \tag{10}$$

$$\varepsilon_t = H_t^{1/2} \eta_t, \tag{11}$$

where $R_t = (R_t^S, R_t^G)'$ is the vector of returns of the stock portfolio and gold, respectively, and Θ refers to a (2×2) diagonal matrix of coefficients. $\varepsilon_t = (\varepsilon_t^S, \varepsilon_t^G)'$ denotes the vector of the error terms of the conditional mean equations for the stock portfolio and gold, respectively. $\eta_t = (\eta_t^S, \eta_t^G)'$ refers to a sequence of independently and identically distributed (i.i.d.) random errors with $E(\eta_t) = 0$ and

$\text{Var}(\eta_t) = I$. H_t is the matrix of conditional variances of the stock portfolio and gold returns such that $\text{vec}(H_t) = (h_t^S, h_t^{SG}, h_t^{SG}, h_t^G)'$.

The CCC-GARCH(1,1) model specifies H_t as follows

$$H_t = D_t K D_t, \tag{12}$$

where $D_t = \text{diag}\left(\sqrt{h_t^S}, \sqrt{h_t^G}\right)$ and K is a (2×2) matrix containing the constant conditional correlations ρ_{ij} with $\rho_{ii} = 1$, $\forall i = S, G$. The conditional variances and covariance are given by

$$h_t^S = c_S + \alpha_S(\varepsilon_{t-1}^S)^2 + \beta_S h_{t-1}^S, \tag{13}$$

$$h_t^G = c_G + \alpha_G(\varepsilon_{t-1}^G)^2 + \beta_G h_{t-1}^G, \tag{14}$$

$$h_t^{SG} = \rho\sqrt{h_t^S h_t^G}. \tag{15}$$

This model is estimated via maximum likelihood.

As for the optimal hedge ratio to minimize the conditional variance of returns of the portfolio, Kroner and Sultan (1993) consider a two-asset portfolio, equivalent to a portfolio composed of sectorial Chinese stocks and gold in our study. To minimize the risk of this hedged portfolio, a long-position of one Yuan on the stock segment must be hedged by a short position of β_t^{SG} Yuan of gold. This optimal hedge ratio is therefore given by

$$\beta_t^{SG} = \frac{h_t^{SG}}{h_t^G}. \tag{16}$$

Furthermore, the hedging effectiveness can be evaluated by examining the realized hedging errors which are determined as follows (Ku *et al.*, 2007)

$$HE = \frac{\text{Var}_{\text{unhedged}} - \text{Var}_{\text{hedged}}}{\text{Var}_{\text{unhedged}}}, \tag{17}$$

where the variance of the hedged portfolios $\text{Var}_{\text{hedged}}$ is obtained from the variance of the returns of the gold-stock portfolios, the variance of the unhedged portfolios $\text{Var}_{\text{unhedged}}$ is obtained from the variance of the stock-only portfolios. A higher HE ratio indicates a greater hedging effectiveness measured by decreasing the portfolio's variance.

4 Data and preliminary analysis

To investigate the relationship between gold quoted at the SGE and Chinese sectorial stocks, our daily dataset running from January 9, 2009, to January 9, 2015, is collected from the websites of the Shanghai Gold Exchange (SGE) and the Shanghai Stock Exchange (SSE). The starting date is conditioned by the availability of data on Chinese sectorial stock indexes. Therefore, our dataset is composed of 1,314 daily observations. More details about gold prices on the SGE and sectorial stocks on the SSE are presented in the following paragraphs.

Gold prices from the Shanghai Gold Exchange (SGE)

Au99.99 and Au99.95 are two principal gold spot assets traded on the SGE since its opening (99.99 and 99.95 indicate the purity of gold over 100%). We choose the Au99.95 asset in our analysis because it is considered to be the reference gold spot asset in annual reports of the SGE with highest transaction volumes most of the time. Its prices are in Chinese Yuan per gram and are available on the SGE website. In 2015, the SGE offers 13 products (spot and futures) covering gold, silver and platinum on the Main Board. The latter is composed of 167 domestic members, 8,000 corporate customers and over 7,000,000 individual investors that trade on the SGE through their carrying members. As for the International Board (launched recently in September 2014), there are 40 members, such as HSBC, Goldman Sachs, Deutsche Bank, etc., with three products (iAu100g, iAu99.99 and iAu99.95).[8]

Sectorial stock indexes from the Shanghai Stock Exchange (SSE)

Daily data on sectorial stocks based on the SSE as the biggest stock exchange in China are available from January 9, 2009. The sectorial indexes that are considered by the SSE are: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunication Services and Utilities. We use the total return index to take into account dividends paid on stocks under consideration. These indexes are calculated on the stocks in the "A-shares" list, meaning all stocks available to domestic investors, excluding IPOs within 3 months (see the SSE website for more details). Furthermore, all stocks at the bottom 15% by trading value and at the bottom 2% by cumulative market capitalization are deleted. For sectors which have

[8] Following information given by *bullionstar*, the transaction volume of iAu99.99, that is the most traded on the International Board, increased strongly between 2014 and 2015 and reached its maximum on April 8, 2015, with 31 tons per day. See: `https://www.bullionstar.com/blogs/koos-jansen/shanghai-international-gold-exchange-comes-to-life/`.

less than 30 stocks, all the stocks enter the index. If this is not the case, stocks are ranked by daily average market capitalization and only the top ranked stocks are chosen until the cumulative market capitalization coverage reaches 80% of the total value or the number of stocks reaches 50. The constituents of each index are adjusted semi-annually. In August 2015, the number of stocks that are considered in each sector is: 50, 30, 30, 30, 30, 50, 31, 50, 11 and 30, respectively to the list of sectors that are presented above.

Descriptive statistics

Figure I presents daily values of indexes on sectorial stocks and gold prices in China from January 2009 to January 2015. To save spaces, we have grouped similar sectors in one graph.

*** Insert Figure I about here ***

From Figure I, we notice that both gold and stocks were very volatile in China from 2009 to 2015. It thus appears to be useful to study the tail dependence (i.e. joint extreme co-movement) of the two assets. At the beginning of the sample period, sectorial stock indexes seem to exhibit a high degree of co-movements while this pattern seems to become lower as time evolves. Furthermore, the industrial sectors (energy, industrials and materials) behave differently compared to other sectors. Indeed, they show a decreasing tendency from 2013 while other sectors exhibit an increasing tendency. More importantly, most of the time, gold prices evolved inversely with these stocks and two sub-periods can be distinguished. The first period is from January 9, 2009, to September 9, 2011, when gold prices were increasing and reached its peak on September 9, 2011. This period is also characterized by an increasing tendency of stock prices for most sectors. The second period runs from September 10, 2011, to January 9, 2015, and is characterized by the inverse relationship between gold and stocks, increasing for stocks and decreasing for gold. As a preliminary analysis, we assess the linear dependence between all assets with the simple correlation coefficient (Table I).

*** Insert Table I about here ***

As expected, the correlation between different sectors is relatively high, ranging between 0.5 and 0.9. We notice that the correlation of the consumption (discretionary and staples) and energy sectors with the others is the highest. The financial sector is the less correlated to the other sectors. In all cases, the correlation between gold and sectorial stocks is low, around 0.1. The sector the less correlated with gold is utilities and the highest is materials. This may be explained by the fact that gold may be used more in companies of the materials than of the utilities sector.

From Table II, presenting descriptive statistics, we note that gold is less profitable than sectorial stocks in most cases, except for the energy sector for which the annualized rate of return is only 1.75%, vs. over 4% for gold. The most profitable sectors are health care and information, almost 20% per year. The standard deviations are very high in all cases, from 20% to 34% per year. The highest ones are observed for the information and energy sectors (over 30%) and the lowest one for gold (about 19%). The skewness coefficients are negative in most cases (except for the energy and the financial sectors). This means that, in most cases, the distribution of returns is skewed to the left. The excess kurtosis is the highest for gold (about 15), meaning that there are the most extreme values for gold returns. This is followed by the financial sector (about 6). As usually found, all the normality tests (JB and KS) show that the distributions of all return series are not normal.

*** Insert Table II about here ***

From this preliminary analysis, we find that investments in stocks are more profitable compared to gold for China between 2009 and 2015. The most profitable sectors are health care and information technology. However, gold can provide profitable impact to sectorial stock portfolios due to its lower variance and low correlation with stocks. As a next step, the tail dependence of the return distributions and its implications in the portfolio diversification between gold and sectorial stocks in China will be investigated.

5 Empirical results and discussions

5.1 GJR-GARCH estimates and copula parameters

Before assessing the tail dependence between gold and different Chinese sectorial stocks, we first present the results of the GJR-GARCH model based on the univariate time series. As mentioned in Section 3, we apply an ARCH filter to deal with serial correlation and conditional heteroscedasticity of our daily returns. Table III reports the estimated parameters for all investigated assets.

*** Insert Table III about here ***

The α coefficients which measure the adjustment to past shocks are low but significant for all sectors, except for utilities and telecommunication. Interestingly, the returns of the telecommunication sector are characterized by an asymmetric negative impact of shocks on their volatility due to the significance of the γ coefficient. Therefore, except for the utilities sector, all other sectors under observation are described by significant GARCH effects. Moreover, the β coefficients which measure the persistence of the process (i.e., the extent to which a given volatility shock feeds through into the next period's volatility) take values between 0.88 and 0.94 and are significant for most sectors, except for energy, health care, information, telecommunication and utilities. We then account for these sector-specific stylized facts by filtering the returns based on our GJR-GARCH approach. Using the filtered return series, we carry on by assessing different copula measures and their respective parameters.

Table IV presents the tail dependence between all assets and gold which is measured by different copulas. In line with the results from Table I, the dependence between gold and the investigated stocks appears to be weak and the applied Gaussian and t copulas lead to values that are similar to the linear correlation coefficients reported in Table I. According to the applied AIC information criterion, the t copula describes the most adequate approach to assess the gold dependence of most of the analyzed stock sectors (energy, financials, industrials, materials, telecom and utilities). Following Genest *et al.* (2009) we have also applied the Cramér-von Mises test to justify this choice. Although the dependence per se is weak, the t copula indicates significant tail dependence. Moreover, the relatively small values for the degrees of freedom confirm the existence of the tail dependence[9] between gold and sectorial Chinese stocks. This implies that extreme events tend to occur jointly in gold and stock markets. For four sectors (consumer discretionary, consumer staples, health care and information) the Gumbel copula appears to characterize the dependence with gold most adequately. This implies an asymmetric dependence that is only observed for positive extreme returns and indicates that extreme losses of gold and sectorial stock returns do not occur jointly.

*** Insert Table IV about here ***

[9] Indeed, for high values of degrees of freedom, the t copula converges to the Gaussian copula. Please refer to Section 3 for details.

Overall, our results on copulas show that gold and sectorial stocks in China are characterized by tail dependence. This means that extreme returns of gold and sectorial stocks are correlated. In other words, extreme events may have impacts on gold and sectorial stocks jointly. The weak values of copulas suggest that this dependence is low. Thus, an extreme event can have impact on both gold and stocks jointly but the way that each asset responds to this extreme event is not similar. This pattern reveals the potential positive effect of gold in the diversification of Chinese stock portfolios. The highest value of the t copula is observed for the materials sector (0.22) and the lowest values for the health care and utilities sectors (0.07). This means that the tail dependence of returns is the highest between gold and the materials sector. This may be explained by the fact that gold may be used by firms belonging to the materials sector, which is not the case for the health care and utilities sectors. The energy sector has also a higher t copula value compared to other sectors (0.15). This may be explained by the close relationship between gold and energy firms such as firms involved in oil and gas activities. Indeed, it is well known that gold and oil can have similar behavior regarding their relationship with stocks (e.g., Mensi *et al.*, 2013; Ewing and Malik, 2013; Sadorsky, 2014; Caporale *et al.*, 2015). To further investigate this issue and as a robustness check, we will also study the tail dependence between oil and sectorial stock returns in China and its insights in the diversification of portfolios in Section 6 below. The main question tackled in the next section is: How can investors profit from this observed weak tail dependence in their asset allocation?

5.2 Insights for the diversification of portfolios

As explained in Section 3, to investigate the profit of the weak tail dependence between gold and sectorial stocks in China, we base our analysis on the comparison of four types of portfolios: 100% stocks, 50% stocks+50% gold, and weights of gold determined by the minimal-variance portfolio (Markowitz, 1952) and by the optimal weight proposed by Kroner and Ng (1998). The first sub-section will focus on the efficient frontier analysis while the second sub-section will compare the four above-mentioned portfolios using the hedging effectiveness measure (Ku *et al.*, 2007).

5.2.1 Efficient frontiers

We apply the classical Markowitz approach and minimize the portfolio variance with respect to the expected portfolio return. In this context, we consider two different setups: (a) a portfolio in the absence of short selling (only positive weights of assets), where the maximum weight for each individual asset is set to 30% to ensure a realistic risk diversification, (b) a portfolio in the presence of short selling (with also negative weights of assets), where the minimum and maximum weight of each individual asset is set to -30% and 30%, respectively.

For both setups, we examine the following two scenarios:

(1) The portfolio manager exclusively invests in Chinese stocks.

(2) The portfolio manager invests in Chinese stocks and gold.

*** Insert Figure II about here ***

Figure II plots the mean-variance efficient frontiers for the two above-mentioned scenarios without short sales (Panel A) and with short sales (Panel B). Obviously, adding gold leads to portfolios that are characterized by lower risk for a given expected return and a higher return for a given level of risk. This is because the efficient frontiers including gold are both higher than the one with only stocks (with all sectors together, as a curve, or each sector separately, as a point, on the graph). As can be seen in Panel B, including short sales does not change the result qualitatively. To stress this finding, we compare the portfolio allocations that lead to the minimum degree of risk for each scenario (i.e., the portfolio with the lowest variance). For a given investment of 1,000,000 Yuan, the respective amounts for the expected return and risk of each portfolio are presented in Table V. In addition, Figure III shows the weights of each asset included in all portfolios situated on the efficient frontier presented by boxplot diagrams.

*** Insert Table V about here ***

Obviously, adding gold to Chinese stock portfolios[10] lowers the risk. However, we notice that the expected return of the only-stock portfolio is higher than the one with gold. This is explained by the fact that within the study period (2009-2015), the rates of return are higher for stocks than for gold (see Table II).

*** Insert Figure III about here ***

[10] We refer to the portfolio composed of all stock sectors, as shown in the efficient frontiers in Figure II.

In Figure III, the weight of each asset in efficient frontier portfolios is shown (we refer to the portfolio composed of all stock sectors). The sum of all the weights presented in the graphs is always 100%, and the maximal (minimal) weight for one asset is 30% (-30%) when short sales are used. The graphs in the first line (without short sales) show that when gold is not included, the efficient portfolios are essentially composed of six sectors: consumer discretionary (No. 1), consumer staples (No. 2), financials (No. 4), health care (No. 5), information (No. 7) and utilities (No. 10). When gold is included, the weight of the financials (No. 4), information (No. 7), and utilities (No. 10) sectors becomes 0 while the weights of the energy (No. 3), industrials (No. 6) and materials (No. 8) sectors increase strongly. The weight of gold is around 0% and 15% in 50% of the portfolios (indicated by the 25th and 75th percentiles). As we have shown in Table V, including gold lowers the standard deviation but also the return. Overall, the graphs in the first line (without short sales) show that the composition of assets can change significantly when including gold into stock portfolios. The graphs in the second line show that the weight of each sector also changes when using short sales. Furthermore, the weight of gold is very large in each portfolio when using short sales, i.e., 30%. This finding suggests that gold should be more efficient in the diversification of portfolios when allowing for short sales. The results in Table V confirm this analysis as it shows that the standard deviation of the minimal-variance portfolio is lower using short sales.

To have a clearer view on the effect of gold in each stock sector, we continue our analysis with four different types of portfolios for each sector separately diversified with gold.

5.2.2 The hedging effectiveness of gold in Chinese sectorial stock portfolios

As explained in Section 3, we compare only-stock portfolios (PF1) with three alternatives: PF2 is composed of 50% stock and 50% gold; PF3 is composed by following the minimal-variance portfolio from the mean-variance efficient frontier; and PF4 is composed by following the optimal weight of gold calculated using the CCC-GARCH model (Kroner and Ng, 1998). Table VI presents the weight of gold in PF3 and PF4 as well as the hedge ratio (Kroner and Sultan, 1993) for each sector (see Section 3).

*** Insert Table VI about here ***

From Table VI, we find that there is no significant difference between the optimal weights calculated by Kroner and Ng (1998) and those in the minimal-variance portfolio proposed by Markowitz (1952). In the first case, the objective is to minimize the risk which is measured by the conditional volatility while in the second case, it is measured by the variance. On average, the difference between the two methods is only 0.42%. In all cases, the weight of gold to include in each sector stock portfolio is very high, ranging between 58% and 76%. The highest weights of gold are observed for the energy, information and materials (from 74% to 76%) and the lowest for the utilities sector (58%). Thus, we find that sectors in which gold can be involved in their activities (such as energy, information and materials) are the most suitable to be diversified by gold investments.

The hedge ratio (or beta) indicates that a long position of 100 Yuan on stocks should be hedged by a short position on gold whose value corresponds to the hedge ratio, in order to minimize the conditional variance of the portfolio returns. The last column of Table VI shows that investors should take a short position on gold between 10 and 34 Yuan (using futures contracts available on the Shanghai Gold Exchange). The highest value of the short position on gold is observed for the materials sector and the lowest one for the utilities sector. Again, we find that stocks of the materials sector are the most suitable to be diversified with gold while gold provides the least diversification potential for utilities sector stocks.

Table VII presents the hedging effectiveness (Ku *et al.*, 2007) when gold is included in Chinese sectorial stock portfolios.

*** Insert Table VII about here ***

From Table VII, we note that in all cases, including gold helps to reduce the volatility of returns of Chinese sectorial stock portfolios. The hedging effectiveness is between 53% and 70%. This means that including gold can help to reduce between 53% and 70% of the variance of returns of sectorial stock portfolios. We also notice that the hedging effectiveness is greater for minimal-variance portfolios and CCC-GARCH portfolios than for the equal-weighted ones. This may be explained by the lower weights of gold in the equal-weighted portfolios, compared to the two above-mentioned portfolios (see Table VI). The information sector has the highest hedging effectiveness (70%), followed by energy (68%) and materials (65%). Again, the utilities sector has the lowest hedging effectiveness (53%).

6 Robustness check: Is oil a better hedge than gold?

As analyzed in Section 5.1, gold and the energy sector display the highest tail dependence. We thus hypothesize that this high dependence can be due to the close relationship between gold and energy firms, with the latter often strongly related to oil. Indeed, it is well known that gold and oil can have similar behavior regarding their relationship with stocks (e.g., Mensi *et al.*, 2013; Ewing and Malik, 2013; Sadorsky, 2014; Caporale *et al.*, 2015). The objective of this section is thus to verify this conjecture in the Chinese context. For that, we will conduct the same calculations as we have done for gold, meaning GJR-GARCH filter, tail dependence with different copulas, efficient frontiers, and the comparison between four types of portfolios. We use oil prices provided by the West Texas Intermediate (WTI) and available on the website of the Federal Reserve Bank of Saint Louis due to a lack of a Chinese domestic oil market.[11] These are nominal prices expressed in the USD. Thus, to be consistent with data on stocks and gold prices, we have converted oil prices into the Chinese Yuan using the bilateral exchange rate against the US dollar, also available on the website of the Federal Reserve Bank of Saint Louis. In order to save space, most of the corresponding results have been presented in the previous tables and figures and we will only discuss the main findings in this section.

Our findings on copula parameters (see Table VIII) show that the t copula also dominates other copulas for the tail dependence between oil and sectorial stock returns. We find that the magnitude of the tail dependence between oil and sectorial stocks is also similar to that of gold. However, the degrees of freedom for the t copula are a bit higher for oil than for gold. Consequently, the tail dependence between Chinese stocks and gold is stronger than that for oil (see Section 3). This means that the likelihood of extreme joint movements with stocks tends to be higher for gold than for oil. This suggests that Chinese stocks tend to react more to extreme variations of gold prices quoted on the Shanghai Gold Exchange than international oil prices. Moreover, following the t copula results, and as we hypothesized above, the tail dependence between oil and the energy sector is the highest, followed by the financials, industrials and telecommunication sectors. This is different from gold for which the highest t copula value is found for the materials sector, followed by the energy, industrials and information sectors. This difference may be explained by the fact that gold is used in the production process of firms from the materials sector, while oil is used by energy firms.

[11] The absence of a local oil market in China, contrary to the gold market, can be explained by the fact that China is the world largest net oil importer following the US Energy Information Administration (2014). See: `http://www.eia.gov/todayinenergy/detail.cfm?id=15531`.

*** Insert Table VIII about here ***

Our efficient frontier findings (reported in Figure II above) show that adding either oil or gold leads to portfolios characterized by lower risk for a given expected return and a higher return for a given level of risk. We also notice that the efficient frontier with gold outperforms the one with oil, since the former is on top of the latter. This is explained by the fact that the standard deviation of oil returns is much higher than that of gold (34% vs. 19%). As for the rate of return and standard deviation of the minimal-variance portfolio (Table V above), portfolios with oil have higher rates of return but also higher standard deviations than those with gold. This is explained by the fact that the return and standard deviation of oil are both higher than those of gold (7% vs. 4% for the returns and 34% vs. 19% for the standard deviations).

Referring to the weight of oil in PF3 and PF4 (Table VI above), we notice that, in all cases, the optimal weight of gold is higher than that of oil (about 70% vs. 40%). This suggests that gold is more efficient to reduce the risk of Chinese stock portfolios compared to oil. The highest weights of gold are observed for the energy, information and materials sectors (ranging from 74% to 76%). For oil, the sectors are the same but the weights of oil are much lower than those of gold, ranging from 42% to 44%. As for the hedge ratio (Table VII above), the highest value of the short position on gold is observed for the materials sector and the lowest for the utilities sector. For oil, the lowest and highest values are 5 and 15 Yuan for the health care and utilities sectors, respectively. Finally, referring to the hedging effectiveness (Table VII above), in all cases, gold is more efficient than oil. The information sector has the highest hedging effectiveness and the utilities sector has the lowest one, with both oil and gold.

Overall, this robustness check shows that gold and oil have effectively similar impacts on Chinese sectorial stocks: with similar results on copula coefficients and efficient frontiers. However, the principal difference is that gold quoted on the Shanghai Gold Exchange tends to have higher tail dependence with Chinese stocks compared to oil. Furthermore, the oil market tends to be more correlated with the energy sector while the gold market is more correlated with the materials sector. In our view, this result is consistent with the implication of oil in the energy sector and gold in the materials sector. In general, oil offers higher rates of return but also higher risk than gold. This implies that the weight of gold to include in Chinese sectorial stock portfolios is higher than that of oil to minimize the risk (measured by the variance or conditional variance). In all cases, stocks of the utilities sector seem to be the less efficient in the diversification with either gold or oil. Finally, gold has a higher hedging effectiveness than oil in Chinese sectorial stock portfolios.

7 Conclusion

This study has analyzed the tail dependence of returns between gold quoted on the Shanghai Gold Exchange and Chinese sectorial stocks based on different copulas. We have also analyzed implications of this dependence on the hedging of these portfolios. Based on daily data from January 2009 to January 2015, our results show that the dependence between gold and Chinese sectorial stocks is characterized by weak but significant tail dependence which can be symmetric or asymmetric depending on the sector under consideration. This suggests a positive role of gold in Chinese sectorial stock portfolios in the sense that it helps to reduce risk. The optimal weight of gold in sectorial stock portfolios can be very high, over 60%. Following our hedging effectiveness measure, gold is the most efficient diversifier for the information, telecommunication, energy, and materials sector. On the opposite, gold is the least efficient diversifying the utilities sector.

As a robustness check and a general perspective of our results, we have also compared gold to oil since it is well known that these two commodities can have similar impacts on stock portfolios. Our results show that gold quoted on the Shanghai Stock Exchange is overall more effective than oil in the diversification of Chinese stock portfolios. Furthermore, oil tends to be more efficient for stocks of the energy sector while gold is more beneficial as a hedge when diversifying stocks in the materials sector.

Overall, our findings show that investors who are interested in Chinese stocks can use gold quoted on the Shanghai Gold Exchange to diversify their portfolios. The sectors which are the most consistent with gold are energy, information, telecommunication and materials. Gold is the least efficient diversifying the utilities sector. This study extends the narrow academic literature on the Shanghai Gold Exchange which has been developed quickly from 2002. Since China is on the verge of becoming the most important gold producer and consumer worldwide, the evolution of gold prices on the Shanghai Gold Exchange will surely attract further attention with its full opening to international investors.

As a further look on our results, Chinese stock prices have fallen significantly in the summer of 2015, with gold being unable to provide a short-run hedging function (Serapio and Jadhav, 2015). Even if this period was not included in our sample period due to the earlier start of this study, this demonstrates that the risk reducing function of gold can be time-varying and investors cannot rely on its hedging role in a definite manner. This implies that both investors and academics should pay more attention on the time-varying aspect of gold investments. On the other hand, our results on the weak hedging ability of oil for Chinese stocks confirm those found in recent studies, such as Caporale *et al.* (2015) and Nguyen and Bhatti (2012).

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Tables

TABLE I **Linear Correlation**

	Disc	**Stap**	**Energy**	**Finance**	**Health**	**Industry**	**Info**	**Material**	**Telec**	**Utilit**	**Gold**	**Oil**
Discretionary	**1**	0.84	0.76	0.69	0.74	0.89	0.88	0.83	0.78	0.83	0.13	0.1
Staples		**1**	0.65	0.54	0.8	0.77	0.8	0.73	0.69	0.74	0.13	0.09
Energy			**1**	0.76	0.51	0.83	0.67	0.87	0.64	0.75	0.16	0.15
Financials				**1**	0.42	0.77	0.54	0.73	0.57	0.69	0.12	0.13
Health Care					**1**	0.64	0.74	0.6	0.68	0.62	0.12	0.06
Industrials						**1**	0.8	0.88	0.75	0.87	0.11	0.14
Information							**1**	0.76	0.81	0.76	0.11	0.08
Materials								**1**	0.7	0.8	0.23	0.12
Telecommunication									**1**	0.71	0.11	0.1
Utilities										**1**	0.1	0.11
Gold											**1**	0.13
Oil												**1**

Note: All coefficients are significant at 1%.

TABLE II **Descriptive Statistics**

	Average	**SD**	**Skewness**	**Kurtosis**	**JB**	**KS**
Discretionary	16.82%	26.83%	-0.32***	2.67***	412***	0.05***
Staples	13.49%	24.83%	-0.45***	1.65***	194***	0.05***
Energy	1.75%	30.63%	0.10	2.97***	485***	0.06***
Financials	13.03%	27.82%	0.52***	6.03***	2043***	0.07***
Health Care	19.46%*	26.74%	-0.07	2.08***	237***	0.05***
Industrials	5.32%	24.93%	-0.43***	2.10***	280***	0.06***
Information	19.78%	31.17%	-0.46***	1.05***	107***	0.05***
Materials	7.52%	29.81%	-0.29***	2.69***	414***	0.06***
Telecommunication	7.80%	28.63%	-0.27***	1.51***	139***	0.05***
Utilities	8.66%	22.38%	-0.63***	2.84***	529***	0.07***
GOLD	4.31%	19.17%	-0.83***	14.89***	12264***	0.08***
OIL	6.77%	34.33%	0.19***	5.10***	12645***	0.08***

Note: Mean and SD (standard deviation) are in annualized values, estimated by multiplying the daily values by 252 and $\sqrt{252}$, respectively. *** means that the value is significant at the 1% threshold. No asterisk means that the value is not significant. JB (Jarque-Bera) and KS (Kolmogorov-Smirnov) are tests for the normality of the distribution in which *** means that it is not normal at the 1% level.

Table III **GJR-GARCH Parameters**

	Oil	**Gold**	**Disc**	**Staple**	**Energy**	**Finance**	**Health**	**Industry**	**Info**	**Material**	**Telecom**	**Utilities**
$\boldsymbol{\Omega}$	2.617	3.854	2.088	2.638	0.000	2.353	2.365	1.968	0.000	1.814	34.65	0.000
t-Stat	137.5	536.3	447.2	406.3	0.000	465.7	48.03	244.1	0.000	416.6	0.000	0.000
α	0.017	0.089	0.071	0.092	0.227	0.064	0.221	0.055	0.208	0.055	0.000	0.270
t-Stat	1.385	5.228	5.123	5.286	6.812	4.977	6.330	4.219	11.29	4.553	0.000	0.000
γ	0.108	0.021	0.013	0.002	0.000	0.008	0.000	0.015	0.000	0.007	0.249	0.000
t-Stat	6.581	1.165	1.072	0.109	0.000	0.620	0.000	0.927	0.000	0.703	4.356	0.000
β	0.928	0.875	0.919	0.887	0.397	0.931	0.215	0.923	0.416	0.941	0.000	0.729
t-Stat	60.74	37.89	53.62	34.56	0.000	61.91	0.861	39.58	0.000	62.85	0.000	0.000
AIC	6,772.1	8,022.1	7,128.2	7,314.9	6,688.1	7,042.4	7,016.1	7,268.3	6,570.5	6,900.1	7,564.7	6,810.3
Q-Stat	0.85	0.16	0.45	0.60	0.87	0.29	0.00	0.43	0.15	0.62	0.14	0.83
LM	0.95	0.09	0.30	0.05	0.64	0.09	0.00	0.27	0.17	0.19	0.30	0.64

Note: Ω represents the constant, α measures the GARCH effect, γ captures the asymmetric impact of shocks on the volatility and β indicates the persistence of the process. AIC denotes the Akaike information criterion, Q-stat represents the p-value for the Ljung-Box test statistic for serial correlation, and LM gives the p-value for the Lagrange multiplier test statistic for serial correlation up to order 20.

Table IV **Copula Parameters between Gold and Sectorial Stocks in China**

	Disc	**Staple**	**Energy**	**Finance**	**Health**	**Industry**	**Info**	**Material**	**Telecom**	**Utilities**
Gauss	0.12	0.10	0.15	0.10	0.08	0.10	0.10	0.22	0.09	0.07
AIC	-15.47	-12.07	-28.58	-10.00	-6.60	-12.05	-11.36	-65.41	-9.17	-4.84
CvM	0.4	0.2	0.0	0.3	0.3	0.5	0.6	0.2	0.4	0.8
t	0.11	0.09	0.15	0.10	0.07	0.10	0.10	0.22	0.09	0.07
DoF	15.35	12.59	12.28	8.95	16.51	14.26	30.55	14.31	20.38	20.33
AIC	-21.13	-20.47	-36.60	-27.16	-12.10	-19.18	-12.83	-71.78	-12.06	-8.11
CvM	0.9	0.4	0.2	0.9	0.2	0.3	0.7	0.7	0.5	0.4
Frank	0.58	0.52	0.86	0.56	0.41	0.59	0.53	1.32	0.49	0.37
AIC	-9.87	-7.50	-24.07	-8.91	-4.13	-10.29	-8.07	-58.54	-6.48	-2.87
CvM	0.1	0.0	0.0	0.3	0.1	0.0	0.1	0.1	0.0	0.1
Clayton	0.11	0.08	0.17	0.12	0.06	0.12	0.09	0.26	0.09	0.07
AIC	-10.53	-5.71	-25.64	-13.62	-2.08	-13.64	-6.96	-59.24	-7.83	-4.33
CvM	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.2	0.0	0.1
Gumbel	1.07	1.07	1.09	1.06	1.05	1.06	1.06	1.14	1.05	1.04
AIC	-23.67	-23.61	-26.24	-15.34	-18.58	-9.72	-13.30	-55.10	-9.09	-6.69
CvM	0.3	0.0	0.2	0.1	0.0	0.0	0.2	0.1	0.3	0.0

Note: The values in each first line present the copulas estimated by the Gaussian, Student t, Frank, Clayton and Gumbel approaches as described in Section 3. DoF denotes the degrees of freedom for the t copula. AIC denotes the Akaike information criterion. CvM gives the p-value for the Cramér-von Mises test based on Kendall's process.

Table V **Minimal-Variance Portfolios in Three Different Scenarios with and without Short Selling**

In Yuan	Expected Return	Expected Risk
Without Short Selling		
Only Stocks	531.6	13535.93
Stocks + Gold	404.84	10499.87
Stocks + Oil	452.65	11983.45
With Short Selling		
Only Stocks	395.54	12870.04
Stocks + Gold	305.5	9797.5
Stocks + Oil	375.54	11506.78

Note: Risk is given by the standard deviation. The figures in this table show the return and standard deviation based on $1,000,000$ Yuan invested in the minimal-variance portfolio. The results including oil will be analyzed in Section 6 below.

Table VI **The Weight of Gold in PF3, PF4 and the Hedge Ratio**

	PF3: Minimal-Variance		PF4: CCC-GARCH		Hedge Ratio	
Sectors	**Gold**	**Oil**	**Gold**	**Oil**	**Gold**	**Oil**
Discretionary	68.52%	36.59%	68.00%	38.33%	17.60%	8.67%
Staples	64.49%	32.81%	64.17%	34.57%	16.26%	8.00%
Energy	75.49%	43.36%	74.64%	44.15%	23.61%	15.42%
Financials	70.05%	38.09%	69.16%	39.57%	15.35%	11.52%
Health Care	68.02%	36.95%	67.91%	38.98%	15.53%	5.38%
Industrials	64.40%	32.24%	64.64%	34.50%	14.04%	10.87%
Information	74.95%	44.82%	74.68%	46.60%	17.29%	7.75%
Materials	76.15%	42.00%	74.93%	42.99%	34.16%	12.98%
Telecommunication	71.19%	39.99%	71.33%	42.27%	15.85%	10.00%
Utilities	58.50%	27.52%	58.12%	29.02%	9.99%	8.53%

Note: The calculations of these values are explained in Section 3. The results for oil will be analyzed in Section 6 below.

Table VII **Hedging Effectiveness**

	PF2: 50% Stocks		PF3: Minimal-Variance		PF4: CCC-GARCH	
	Gold	**Oil**	**Gold**	**Oil**	**Gold**	**Oil**
Discretionary	57.51%	42.23%	62.04%	31.84%	62.04%	31.77%
Staples	55.08%	34.30%	58.01%	28.58%	58.01%	28.50%
Energy	60.26%	52.28%	68.01%	36.23%	68.00%	36.22%
Financials	58.99%	44.84%	64.26%	31.88%	64.25%	31.83%
Health Care	58.02%	43.30%	62.41%	33.97%	62.41%	33.87%
Industrials	55.95%	33.50%	58.89%	26.24%	58.89%	26.11%
Information	62.24%	55.92%	70.00%	41.00%	70.00%	40.93%
Materials	57.34%	50.22%	65.01%	36.03%	65.00%	36.01%
Telecommunication	60.11%	48.35%	65.96%	34.99%	65.96%	34.88%
Utilities	52.55%	20.80%	53.68%	22.83%	53.68%	22.76%

Note: This table presents the hedging effectiveness of PF2, PF3 and PF4 (including gold) compared to PF1 (only stocks) as presented in Section 3. The higher the value is, the greater the hedging effectiveness. The results for oil will be analyzed in Section 6 below.

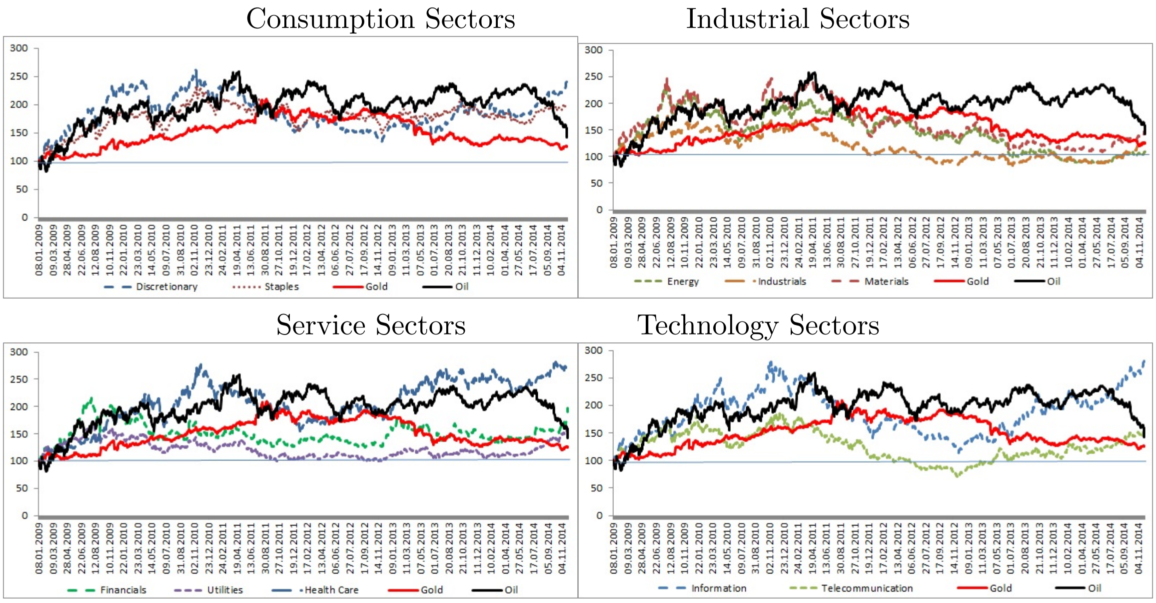
Table VIII **Copula Parameters with Oil**

	Gold	**Disc**	**Staple**	**Energy**	**Finance**	**Health**	**Industry**	**Info**	**Material**	**Telecom**	**Utilities**
Gauss	0.14	0.11	0.09	0.15	0.13	0.06	0.13	0.08	0.12	0.10	0.10
AIC	-23.38	-12.82	-7.90	-27.13	-20.76	-3.13	-19.04	-7.27	-16.79	-12.51	-12.44
CvM	0.8	0.6	0.3	0.9	0.9	0.2	0.7	0.8	0.5	0.8	0.5
t	0.13	0.10	0.08	0.15	0.14	0.06	0.12	0.08	0.12	0.10	0.10
DoF	11.47	30.12	21.53	27.36	15.07	30.04	21.65	17.94	19.38	16.53	63.54
AIC	-33.38	-14.23	-10.41	-28.76	-27.46	-4.49	-21.78	-11.35	-19.74	-16.96	-12.76
CvM	0.8	0.5	0.2	0.7	0.9	0.7	0.5	0.5	0.	0.1	0.1
Frank	0.74	0.56	0.37	0.77	0.79	0.28	0.65	0.37	0.61	0.48	0.56
AIC	-17.69	-9.16	-3.02	-19.33	-20.20	-0.84	-13.31	-3.04	-11.06	-6.36	-9.49
CvM	0.3	0.2	0.3	0.1	0.2	0.1	0.1	0.2	0.1	0.3	0.1
Clayton	0.16	0.11	0.09	0.15	0.15	0.06	0.14	0.08	0.11	0.10	0.10
AIC	-25.46	-12.27	-6.73	-20.05	-20.28	-2.36	-19.01	-4.86	-11.22	-9.06	-10.10
CvM	0.0	0.3	0.2	0.1	0.0	0.3	0.2	0.1	0.0	0.1	0.3
Gumbel	1.08	1.05	1.05	1.09	1.07	1.03	1.07	1.05	1.07	1.06	1.06
AIC	-22.53	-7.09	-7.38	-25.41	-15.98	-1.09	-13.65	-7.62	-15.81	-14.08	-9.48
CvM	0	0.2	0.0	0.3	0.6	0.4	0.2	0.3	0.0	0.2	0.2

Note: See Table IV for details.

Figures

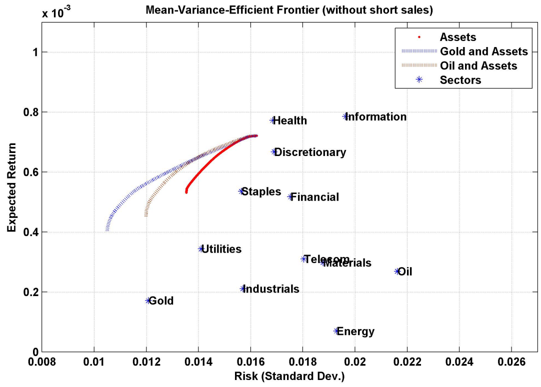
FIGURE I **Daily Values of Indexes on Sectorial Stocks and Gold in China from 2009 to 2015**



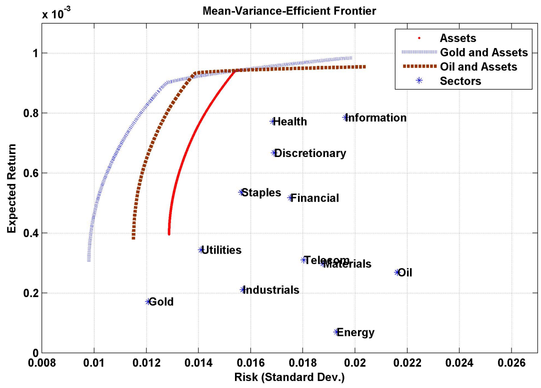
Note: For an easier comparison, we have fixed all values at the same basis of 100 on January 9, 2009.

FIGURE II **Mean-Variance Efficient Frontiers**

A. Without Short Sale

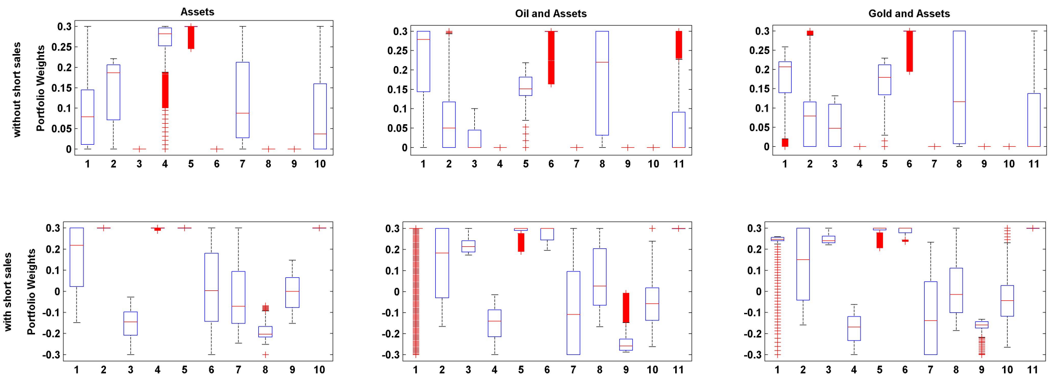


B. With Short Sale



Note: These graphs show the mean-variance efficient frontiers for three different portfolios: (1) including all sectorial Chinese stocks, (2) including all sectorial Chinese stocks + gold, and (3) including all sectorial Chinese stocks + oil. The latter portfolio with oil serves as a robustness check and is discussed in Section 6. The points presented in this graph correspond to only one sectorial stock or to only one asset (gold or oil).

Figure III **Asset Weights in Efficient Frontier Portfolios**



Note: This graph presents the weight of each asset in the efficient portfolios by a boxplot diagram. The central mark in the box indicates the median, the edges of the box are the 25th and 75th percentiles and the whisker limits describe the extreme data points among all portfolios that are on the efficient frontier. Outliers are marked individually (in red). The assets are numbered on the horizontal axis according to their appearance order in the tables. 1=Discretionary, 2=Staples, 3=Energy, 4=Financials, 5=Health Care, 6=Industrials, 7=Information, 8=Materials, 9=Telecom, 10=Utilities, 11=Gold or Oil. The graphs in the first (second) line refer to the case without (with) short selling. The weights of assets for portfolios including oil refer to the robustness check discussed in Section 6.