Int. Journal of Economics and Management 12 (2): 457-471 (2018)

IJEM
International Journal of Economics and Management
Journal homepage: http://www.ijem.upm.edu.my

Dependence Structure between the TEHRAN Stock Exchange and the Derivatives Market of the IRAN Mercantile Exchange: Copula-GARCH Approach

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ABSTRACT

This paper attempts to analyze the dependence structure between returns on the Tehran Stock Exchange (TEPIX) index and (Bahar-Azadi) Gold Coin Futures (GCF) during the period from December 13, 2008 to December 21, 2015. To address this issue, we employ different copula models that allow for capturing extreme dependence (tail dependence) and asymmetry. The empirical results show that the dependence structure between the return series is low and positive. Furthermore, we find evidence of time-varying upper tail dependence, which highlights that the return series co-move in a bullish market. Our results suggest that investors and risk managers may obtain diversification benefits from GCF, especially during market upturns.

JEL Classification: G13, G12, G11, C58, C52

Keywords: Copula-GARCH Model, Co-Movement, IRAN Mercantile Exchange, TEHRAN Stock Exchange.

Article history:
Received: 28 July 2017
Accepted: 27 May2018

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INTRODUCTION

Historically, gold has been used in industrial components and for jewelry. It also serves as an investment asset, a store of value and monetary exchange. Moreover, governments hold gold as part of their reserves. During an uncertain economic environment, (risk adverse) investors purchase gold as a safe-haven commodity against inflation. They also use gold as an alternative source of investment in periods of stock market downturns. Hence, stock and gold prices are expected to have co-movement between them.

During the last decade, Iran's economy has witnessed some extreme events, e.g., US and Western sanctions. The resulting stagnation has had substantial negative impacts on investment returns of different classes of financial assets. In particular, speculation behavior in the Tehran Stock Exchange (TSE) has formed a price bubble, making the TSE market more volatile. These events occurred during a period when commodities emerged as a financial asset class, which drove the interests of investors to gold to diversify equity portfolios.

In the literature, the potential of gold for portfolio diversification has traditionally been of great interest (Hammoudeh et al., 2004; Ewing and Malik, 2013; Nguyen et al., 2015). In this study, we focus on the (Bahar-Azadi) Gold Coin Futures (GCF) and investigate the dependence between GCF and the Tehran Stock Exchange Index (TEPIX). Stocks and (Bahar-Azadi) gold coin futures constitute a major asset class traded on the TSE and the derivatives market of the Iran Mercantile Exchange (IME), respectively. The TSE and the IME are also two principal components of Iran's financial markets.

Moreover, the theory predicts that commodities exhibit low correlations with stocks because the determinants of commodity prices, including supply and demand, inventory and stocks (Gorton and Rouwenhorst, 2006; Chong and Miffre, 2010), are different from those of equity prices. Therefore, they can be viewed as an alternative asset class offering diversified benefits.

In his seminal paper, Markowitz (1952) considers the correlation between asset returns under the assumption of normality, under which the relationship is symmetric and linear. Empirical evidence shows that the correlation between financial assets can change significantly during periods of market crashes and booms; however, the correlation between them is very low (Embrechts et al., 2002). Consequently, the modeling dependence structure between Iran's financial markets by linear correlation measures can lead to misleading results. Therefore, in this paper, we adopt copula approaches to explore both the dependence structure and the possible co-movement between the markets.

This study contributes to the existing literature by investigating the interdependence between GCF returns and the TEPIX returns for Iran and generalizes several empirical studies in terms of the methodology and the sample data. It is believed that this paper is the first to examine interrelationships between the TSE and the derivatives market of the IME. Second, in this paper, we specify the marginal models for each return series by applying the GARCH-family process to capture the stylized facts (fat-tail and autocorrelation) of return distributions, and appropriate copula functions are then fitted in order to more completely describe the dependence structure between them and their evolution through time. Copulas also allow for the possibility of joint extreme co-movement and asymmetry between return series. Moreover, knowledge of the nature of dependence between GCF and the TEPIX is of great interest to investors, risk managers, and policymakers to design effective risk management and hedging strategies and to calculate optimal asset allocations and to make decisions about portfolio allocations. In fact, no study has applied different copulas to model dependence structures between Iran's financial markets. For comparison purposes, we employ the most widely used copulas, including static as well as time-varying Gaussian, Student's t, Gumbel, rotated Gumbel, and Symmetrized Joe-Clayton (SJC) copulas. Third, we use daily data collected from the official websites of the TSE and the IME. The sample covers the period from December 13, 2008, to December 21, 2015, which allows us to account for economic and political events, particularly recent economic sanctions where extreme co-movements between the markets are expected.

The remainder of the paper is organized as follows. Section 2 reviews the related empirical literature on the dependence structure between equity and commodity futures markets. Section 3 introduces the theoretical framework used to assess the dependence structure between GCF and the TEPIX index returns. Section 4 reports and discusses some preliminary findings and the main empirical results. Finally, section 5 presents the conclusion of this paper and its policy implications.

REVIEW OF LITERATURE

The linkage between stock and commodity futures markets has received a great deal of attention in the financial literature over the past decades. Hammoudeh et al. (2004), Ewing and Malik (2013) and Nguyen et al. (2015) use causality and Johansen cointegration methods as measures of dependence between commodities and financial markets.

Several studies have taken the correlation and dynamic conditional correlation (DCC) frameworks to measure the dependence structure between returns. Gorton and Rouwenhorst (2006) find evidence of negative correlation between returns of commodity futures and the stock market during the period of 1959 to 2004. Büyüksahin et al. (2010), using DCC and recursive cointegration approaches from 1991 to 2008, document the time-varying relationship between commodity markets and equity indices. Büyüksahin and Robe (2011), using the time-varying correlation model, show that the correlation between returns on commodity futures and the equity market become stronger in times of financial market stress. Chan et al. (2011), employing a regime-switching model, identify two regimes: a low volatility regime with positive stock returns, and a high volatility regime with negative stock returns. These results document evidence of a connection between stocks, oil, and real estate. Chong and Miffre (2010), employing the DCC model, find that there are time-varying and asymmetric negative correlations between equities and commodity futures.

The multivariate generalized autoregressive conditional heteroscedasticity (GARCH) family models have also been used to study the dynamics of correlation between stock and commodity futures. Choi and Hammoudeh (2010) and Creti et al. (2013) apply the DCC-GARCH model and document that the correlations between commodities and between stocks have decreased and have increased, respectively, during extreme events. Mensi et al. (2013) investigate the correlation between the S&P500 and some commodities using multivariate Vector Autoregression (VAR)-GARCH methodology during a sample period from 2000 to 2011. They identify that stock prices affect commodities' prices, including gold prices. Arouri et al. (2015), using a VAR-GARCH model, show that gold price is an effective hedging tool for portfolio diversification, while it can serve as a safe haven for Chinese stocks during a global financial crisis. Silvennoinen and Thorp (2013), employing double smooth transition conditional correlation (DSTCC-GARGH) models, find that dependence between equities and commodities increased significantly during the recent financial crisis.

Due to the limitations and drawbacks of linear coefficients of dependence, empirical studies largely suggested using copula functions to investigate the co-movement between financial markets. Some of these studies have analyzed the dependence structure between stocks and commodities but largely have focused on energy and currency prices (Nguyen and Bhatti, 2012; Aloui et al., 2013; Sukcharoen et al., 2014; Gatfaoui, 2016). For example, Aloui and Ben Aïssa (2016) extend the vine copula model to investigate the dynamic dependency between the WTI crude oil, the Dow Jones Industrial Average stock index and the trade-weighted US dollar index returns. The empirical results document the symmetric and time-varying dependence underlying them. Karmakar (2017), using copula models, studies the relationship between different currency return series in India. The estimation results of upper and lower tail dependence coefficients imply that the currency markets co-move more in a boom market than in a crash market. Raji et al. (2017) apply a quantile regression methodology to study the linkage between the stock price index and foreign exchange rate of six African countries, including Mauritius, Namibia, Nigeria, South Africa and Zambiafrom 2007 to 2015. The empirical results show the negative association between African financial markets. This means that at the higher (lower) points of exchange rate distribution, the stock index returns are higher (lower), except for Namibia. Kamal and Haque (2016), applying copula models, document the right tail dependence between stock markets and foreign exchange markets of South Asian countries. The results imply that to earn capital gains, foreign investors should take into account the negative relationship between markets in their international investment decisions.

In this context, several studies have analyzed the dependence structure between equity and commodity futures but mainly have conducted studies on developed economies. Delatte and Lopez (2013), using different copula approaches, found that the dependence between returns on the S&P500 and agricultural, metals and energy commodity futures is time-varying, symmetrical and occurs most of the time. Pastpipatkul et al. (2015) use a C-vine copula and a D-vine copula to study the dependence structure between the Tokyo Stock Exchange, London Stock Exchange, and U.S. Dow Jones Industrial Average, and oil prices and gold futures prices. The results show that there is a positive dependence between the London stock market and the commodity markets. Furthermore, the paper concludes that gold futures may be served as a safe haven in equity portfolios.

Recently, the static and time-varying dependence between stock markets and commodity futures markets have also been examined for developing markets. Caillault and Guegan (2005), using different copula families (Student's t copula, Gumbel copula, and Clayton copula), study the dependence structure between three emerging Asian markets for the sample period from 1987 to 2002. The estimation results indicate the existence of dependences between the Thai SET index, Malaysian KLCI index and Indonesian JCI index. Hammoudeh et al. (2014), using static and time-varying copulas, find evidence of low and positive dependence between five main Chinese commodity futures (oils, nonferrous metal, grain, soft commodity and petrochemicals indices) and the Shanghai Stock Exchange from 2000 to 2013. They document the advantage of commodity futures for portfolio diversification. Pastpipatkul et al. (2016), using the Gaussian Markov-switching dynamic copula, investigate the dependence of the underlying gold market and stock markets of Thailand, Indonesia and the Philippines. They conclude that gold can serve as a hedging tool for the three stock markets during market stress. Liu et al. (2017) develop a new time-varying optimal copula approach to represent the optimal dependence structure between time series. The empirical results show that dependence structure between security and commodity markets is time-varying.

Empirical studies in the literature are mostly conducted on developed and other developing economies. To the best of our knowledge, this is the first study of the time-varying interrelationship between the commodity futures market and the stock market for Iran. Since the beginning of the (Bahar-Azadi) gold coin futures trading in July 2008, some studies have analyzed the relationship between the TSE and some commodity prices. Zare and Rezaei (2006) use a VCM model to examine the relationship between the TSE and some commodities. They provide evidence that spot gold coin prices have a significant positive impact on the stock price index. Najafabadi et al. (2012), using static Clayton copula, investigate the relationship between the TSE market and spot prices of oil and gold from 1998 to 2011. They find that the TSE is indirectly influenced by gold prices through oil commodity prices. TalebZadeh (2013), using Pearson correlation criteria, find a significant positive relationship between the gold coin spot and futures prices. Hassanzadeh and Kianvand (2012) apply the VECM method and find that spot gold prices have a negative impact on the TSE index.

However, none of the studies mentioned above employs a time-varying copula approach and allows for choosing the appropriate copulas among the most frequently used copula families. This study aims to fill the gap by applying the copula function to analyze the dependence structure between the TSE and the derivatives market of the IME during the period from December 13, 2008 to December 21, 2015. Moreover, we apply time-varying copulas to investigate the evolution of the relationships between the markets.

RESEARCH METHODOLOGY

Copula Function

A copula is a function, which couples or ties a multivariate distribution function to its univariate marginal distributions. In other words, a copula allows researchers to separately model the margins and the underlying dependence structure without losing any information from the original multivariate distribution.

Let $F(R_{tepix,t}, R_{gcf,t}|\Omega_{t-1})$ be a multivariate distribution function with margins $F_{tepix}(R_{tepix,t}|\Omega_{t-1})$ and $F_{gcf}(R_{gcf,t}|\Omega_{t-1})$, for the TEPIX index returns, $R_{tepix,t}$, and GCF closing price returns, $R_{gcf,t}$, respectively. According to Sklar's theorem (1959), there exists a copula C as a joint conditional distribution of returns

$$F\big(R_{tepix,t}, R_{gcf,t}|\Omega_{t-1}\big) = C\left(F_{tepix}\big(R_{tepix,t}|\Omega_{t-1}\big), F_{gcf}\big(R_{gcf,t}|\Omega_{t-1}\big)\right) \tag{1}$$

where Ω_{t-1} denotes all relevant information sets known at $t-1$.

The definition of the copula function in Equation (1) is given in terms of cumulative distribution functions. Assuming that all conditional density functions are differentiable, the conditional joint density $f\big(R_{tepix,t}, R_{gcf,t}|\Omega_{t-1}\big)$ is obtained as follows:

$$\begin{aligned} f\big(R_{tepix,t}, R_{gcf,t}|\Omega_{t-1}\big) \\ = c\left(F_{tepix}\big(R_{tepix,t}|\Omega_{t-1}\big), F_{gcf}\big(R_{gcf,t}|\Omega_{t-1}\big)\right) \times f_{tepix}\big(R_{tepix,t}|\Omega_{t-1}\big) \times f_{gcf}\big(R_{gcf,t}|\Omega_{t-1}\big) \end{aligned} \tag{2}$$

In this representation, $c(u_t, v_t) = \partial^2 C(u_t, v_t|\Omega_{t-1}) / \partial u_t \partial v_t$ with $u_t = F_{tepix}\big(R_{tepix,t}|\Omega_{t-1}\big)$ and $v_t = F_{gcf}\big(R_{gcf,t}|\Omega_{t-1}\big)$, is the conditional density of the copula. The conditional marginals u_t and v_t are in standard uniform. Moreover, $f_{tepix}\big(R_{tepix,t}|\Omega_{t-1}\big)$ and $f_{gcf}\big(R_{gcf,t}|\Omega_{t-1}\big)$ are conditional marginal densities of $R_{tepix,t}$ and $R_{gcf,t}$, respectively. From

Equation (2), it is obvious that the density $c(u_t, v_t)$ contains information regarding the dependence structure between R_{tepix} and R_{gcf}, while the F_{tepix} and F_{gcf} describe the marginal behaviors.

Copulas can also be used to specify the dependence in the joint tails of multivariate distributions. Tail dependence characterizes the behavior of copulas when the values of the marginal conditional distribution functions, F_{tepix} and F_{gcf}, reach their bounds of zero (lower tail dependence) or one (upper tail dependence) simultaneously

$$\lambda_L(\upsilon) = \lim_{\upsilon \to 0} P\left[X \le F_{tepix}^{-1}(\upsilon) \middle| Y \le F_{gcf}^{-1}(\upsilon)\right] = \lim_{\upsilon \to 0} \frac{C(\upsilon, \upsilon)}{\upsilon} \tag{3}$$

$$\lambda_U(\upsilon) = \lim_{\upsilon \to 1} P\left[X \ge F_{tepix}^{-1}(\upsilon) \middle| Y \ge F_{gcf}^{-1}(\upsilon)\right] = \lim_{\upsilon \to 1} \frac{1 - 2\upsilon + C(\upsilon, \upsilon)}{1 - \upsilon} \tag{4}$$

where F_{tepix}^{-1} and F_{gcf}^{-1} are the marginal quantile functions and where $\lambda_L(\upsilon)$ and $\lambda_U(\upsilon) \in [0, 1]$.

In particular, when lower (upper) tail dependence is positive $\lambda_L > 0$ ($\lambda_U > 0$), the probability of observing small (large) returns of a series together with small (large) returns of another series is not zero.

Copula Models

Copula models fall into two families: elliptical and Archimedean. Elliptical copulas are symmetric, but Archimedeans allow for asymmetry in joint tail dependence (Nelsen, 1999). Table 1 provides a brief description of the elliptical and Archimedean copula families and their corresponding dependence parameters. Our copula models allow capturing extreme dependence (tail dependence) and asymmetry.

Table 1 Copula function

Copula	Elliptical Copulas	Lower Tail Dependence (λ_L)	Upper Tail Dependence (λ_U)
Gaussian	$C^{Gaussian}(u_t, v_t; \rho) = \Phi(\varphi^{-1}(u_t), \varphi^{-1}(v_t))$ with Φ^{-1} is the standard normal quantile function, and the linear correlation coefficient ρ is Pearson's measure of correlation, $-1 < \rho < 1$.	0	0
Student's t	$C^{Student-t}(u_t, v_t; \rho, \nu) = T_\nu\left(t_\nu^{-1}(u_t), t_\nu^{-1}(v_t)\right)$ with t_ν^{-1} is the quantile function of the univariate Student's t-distribution with correlation matrix ρ and degree of freedom ν; and ρ is the linear correlation coefficient.	$2t_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{1-\rho} / \sqrt{1+\rho}\right)$	$2t_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{1-\rho} / \sqrt{1+\rho}\right)$
	Archimedean Copulas		
Gumbel	$C^{Gumbel}(u_t, v_t; \delta) = \exp\left\{-\left[(-\ln u_t)^\delta + (-\ln v_t)^\delta\right]^{1/\delta}\right\}$, the dependence parameter δ can take any value in $[1, +\infty)$. The Gumbel copula exhibits upper tail dependence and no left tail dependence (Gumbel, 1960).	0	$2 - 2^{1/\delta}$
Rotated Gumbel	$C^{Rotated_{Gumbel}}(u_t, v_t; \delta) = u_t + v_t - 1 + C^{Gumbel}(1 - u_t, 1 - v_t; \delta)$, the dependence parameter $\delta \in [1, +\infty)$. The Rotated Gumbel copula exhibits left tail dependence and no upper tail dependence (Gumbel, 1960).	$2 - 2^{1/\delta}$	0
Sym-JC	$C^{Sym-JC}\left(u_t, v_t; \lambda_U^{Sym-JC}, \lambda_L^{Sym-JC}\right) = 0.5\left(C^{JC}\left(u_t, v_t; \lambda_U^{JC}, \lambda_L^{JC}\right) + C^{JC}\left(1 - u_t, 1 - v_t; \lambda_U^{JC}, \lambda_L^{JC}\right) + u_t + v_t - 1\right)$, $C^{JC}\left(u_t, v_t; \lambda_U^{JC}, \lambda_L^{JC}\right) = 1 - \left(1 - \{[1 - (1 - u_t)^\kappa]^{-\gamma} + [1 - (1 - v_t)^\kappa]^{-\gamma} - 1\}^{-1/\gamma}\right)^{1/\kappa}$, with dependence parameters, $\kappa = 1/\log_2\left(2 - \lambda_U^{JC}\right)$ and $\gamma = -1/\log_2\left(\lambda_L^{JC}\right)$, where $\lambda_U^{Sym-JC}(v) \in (0,1)$ and $\lambda_L^{Sym-JC}(v) \in (0, 1)$ measure the tail dependences (Clayton, 1978).	$2 - 2^{1/\kappa}$	$2^{-1/\gamma}$
Plackett	$C^{Plackett}(u_t, v_t; \pi) = \frac{1}{2(\pi-1)}\left(1 + (\pi - 1)(u_t + v_t) - \sqrt{\left(1 + (\pi - 1)(u_t + v_t)\right)^2 - 4\pi(\pi - 1)u_t v_t}\right)$, the dependence parameter $\pi \in [0, +\infty)\backslash\{1\}$. This copula is tail independent (Plackett, 1965).	0	0
Frank	$C^{Frank}(u_t, v_t; \lambda) = \frac{-1}{\lambda}\log\left(\frac{(1-e^{-\lambda}) - (1-e^{-\lambda u_t})(1-e^{-\lambda v_t})}{(1-e^{-\lambda})}\right)$, the dependence parameter $\lambda \in (-\infty, +\infty)\backslash\{0\}$. This copula is tail independent (Frank, 1979).	0	0

Modeling Marginal Distributions

As shown in Table 2, the distributions of the returns on the TEPIX index and closing prices of GCF display fat-tail, skewness, volatility clustering and autocorrelation. To capture these features, we specify an ARMA(p,q) model with the GARCH (1,1) process. The conditional mean equation or the TEPIX or GCF returns, denoted by R_t, is specified by

$$R_t = \mu + \sum_{j=1}^{p} \alpha_j R_{t-j} + \sum_{i=1}^{q} \beta_i \eta_{t-i} + \eta_t \tag{5}$$

where μ is a constant term and where α_j and β_i are autoregressive and moving average terms, respectively. The error term, η_t, is a product of conditional volatility, σ_t, and news, ε_t, at time t. We assume that the return innovation, η_t, in Equation (5) follows Student's t-distribution with ν degrees of freedom,

$$\sqrt{\frac{\nu}{\sigma_t^2(\nu-2)}}\varepsilon_t|\Omega_{t-1} \sim \text{ i.i.d } t_\nu \tag{6}$$

We assume that the conditional volatility follows the GARCH(1,1) process as follows:

$$\sigma_t^2 = \Phi_0 + \lambda_1 \eta_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 \tag{7}$$

where σ_{t-1}^2 and η_{t-1}^2 represent the GARCH component and the ARCH component, respectively. In this paper, the AIC, BIC and LLF are used to select the optimal lag length for the conditional mean process of the ARMA-GARCH model

Estimation Method

The parameters of the copula density and the marginal models, $\theta \in \Theta$, in Equation (2) are estimated by maximizing the log-likelihood function:

$$\begin{aligned} \log\left[f\left(R_{tepix,t}, R_{gcf,t}|\Omega_{t-1}\right)\right] &= \log\left[c\left(F_{tepix}\left(R_{tepix,t}|\Omega_{t-1}\right), F_{gcf}\left(R_{gcf,t}|\Omega_{t-1}\right)\right)\right] + \log\left[f_{tepix}\left(R_{tepix,t}|\Omega_{t-1}\right)\right] \\ &+ \log\left[f_{gcf}\left(R_{gcf,t}|\Omega_{t-1}\right)\right] \end{aligned} \tag{8}$$

Generally, in a multivariate framework where the dimension is large, achieving a simultaneous maximization of above log-likelihood function for all parameters is difficult. Joe (1997) proposed a two-step parametric estimation procedure known as Inference Functions for the Margins (IFM). The first step consists of estimating the parameters of marginal distributions of return series by fitting the best ARMA-GARCH process to the data via maximum likelihood. Then, the probability integral transform is applied to the standardized residuals, computed from estimated marginal models, to provide estimated values of probabilities $\hat{u}_t$ and $\hat{v}_t$, $t = 1, \dots, T$. In the second step, conditional on these values, the copula parameters, θ_c, are estimated via solving the following problem

$$\hat{\theta}_c = \underset{\theta_c}{\operatorname{argmax}} \sum_{t=1}^{T} \ln c(\hat{u}_t, \hat{v}_t|\Omega_{t-1}; \theta_c) \tag{9}$$

where θ_c denotes the parameters in the model for c_t, $\hat{u}_t = F_{tepix,t}\left(R_{tepix,t}\middle|\Omega_{t-1}; \hat{\theta}_{tepix}\right)$ and $\hat{v}_t = F_{gcf,t}\left(R_{gcf,t}\middle|\Omega_{t-1}; \hat{\theta}_{gcf}\right)$.

Data and Empirical Results

We use the daily index of the TEPIX and the closing price of (Bahar-Azadi) gold coin futures. The sample period extends from December 13, 2008 to December 21, 2015, generating a total of 1532 observations.

The TEPIX is a weighted market value of prices of all shares listed in the TSE, representing the TSE market

performance.

GCF contracts are the most actively futures contracts in the derivatives market of the IME. We collect the TEPIX index and GCF closing price series from the TSE and the Tehran Gold, Jewelry and the Coin Union official websites, respectively.

Moreover, we use continuously compounded daily logarithmic returns, calculated as $R_t = \ln(P_t/P_{t-1}) \times 100$, where P_t is the TEPIX index or the closing prices of GCF at day t.

RESULTS AND DISCUSSION

Table 2 Descriptive statistics of the TEPIX and GCF return series from December 13, 2008 to December 21, 2015

	RTEPIX	RGCF
Mean	0.125658	0.099441
Std. Dev	0.812853	1.687900
Skewness	0.887595	1.652674
Kurtosis	10.75340	20.00835
Maximum	7.396389	17.74895
Minimum	-4.520978	-9.227331
Jarque-Bera	4038.510*	19163.36*
	(0.00000)	(0.00000)
Q(12)	332.26*	54.159*
	(0.00000)	(0.00000)
$Q^2(12)$	48.812*	56.082*
	(0.00000)	(0.00000)
ARCH(12)	25.22993*	581.2960*
	(0.00000)	(0.00000)

Note: numbers in *parentheses* are the p-values for the corresponding diagnostic tests. Asterisk (*) indicates rejection of the null hypothesis at the 5% significance level.

Table 2 presents the descriptive statistics of daily return series. We can see that both return series exhibit positive skewness and excess kurtosis. The positive skewness indicates that marginal distributions of the return series are asymmetric, and extreme observations are placed more in the right tail of return distributions. The positive value of kurtosis indicates that the univariate distributions of the TEPIX index and GCF closing price return are leptokurtic. These results imply that return series exhibit fat-tailed behavior. In addition, the Jarque-Bera normality test implies that the return series are not (unconditionally) normally distributed, which confirms the results of the skewness and kurtosis statistics. The result of the Ljung–Box Q statistic test for serial correlation of order 12 suggests the presence of autocorrelation in the return series of the TEPIX index and GCF. Moreover, the Ljung-Box Q^2 statistic test of order 12 indicates that the squared return series show significant serial correlation, which reveals non-linear dependence and volatility clustering in the return series. Further, the LM test statistics indicate the presence of ARCH effects in the return series. Overall, the results of Table 2 support the use of the GARCH-family model to filter return series.

The (unconditional) Pearson linear correlation coefficient of -0.0336 is obtained, which indicates the weak and inverse correlation between the TSE and the derivatives market of the IME[†]. This implies that GCF may be an effective tool for portfolio diversification.

However, linear correlation is not an appropriate measure of dependence, so we use copulas to examine the dependence structure between returns of the TEPIX and GCF. For this purpose, we first use an empirical copula table of Knight et al. (2005) as a benchmark.

After dividing each sorted (in ascending order) return series evenly into 10 bins, we count the number of observations in each joint quantile. The observations with the lowest values are in bin 1, and the observations with the highest values are in bin 10. If two series are independent, the numbers in each cell will be about the same. If two series are perfectly positively or negatively correlated, observations will mostly lie on the diagonal connecting the upper-left with the lower-right corners and the lower-left with the upper-right corners, respectively. If there is lower tail dependence between the two series, more observations will be in the cell (1, 1), and if there is upper tail dependence, a large number of observations will be in the cell (10, 10).

Table 3 presents the empirical copula table for the TEPIX and GCF return series. The cells (1, 1) and (10, 10) contain 15 and 24 observations, respectively, out of 1532 observations. This suggests the evidence of the potential co-movement between the TEPIX and GCF return series. Comparing two cells, we note weak evidence of possible asymmetries in tails.

Table 3 Empirical copula for return series

15	13	13	11	14	13	10	13	20	30
21	15	14	14	13	11	11	10	17	14
19	10	8	10	13	14	6	10	16	19
30	21	23	28	24	30	20	21	28	26
11	6	9	17	10	16	13	4	5	4
15	8	10	17	15	26	22	14	5	4
16	11	11	16	20	26	25	20	2	1
13	11	9	18	21	22	26	21	4	8
14	13	15	20	29	20	23	17	13	12
19	20	20	10	5	12	10	16	20	24

Note: The vertical axis (from top to bottom) ranks (in ascending order) for the RGCF; the horizontal axis (from left to right) ranks (in ascending order) for the RTEPIX.

Specification of Marginal Distributions

We first estimate the ARMA(p,q)-GARCH(1,1) process for each return series. As the return series exhibit features of fat-tail, skewness, volatility clustering, and autocorrelation, we consider Student's t innovations in modelling marginals. For the TEPIX index returns and GCF returns, the significance tests and the AIC, BIC and LLF criteria suggest an ARMA(3,1)-GARCH(1,1) and ARMA(3,3)-GARCH(1,1) process, respectively.

Table 4 reports the estimated results of the marginal coefficients. The empirical results show that, for the conditional mean equations, all estimated coefficients are statistically significant at the 5% level, except the intercept term, μ, in the TEPIX returns series. Moreover, for the conditional variance equations, all estimated coefficients: the intercept, the ARCH coefficients, and the GARCH coefficients, are positive and statistically significant.

Table 4 Parameter estimations of the marginal models

	RTEPIX	**RGCF**
Mean Equation		
μ	0.05323	0.037425
	(0.8680)	(0.3435)

[†] The results of the Pearson linear correlation are not reported due to limited space but are available from the author on request.

Table 4 Cont.

$\boldsymbol{\alpha_1}$	1.217048	0.402412
	(0.0000)*	(0.0000)*
$\boldsymbol{\alpha_2}$	-0.412454	-0.338395
	(0.0000)*	(0.0000)*
$\boldsymbol{\alpha_3}$	0.130609	0.923379
	(0.0000)*	(0.0000)*
$\boldsymbol{\beta_1}$	-0.823092	-0.373755
	(0.0000)*	(0.0000)*
$\boldsymbol{\beta_2}$	-	0.331092
		(0.0000)*
$\boldsymbol{\beta_3}$	-	-0.937182
		(0.0000)*
Variance Equation		
$\boldsymbol{\phi_0}$	0.004957	0.018779
	(0.0472)	(0.0000)*
$\boldsymbol{\lambda_1}$	0.157151	0.097976
	(0.0000)*	(0.0000)*
$\boldsymbol{\gamma_1}$	0.879583	0.877198
	(0.0000)*	(0.0000)*
Residual Diagnostics		
Q(12)	7.0733	14.913
	(0.853)	(0.246)
Q^2(12)	4.8325	2.1550
	(0.963)	(0.999)

Note: the p-values for the significance test are in parentheses. Asterisk (*) indicates significance at the 5% level.

Finally, we perform residual diagnostics. From Table 4, the Ljung-box Q statistic test of order 12 fails to reject the no serial correlation null hypothesis in residuals. Similarly, Ljung-box Q^2 statistic test of order 12 fails to reject the null hypothesis of serial correlations in squared residuals. These findings confirm that the marginal models adequately capture the return distributions.

Testing for the density mis-specification is a critical step in constructing the copula model because mis-specified models for the marginal distributions may cause overestimating of the dependence structure (Patton, 2006). Here, we perform the goodness of fit tests, usually used to check if the probability integral transformations of the standardized residuals are uniform (0, 1).

Table 5 reports the results of these tests. The p-values of the LM test of regressing four moments using $(u_t - \bar{u})^k$ and $(v_t - \bar{v})^k$, where $k = 1, 2, 3, 4$ on their own 20 lagged terms are all above the 5% significance level. Therefore, the null hypothesis of no serial correlation in the probability integral transforms $\hat{u}_t$ and $\hat{v}_t$ cannot be rejected. Hence, they are i.i.d.

Table 5 Goodness of fit tests

	RTEPIX	RGCF
First Moment	0.8016	0.4259
Second Moment	0.7793	0.9246
Third Moment	0.4299	0.6743
Fourth Moment	0.6757	0.5803
K-S test	0.6034	0.2868
C-vM test	0.8152	0.6516
A-D test	0.8955	0.8042

Note: the p-values for the goodness of fit test are reported at the significance level 5%.

All the p-values of the K-S test, C-vM test, and A-D test are above the 5% significance level, suggesting that the probability integral transformations of the standardized residuals are uniform (0, 1). Therefore, the marginal models areadequately specified and then can be used for estimating the copula's parameters.

Specification of Dependence Structure

In this paper, to estimate the dependence structure between returns on the TEPIX and GCF, we employ seven static copulas, Gaussian, Student's t, Gumbel, Rotated Gumbel, Plackett, Frank, and Sym-JC copulas, and five time-varying copulas, Gaussian, Student's t, Gumbel, Rotated Gumbel, and Sym-JC copulas. The estimation results of these copulas are reported in Table 6[‡]. Panel A of Table 6 reports the results for static copulas and Panel B for time-varying copulas.

The results from Panel A show that the dependence coefficients (correlation parameters) of Gaussian and Student's t copulas, ρ, are negative and statistically insignificant. We also see that the estimated values of ρ are very similar to the Pearson correlation coefficient. The degree of freedom ν of Student's t copula is approximately 7 and is statistically significant at the 5% level. This finding indicates the potential of co-movement and tail dependence between the TEPIX and GCF returns.

Table 6 Results of estimates for static and time-varying copulas

	RTEPIX and RGCF		
Static Gaussian Copula		**Time-Varying Student's t Copula**	
ρ	-0.0384	ψ_0	-0.0817
	(0.1447)		(0.3387)
LLF	1.0635	ψ_2	0.2914
			(0.0293)*
AIC	-2.1256	ψ_1	-1.9901
			(0.0051)*
BIC	-2.1222	LLF	3.3948
Static Student's t Copula		AIC	-6.7870
ρ	-0.0388	BIC	-6.7801
	(0.1819)		
ν	6.7618	Time-Varying Sym-JC Copula	
	(0.0000)*		
LLF	15.7177	ψ_0^U	-13.1698
			(0.0000)*
AIC	-31.4342	ψ_2^U	0
			(0.9999)
BIC	**-31.4307**	ψ_1^U	0
			(0.9989)
Static Placket Copula		ψ_0^L	-13.1698
			(0.0000)*
π	0.8848	ψ_2^L	0
	(0.0000)*		(0.9546)
LLF	1.0645	ψ_1^L	0
			(0.8795)
AIC	-2.1277	**LLF**	5.3040
BIC	-2.1243	**AIC**	10.6158
Static Frank Copula		**BIC**	10.6367
λ	0.0001	Time-Varying Gumbel Copula	
	(0.0000)*		
LLF	-0.0008	ψ_0	-2.8242
			(0.0000)*
AIC	0.0030	ψ_1	2.1580
			(0.0000)*
BIC	0.0065	ψ_2	1.3339
			(0.0000)*
Static Sym-JC Copula		**LLF**	**3.9502**
λ_U^{SJC}	0.1907	**AIC**	**-7.8964**
	(0.0000)*		
λ_L^{SJC}	0.1907	**BIC**	**-7.8860**
	(0.0000)*		
LLF	-1.6426	Time-Varying Rotated Gumbel Copula	
		ψ_0	-1.9300
			(0.0000)*
AIC	3.2864	ψ_1	1.4683
			(0.0000)*
BIC	3.2899	ψ_2	1.0953
			(0.0000)*
Time-Varying Gaussian Copula		**LLF**	1.9123
ψ_0	-0.0866	**AIC**	-3.8207
	(0.4072)		
ψ_2	0.4423	**BIC**	-3.8103
	(0.0284)*		
ψ_1	-1.9927		
	(0.0091)*		
LLF	3.2856		
AIC	-6.5686		
BIC	-6.5616		

[‡]. For static Gumbel and Rotated Gumbel copulas the estimated parameters are not statistically significant. We exclude their estimation results from Table 6 due to the limited space but are available on request.

Note: the p-values for the significance test are replaced in parentheses. Asterisk (*) indicates significance level at 5%.

To choose the best fitted copula, along with and Log-Likelihood Function (LLF), we apply the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), as follows:

$$AIC = -2 \times LLF + 2 \times n$$
$$BIC = -2 \times LLF + \log(T) \times n$$

where n denotes the number of parameters of the copula model, and T shows the number of observations (here: 1532). The minimum values of AIC and BIC (in bold) indicate the optimal copula fit.

The estimated dependence parameters of Plackett, Frank, and Sym-JC copulas are all statistically significant at the 5% level and reflect the positive dependence between the TEPIX index and GCF returns. The lower and upper tail dependence parameters of Sym-JC copula are statistically significant and have similar values of approximately 0.1907. Overall, the results from static copulas demonstrate the weak positive symmetric tail dependence between the TEPIX and GCF returns.

Among the copulas with a static dependence parameter, the Student's t copula provides the most suitable performance for describing the dependence structure between return series, based on the values of the LLF, the AIC, and the BIC, reported in Panel A of Table 6.

During the sample period considered in this study, Iran's economy was affected by some political and economic extreme events, e.g., recent sanctions that make the dependence structure between the TSE and the derivative market of the IME change overtime. This evidence calls for the specification of time-varying copulas. The results from Panel B of Table 6 show that the estimated coefficients of all time-varying copulas are statistically significant at the 5% level, except Gaussian copula.

Examination of empirical copula illustrated the potential asymmetries in the relationship between GCF and the TEPIX index returns. However, it should be tested whether or not asymmetric copula models describe the relationships better than the symmetric models. On the other hand, knowledge of the nature of dependence between GCF and the TEPIX is of great interest for investors and policymakers to design effective risk management strategies. Since different copulas exhibit different dependence structures, we compare them on the basis of LLF, AIC and BIC criteria. The empirical results of the AIC and BIC, as well as LLF, show that the static Student's t copula and the time-varying Gumbel copula most adequately describe the dependence structure between the returns of the TEPIX index and GCF. As the dependence parameter of Student's t copula is not statistically significant, the time-varying Gumbel copula is chosen as the best model for describing the dependence structure between the return series. The dominance of the time-varying Gumbel copula over Gaussian copula (static and time-varying) suggests that the linkage between the TEPIX and GCF return series is characterized by the upper tail and is asymmetric. This finding means that it is likely for the TEPIX index returns and GCF price returns to have dependence in case of a boom market rather than the bear market.

Moreover, the number of statistically significant parameters for time-varying copulas is higher than that for static copulas, implying that the static copulas are not superior to the time-varying copulas. This finding also confirms the time-varying nature of the dependence structure between the TSE and the derivatives market of the IME.

The time path and average of the dependence structure between the TEPIX and GCF returns, based on time-varying Gumbel copula, are depicted in Figure 1. The results show that the average dependence (dashed red line) is slightly strong and taking on the values between 1 and 1.2. It is observed that the average dependence is changing during the sample period. These results confirm our assumption of a time-varying dependence structure between returns on the TEPIX index and GCF. In particular, the estimated dependence parameter always has a positive sign over the sample period, indicating the absence of regime switching in the relationship between the TSE and the derivatives market of the IME.

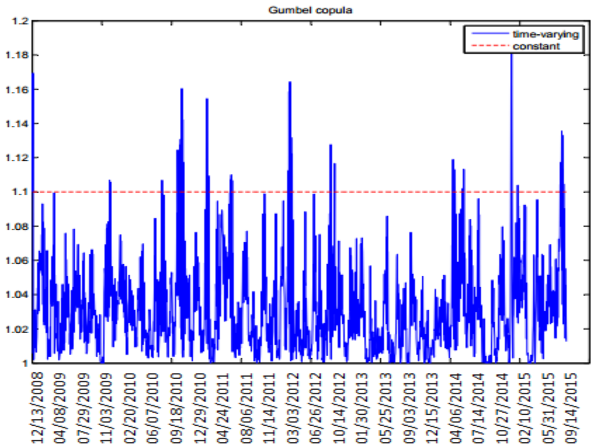

Figure 1 The evolution of the dependence structure of the time-varying Gumbel copula

The time path of upper tail dependence between the TEPIX and GCF returns is shown in Figure 2. It can be observed that the upper tail dependence structure between the return series has high variation during the sample period. The positive value of upper tail dependence in the Gumbel copula implies that there are joint price co-moving tendencies in times of market upturns. Moreover, we observe that in some periods the coefficient of upper tail dependence approaches zero. This finding implies that during a bullish market and other calm periods with a higher probability of joint extreme gains, in some periods the return series are asymptotically independent.

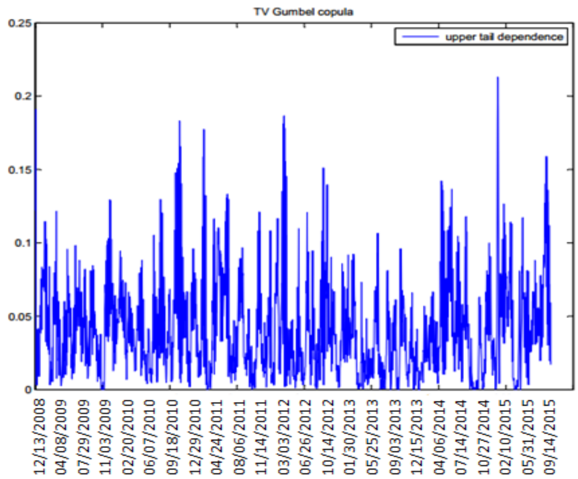

Figure 2 The evolution of upper tail dependence of the time-varying Gumbel copula.

Our findings of positive dependence between the stock market and commodity futures market are confirmed by Zare and Rezaei (2006) and Najafabadi et al. (2012). They employ a VCM and static Clayton copula models, respectively, and conclude that gold coin prices have a positive impact on the TSE index. In contrast to our findings, Hassanzadeh and Kianvand (2012), applying the VECM method, show that gold price has a negative impact on the TSE index.

Hammoudeh et al. (2014) provide evidence for low and positive dependence between Chinese commodity futures and the Shanghai stock exchange. In contrast to our findings, they show that Chinese commodity futures and stock markets co-move more in the case of a bearish than a bullish market. Pastpipatkul et al. (2016) also find that dependence between returns of stock markets with gold is high during the European crisis. Moreover, our finding of time-varying dependence is similar to those obtained by Delatte and Lopez (2013); however, they identify the symmetric dependence between S&P500 and commodity futures, whereas we find the evidence of asymmetric dependence between the stock market and commodities.

CONCLUSIONS

Empirical studies in the literature are mostly conducted on developed and other developing economies. To the best of our knowledge, studies investigating the dependence structure between Iran's financial markets have been scarce, and thus, there is no adequate discussion of it. The existing literature mostly documents that these relationships are frequently constant and linear over time. In this paper, we employ both static and time-varying copulas to study the dependence structure by using data from the TEPIX and GCF closing prices during December 13, 2008 to December 21, 2015.

First, return series are modeled separately with an ARMA(p,q)-GARCH (1,1) process with conditional Student's t innovations. For modeling the dependence structure, we conduct seven static copulas and five time-varying copulas that allow capturing extreme dependence (tail dependence) and asymmetry. The empirical copula table demonstrates the evidence of potential co-movement between the TEPIX and GCF return series as well as asymmetric dependence in upper and lower tail dependences. The empirical findings suggest that the time-varying Gumbel copula, which has right tail dependence, is the best model for describing the dependence structure between return series. Moreover, the estimation results of time-varying Gumbel copula show a low, positive, time-varying and asymmetric dependence between returns on the TEPIX index and GCF during the sample period. Furthermore, the findings show a positive co-movement between the return series during market upturns in our sample. Overall, our findings highlight that the TSE and the derivatives market of the IME must be considered as a very little linked market and that in times of market upturns, they have a tendency to move together.

These findings imply that investors in Iran can make use of gold coin futures to diversify the risks of equity portfolios. Moreover, the evidence of time-varying upper tail dependence suggests that investors and risk managers may obtain diversification benefits from (Bahar-Azadi) gold coin futures, particularly during market upturns. Our findings also have far-fetching policy implications in this respect and provide some basic issues concerning the design of a healthier financial system. With the development of commodity futures, commodities have emerged as a financial asset class for investors. Therefore, knowledge of the nature of dependence and its evolution between different assets in Iran's financial markets is crucial for risk management, calculating optimal asset allocation and for portfolio diversification decisions. Moreover, understanding the interrelationship between the financial assets can help with the pricing of new investment products, particularly during extreme events.

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