Is Gold a Safe Haven? International Evidence revisited

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Abstract:

The literature has not settled down on safe haven property of gold in emerging and developing countries. Therefore, in this study, we revisit the international evidence on hedging and safe haven role of gold for 34 emerging and developing countries with a span of daily data covering January 2000 – November 2018. We employ GARCH-copula approach to estimate lower-tail extreme dependencies of the joint distribution of gold and equity returns. We also introduce a new definition for strong safe haven property of an asset. Our findings indicate that while gold serves as a hedge instrument for all countries in our sample, we got evidence of weak safe haven property for gold, for domestic investors, only in 18 countries, and a strong safe haven asset only in six countries.

Keywords: gold emerging markets copula tail dependence safe haven
JEL Codes: C58, F30, G10, G15

1 Introduction

In recent years, the world economy experienced the worst global financial and economic turmoil since the Global Depression. Given the fact that the economies and markets are more integrated than ever, and we have look-alike countries whose currencies and financial markets are moving together, there is an increasing demand amongst investors to seek for a safe haven asset at episodes of economic and financial calamities. The severity of the 2007 financial crisis and the threat of future unpredictable recessions provide strong motivation for an investigation of a safe haven asset.

A safe haven asset is defined as an investment instrument that shows zero or negative correlation with other assets in periods of severe market turmoil. This way, investors that hold a true safe haven asset in their portfolios will shield themselves from extreme losses at extreme market failures. To capture the safe haven asset feature of an investment instrument, we need to analyze the co-movement between that instrument and other assets in the portfolio at extreme market falls. One motivation for the investors to seek a safe haven asset is to minimize risk exposure by having more good quality assets during severe market downturns, which is also known as the flight-to-quality phenomenon. Another motivation is to have greater liquidity during extreme market falls by having more true safe haven assets, also known as the flight-to-liquidity phenomenon.

Additionally, we might have some institutional demand for gold by central banks or the government sector during turbulent times for purposes of strengthening current account sustainability, reducing the risk of sudden capital reversals, and increasing central banks' "war-chest". Especially for emerging and developing countries, gold is seen as the ultimate asset to hold at times of high uncertainty. Therefore, Central Banks increase their reserves with gold to protect their countries from possible currency or financial crises. Given the stylized fact that gold and US dollar are negatively correlated, gold holdings also provide diversification for central banks that hold US dollars as reserves[1]. All these factors, in the case of gold, contribute to the hike in the gold price during market turmoil. In that regard, the relationship between gold and the stock market has historically been an intriguing one; a number of publications have been put forth as researchers attempt to delineate the role gold as a safe haven asset against different currencies and stock market indices[2]. From many aspects, gold can be considered as a natural candidate for a safe haven asset. In both advanced and emerging nations, whenever there is financial distress, we observe a spontaneous attack in the market to buy gold by both retail and professional investors. Also, increasing integration of financial markets leads to synchronization of stock markets across the globe. As a result, at times of market turmoil, it is not uncommon to see co-movements of different asset classes in the same direction. Since predictability and stability become crucial for investors at severe market downturns, gold's safe-haven asset qualities shine as a universal safe-haven for preserving

[1] After the Great Recession in 2008, advanced nations have lowered their gold holdings while central banks of emerging and developing countries did the opposite. One explanation would be that, due to the easy monetary policies of advanced nations, the massive influx of money into the emerging and developing countries might have worried the recipient governments about a sudden reversal in their currencies.

[2] Baur and Lucey (2010), Ciner et al. (2013), Hood and Malik (2013), Aboura et al. (2016) looked at the US markets. Baur and Lucey (2010) and Baur and McDermott (2010) looked at the European markets.

wealth.

There is almost a consensus that gold is a true safe haven asset for the advanced economies' stock markets. Baur and Lucey (2010) find that, except for Australia, Canada, and Japan, gold is a safe haven for major European stock markets and the US. Ciner et al. (2013), Baur and McDermott (2010) and Liu (2019) confirm the safe haven feature of gold for advanced economies[3]. However, when it comes to equity markets in emerging and developing countries, there are mixed results. While Baur and McDermott (2010) and Bekiros et al. (2017) find that gold is not a safe haven asset for large emerging markets such as the BRICS countries, Chkili (2016), on the other hand, using an asymmetric dynamic conditional correlation approach, reach to the conclusion that gold is a safe haven asset for BRICS countries. In a very recent article, Wen and Cheng (2018) find evidence in favor of safe haven role of gold against a small set of emerging nation stock market indices. On the other hand, by extending the analysis of Baur and McDermott (2010) to a sample of 28 emerging and developing countries, Gurgun and Unalmis (2014) reach to an opposite conclusion that gold is, in fact, a safe haven in many emerging stock markets when more data points are utilized. We also have some recent papers that found mixed evidence for the sample of emerging and developing countries. Beckmann et. al (2015) adopted a smooth-transition regression and find evidence of safe haven role for gold against stock indices but their results are country-specific. In light of the previous findings, we revisit the international evidence on safe haven role of gold. Our contribution to the literature is two-fold. First, we tested safe haven property for a broader sample of 34 emerging and developing countries with monthly data spans from January of 2000 till November of 2018. Second, we utilize copulas which allow measuring the degree of association at a different part of the distribution so that we can focus only on the degree of association at extreme market conditions, not from central observations. The copula approach has the limitation that it can only be used to test weak safe haven property as it provides a non-zero probability of extreme price movements to test for non-correlated series. We propose applying monte-carlo simulations on the best-fitting copula to properly test the degree of association for testing strong safe-haven feature of gold.

We investigate the role of gold as a true safe haven asset through an analysis of the returns on stock and gold holdings in 34 developing countries and emerging markets over the last few decades. The previous studies mostly use either linear threshold regression (Baur and McDermott (2010)) or copula-based joint tail modeling (Reboredo (2013)) techniques. The former relies on the average measure of dependencies at specific lower quantile levels, generally in between 5% and 1% lower quantile levels. However, as put forward by Reboredo (2013), if there is any tail dependency between gold and stock returns, linear threshold regression approach will not be able to capture it properly, since extreme failures of the market don't happen 5% of the time, 1% of the time, or even 0.001% of the time. We, therefore, model joint extreme movements of gold and equity returns with the use of copula and test the safe haven feature of gold in 34 developing and emerging economies[4]. Our findings indicate that

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[3] Other studies for advanced nations with similar findings are Reboredo (2013), Flavin et al. (2014), Beckman et al. (2015) and Bredin et al. (2015).

[4] We follow Reboredo (2013), Yang and Hamori (2014), Reboredo and Ugolini (2015) in our approach. These papers examined the role of gold as a safe haven asset against developed economies stock market returns and currencies, however, we focus on emerging market and

while gold serves as a hedge instrument for all countries in our sample, we got evidence of weak safe haven property for gold only for 18 out 34 countries and a strong safe haven only for six countries.

We organize the remaining parts as follows: In section 2, we talk about our empirical methodology. Then in section 3, we summarize data and provide descriptive statistics. We present our findings in section 4 and conclude in section 5.

2 Methodology

2.1 Modeling tail dependence

Earlier studies that use threshold regression models generally look at the correlation of investment instrument with a candidate of safe haven asset at specific lower quantile levels, generally in between 5% and 1% lower quantile levels. The problem with this approach is the arbitrary nature of these percentages. Extreme failures of the market don't happen 5% of the time, 1% of the time, or even 0.001% of the time. Such catastrophes are almost impossible to predict in a systematic way and trying to capture this rare event with a linear regression model leave the researchers with too few data point to reach a meaningful conclusion. The Copula-based approach, on the other hand, helps us to look at the dependence structure of two variables at the extreme cases independent from how the marginal distributions are modeled. Even in the hypothetical scenario that both gold and stock returns have the same univariate distribution function, one cannot look at the corresponding tail dependency for the corresponding bivariate distribution function unless both series have the same tail heaviness in their marginal distributions. Copulas help us to avoid this problem by allowing different characteristics for marginal distributions. One can independently model the margins and the dependence structure and define the conditional distribution with the copula.

According to the Sklar's Theorem (Sklar (1959)), any multivariate distribution can be represented through its marginal distributions and a copula function. Given that $F_1(x) = P[X \leq x]$ and $F_2(y) = P[Y \leq y]$ are the cumulative distribution functions for X and Y, respectively and $F(x,y) = P[X \leq x, Y \leq y]$ being the joint distribution function of these two random variables, then a copula function C is defined such that $F(x,y) = C(F_1(x), F_2(y))$. In other words, copula function C maps marginal distributions into to the multivariate distribution function. Denoting the probabilities $u = F_1(x)$ and $v = F_2(y)$, Sklar's theorem proposes that the copula of the joint distribution function for X and Y can be extracted as follows: $F(x,y) = F(F_1^{-1}(u), F_2^{-1}(v)) = C(u,v)$ where $F_1^{-1}(u)$ and $F_2^{-1}(v)$ are the quantile functions of the marginals for X and Y[5]. Accordingly, if we know C, then we can derive the joint distribution function, $F(x,y)$, from the marginal distributions, $F_1(x)$ and $F_2(y)$.

Since we are interested in how the return series for gold and equities are correlated in

developing economies.

[5] The conditional distribution of Y given when the X variate takes the value of x can be written as follows: $F_{y|x}(y) = C_1(F_x(x), F_y(y))$ where the C_1 is the first partial derivative of the copula.

times of stress, we need to measure the amount of dependence in the lower quadrant tail of the joint distribution of gold and equity returns. Hence, we use copulas to measure the bivariate tail dependence. More specifically, we use the coefficient of lower tail dependence to measure the probability of observing small values of Y when the X takes a small value and we define lower-tail dependence as follows:

$$\lambda_L = \lim_{\alpha \to 0} P(Y \leq F_2^{-1}(\alpha) | X \leq F_1^{-1}(\alpha)) \tag{1}$$

Likewise, the upper tail dependence coefficient measures the probability of observing a large Y given that X takes a large value and it is defined as follows.

$$\lambda_U = \lim_{\alpha \to 1} P(Y \geq F_2^{-1}(\alpha) | X \geq F_1^{-1}(\alpha)) \tag{2}$$

2.2 Weak and Strong Safe-Haven Property

By definition, if two assets exhibit negative or zero correlation on average, they are considered to be appropriate hedge instruments for each other. For safe haven property, we need to know whether these two assets are negatively (or un-) correlated during the extreme market conditions. In our specific case, we want to find out if a domestic investor in our sample countries can retain the value of their gold holdings during a stock market crash. However, standard correlation coefficients are only average measures. Alternatively, one can set an exogenous threshold for the lower tail and calculate the correlation for that part of the data only. This approach is technically the intuition behind the threshold regression method used by Baur and McDermott (2010) and the others. Since we have a very limited number of observations to analyze market behavior at extreme market conditions, threshold regression approach may fail to correctly measure dependencies at extremely rare events. So, we look at the possibility of simultaneous extremes by looking at the tail of the distribution of losses by the copula-based approach. However, by using this method, we can only calculate the conditional probability of losses, rather than correlation, in Y (gold in our case), given that X (equities in our case) is also experiencing a big downturn. We follow the literature and define a weak safe haven asset as an investment instrument that shows zero lower tail dependence with another asset (when $\lambda_L = 0$). In other words, if gold is a weak safe haven instrument, an investor will experience no loss in his/her gold holdings during stock market crashes. On the other hand, a positive lower-tail distribution ($\lambda_L > 0$) implies that there is a positive probability of concurrent losses in gold and equities at market turmoils. Since λ_L is only a conditional probability measure, rather than a tail correlation, having $\lambda_L > 0$ does not necessarily imply zero probability of positive gold returns in the event of big losses in equities. More specifically, regardless of the value of λ_L, it is still possible for gold to offer positive returns when equities are at an extreme loss. We define this situation with a negative correlation between stock market (X) and gold (Y) returns at the lower tail of stock returns distribution, $\rho(X, Y | X < X_q) < 0$, where X_q denotes q^{th} percentile of X.

Intuitively, even though having $\rho(X, Y | X < X_q) < 0$ is muchdesired feature on a safe haven asset, it is still risky to hold two assets with $\rho(X, Y | X < X_q) < 0$ if their λ_L is also positive. Given this rationale, we propose the following conditions for strong safe-haven property: an asset is said to have a strong safe haven property only if $\lambda_L = 0$ and $\rho(X, Y | X < X_q) < 0$ hold at the same time. Having $\rho(X, Y | X < X_q) < 0$ is necessary, but definitely not a sufficient condition for strong safe haven property.

[TABLE 1 IN HERE]

We fit 39 different types of copula functions[6] to find the best one for the tail dependence between the stock market and gold returns. Each copula function has a different structure of low and high tail dependencies. For example, as shown in Table 1, Normal, Gaussian, Plackett and Frankel copulas have no tail dependency ($\lambda_L = \lambda_U = 0$) which can give us information about being a weak safe haven asset. Clayton copula has only lower tail dependence and zero dependence on the upper tail ($\lambda_L > 0,\ \lambda_U = 0$). Gumbel copula has only upper tail dependence ($\lambda_L = 0,\ \lambda_U > 0$). Student's t copulas, derived from the multivariate t-distribution, have symmetric and positive tail dependence ($\lambda_L > 0,\ \lambda_U > 0$). As shown in Table 2, stock and gold returns exhibit a negative correlation in 21 countries in our sample. Where there is an empirical negative correlation in the data, copulas such as Clayton's copula, Gumbel's copula, and Frank's copula would not be able to capture negative dependency. Therefore, those copulas needed to be rotated to avoid forcing empirical results to Student t copula. Hence, we employ 39 different types of copulas in our study to be able to yield any kind of dependence structure in the data. We only focus on static copulas as time-varying copulas do not always provide a better fit than static copulas[7].

3 Data, Country coverage, and Descriptive Statistics

With the exception of Gurgun and Unalmis (2014)[8], the existing studies analyzing the relationship between gold and stock market returns in the developing countries mostly have very limited coverage. Instead, we have 34 emerging market economies in our sample and our daily data cover the period from Jan 4, 2000, till November 28, 2016. Table 2 reports the summary statistics of the daily logarithmic returns on domestic stock indices and gold[9] in domestic currency. Equity markets on average have 2.6% annualized daily return, while gold offers a higher annualized daily return at 2.9%. Majority of the countries in our sample have negative skewness in their distribution of stock return series which indicates that there is a likelihood of extreme loss occurrences in these countries. Besides, for all countries in the sample, high kurtosis numbers point out to the existence of extreme stock market returns observed at relatively high frequencies. As for the gold return in domestic currency, we see that majority of the countries have left-skewed distribution for gold returns, except for Argentina, Egypt, Israel, Poland, Russia, South Africa, Thailand, and Turkey. Hence, we can infer that in the sample, we have high probabilities of extreme loss or gain occurrences for gold return.

[TABLE 2 IN HERE]

We also look at the average correlation between stock and gold returns to have an idea of hedging role of gold in normal times. The data shows that average correlation coefficient

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[6] See Brechmann and Schepsmeier (2013) for more details.

[7] See Bekiros et.al (2017) for details.

[8] Gurgun and Unalmis (2014) use linear threshold regression approach following Baur and McDermott (2010) rather than copula-based estimation of extreme tail dependencies.

[9] We use gold price in each country to calculate return on gold.

between daily stock and gold return is either negative (21 countries) or positive but close to zero (13 countries) in the sample, which can be interpreted as a hedging role for gold in these countries.

Given the fact that empirical distribution of stock returns is non-normal and skewed, and also the fact that the variance of the returns is not constant, we first fit a TGARCH(1,1), as introduced by Zakoian (1994), to the return series of gold and equity indices to capture the asymmetric effects of negative shocks compared to positive ones, i.e leverage effect. This way, we expect to remove excess kurtosis in the data yet skewness in the distribution will be retained so that we can test for the true safe haven asset property of gold in extreme cases. The unconditional residuals generated from TGARCH (1,1) are used to model the marginal and joint distributions of gold and stock market return series.

4 Empirical Findings

We model the marginal distributions of gold and stock market returns by estimating the following TGARCH(1,1) to account for fat tails and leverage effect:

$$\begin{aligned} r_t &= \mu + \sigma_t \varepsilon_t \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \end{aligned} \tag{3}$$

where d_{t-1} is a dummy that is equal to one if $\varepsilon_{t-1} < 0$ and is equal to zero otherwise. The parameter estimates for the stock market and gold returns are given in Table 3. The threshold parameter, γ, is statistically significant for all stock market returns, except Bulgaria, Jordan, Kenya, Lithuania, Morocco, and UAE. On the other hand, the threshold parameter, γ, for the gold returns is statistically insignificant only for Bahrain, Bulgaria, Colombia, Kenya, Morocco, Romania and Vietnam. This indicates the asymmetric effect of positive and negative shocks to the stock and gold returns for most of the countries. Besides, this coefficient is positive for stock returns and negative for gold returns. In other words, a negative shock increases the volatility of stock returns, while it decreases the volatility of gold returns.

[TABLE 3 IN HERE]

The unconditional residuals (ε_t) constructed through TGARCH(1,1) are fed into the copula functions to estimate the joint distribution of gold and stock market returns. We fit 39 different copula functions on the residuals and determine the best fitting copula based on AIC criteria. Table 4 reports, for each country, the best fitting copula, AIC, and the implied sign of λ_L for the best fitting copula.

[TABLE 4 IN HERE]

As we see in Table 4, out of 34 countries, in 20 countries gold can serve as a weak safe haven instrument. For all other countries, there is a positive probability for lower tail dependence between gold and stock market return distributions. In the next step, we estimate the tail correlation, $\rho(X, Y | X < X_q)$, between stock and gold returns for those 20 countries to find out whether gold is also a strong safe-haven instrument for the stock market portfolios in those countries. To that goal, we performed a Monte Carlo simulation to draw a sample of size 100,000,000 for each country where gold is shown a weak safe haven asset. These samples are drawn from the joint distribution characterized by the best fitting copula function. Later, we calculated the correlation between stock and gold returns at 0.1% of stock market returns. Even though we had a very big sample size, 0.1% was the smallest percentile that yielded a stable tail correlation at each simulation.

[TABLE 5 IN HERE]

As shown in Table 5, the tail correlation is negative only for Argentina, Bulgaria, Chile, China, Jordan, Kenya, Latvia, Morocco, and South Africa. Hence, based on our definition of strong safe haven asset ($\lambda_L = 0$ and $\rho(X, Y | X < X_q) < 0$), we reach to the conclusion that these six countries are the only ones in our sample where gold can act as a strong safe-haven instrument against extreme losses in the stock market. On the other hand, Liu (2019) looked at 16 countries in an extremal quantile regression model and they found no safe haven property of gold for all sample countries but the US. They mostly look at the advanced nations in their study and there are only four countries in their sample overlapping with ours (Hungary, Russia, South Africa, and South Korea). However, our study confirms that gold serves as a weak safe haven asset in Russia and South Africa.

We also compared our findings with the earlier ones to make better use of the copula approach. Given the caveat that there is no consensus on the best approach to test the safe haven asset feature and date coverage is different across studies, we looked at the overall findings on the safe-haven feature of gold with alternative estimation methods. In a linear threshold approach, Gurgun and Unalmis (2014) found that gold serves as a safe haven for 15 of 29 sample countries in their study. Our study can confirm their findings only for Bulgaria, Chile, Israel, Jordan, and Morocco. We reached to the same conclusion with Gurgun and Unalmis (2014) that gold is not a safe haven asset for Czech Republic, India, Indonesia, Qatar, Romania, Russia, South Africa, UAE, and Vietnam.In another study with the same econometric approach, Baur and McDermott (2010) find safe haven property of gold for Brazil. With the copula approach, we find evidence of lower tail dependence for Brazil and reach an opposite conclusion. Chkili (2016) adopted a dynamic conditional correlation model on testing the safe haven role of gold for the BRICS countries. Our findings contradict in two countries. While they find evidence of a strong safe haven for India and Brazil during the subprime crises, our results cannot confirm it. Additionally, for Brazil, Hungary, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Thailand, and Turkey, while other studies found evidence of safe haven role, our approach does not support that conclusion. On the other hand, for Bahrain, China, Egypt, Jordan, Kenya, Morocco, South Africa, Qatar, Romania, South Africa, UAE, and Vietnam, we overturn the previous findings and find evidence for safe-haven asset role for gold in these countries. Taken all these evidence together, our findings can at best provide mixed findings on the safe-haven feature of gold in the sample countries.

5 Conclusion

Searching for a safe haven asset, especially for the emerging and developing countries, gained more importance after the 2007 financial crisis. The literature for the advanced economies' equity markets reaches the consensus finding that gold is a true safe haven asset at extreme market conditions. As for the major emerging and developing countries, the findings are mixed. In this study, we revisit the international evidence on hedging and safe haven role of gold for 34 emerging and developing countries. Given the limitations of average dependency measures at certain quantiles or the linear threshold regression models, we adopted from the literature copula-based measure of tail dependency by modeling the joint extreme movements of gold and equity returns and tested for safe haven property of gold both in weak and strong form. Our findings indicate that while gold serves as a hedge instrument for all countries in our sample, we got evidence of weak safe haven property for gold only in 20 countries. Besides, among these 20 countries only in nine of them gold acts as a strong safe-haven instrument against extreme losses in the stock market.

Even though we find evidence of the safe-haven role of gold in more than half of our sample countries, it is difficult to generalize our findings due to the mixed evidence in our extended sample and large data span. Differences amongst the sample countries in terms of financial market depth, exporter/importer status in commodity markets, domestic markets' correlation with developed markets, and other domestic market characteristics might play a role in this outcome. We suggest further studies to focus more on the group of markets where gold does not serve as a safe haven asset to see if these countries share certain characteristics when it comes to gold- stock market dynamics.

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Copula	Type	Lower tail	Upper tail
Normal	Symmetric	λ_L=0	λ_U=0
Student's t	Symmetric	λ_L >0	λ_U >0
Clayton	Asymmetric	λ_L >0	λ_U =0
Gumbel	Asymmetric	λ_L =0	λ_U >0
Frank	Symmetric	λ_L =0	λ_U =0
Joe	Asymmetric	λ_L =0	λ_U >0
BB1 (Gumbel-Clayton)	Asymmetric	λ_L >0	λ_U >0
BB6 (Joe-Gumbel)	Asymmetric	λ_L =0	λ_U >0
BB7 (Joe-Clayton)	Asymmetric	λ_L >0	λ_U >0
BB8 (Joe-Frank)	Asymmetric	λ_L =0	λ_U >0
Rotated Clayton copula (180 degrees)	Asymmetric	λ_L =0	λ_U >0
Rotated Gumbel copula (180 degrees)	Asymmetric	λ_L >0	λ_U =0
Rotated Joe copula (180 degrees)	Asymmetric	λ_L >0	λ_U =0
Rotated BB1 copula (180 degrees)	Asymmetric	λ_L >0	λ_U >0
Rotated BB6 copula (180 degrees)	Asymmetric	λ_L =0	λ_U =0
Rotated BB7 copula (180 degrees)	Asymmetric	λ_L >0	λ_U >0
Rotated BB8 copula (180 degrees)	Asymmetric	λ_L >0	λ_U =0
Rotated Clayton copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Gumbel copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Joe copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB1 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB6 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB7 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB8 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0

Rotated Clayton copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Gumbel copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Joe copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB1 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB6 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB7 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated BB8 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Tawn type 1 copula	Asymmetric	λ_L =0	λ_U >0
Rotated Tawn type 1 copula (180 degrees)	Asymmetric	λ_L >0	λ_U =0
Rotated Tawn type 1 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Tawn type 1 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0
Tawn type 2 copula	Asymmetric	λ_L =0	λ_U >0
Rotated Tawn type 2 copula (180 degrees)	Asymmetric	λ_L >0	λ_U =0
Rotated Tawn type 2 copula (90 degrees)	Symmetric	λ_L =0	λ_U =0
Rotated Tawn type 2 copula (270 degrees)	Symmetric	λ_L =0	λ_U =0

Table 1: Copula functions and their implied tail dependence parameters.

			Stock Returns			Gold Returns			
Country	start	end	Mean	Skewness	Kurtosis	Mean	Skewness	Kurtosis	correlation
Argentina	1/3/00	11/28/18	0.07	-0.22	4.26	0.09	**3.90**	84.19	0.05
Bahrain	5/24/00	11/28/18	0.00	-0.63	4.17	-0.03	-0.32	3.86	0.03
Brazil	1/3/00	11/28/18	0.03	-0.10	3.86	0.04	-0.09	11.91	**-0.10**
Bulgaria	8/16/11	11/28/18	0.02	-0.14	5.97	-0.01	-0.35	9.17	**-0.06**
Chile	1/3/00	11/28/18	0.03	0.06	10.82	0.03	-0.12	3.53	0.00
China	1/3/00	11/28/18	0.01	-0.32	5.17	0.02	-0.34	6.31	0.04
Colombia	8/12/11	11/28/18	-0.01	-0.15	2.45	0.01	-0.42	3.57	**-0.02**
Czech Rep	1/3/00	11/28/18	0.01	-0.67	12.89	0.02	-0.19	6.48	**-0.08**
Egypt	1/3/00	11/28/18	0.07	-0.54	3.41	0.03	**10.18**	292.18	0.08
Hong Kong	1/3/00	11/28/18	0.00	-0.10	8.57	0.02	-0.36	5.94	0.07
Hungary	1/3/00	11/28/18	0.03	-0.03	6.15	0.03	0.01	7.35	**-0.15**
India	1/3/00	11/28/18	0.03	-0.20	8.29	0.04	-0.13	6.46	**-0.07**
Indonesia	1/3/00	11/28/18	0.04	-0.65	6.26	0.04	-0.13	6.58	**-0.09**
Israel	1/3/00	11/28/18	-0.01	-0.30	3.14	-0.01	**0.02**	2.84	**-0.13**
Jordan	11/12/00	11/28/18	0.05	4.39	524.44	0.00	-0.09	3.89	0.01
Kenya	1/3/08	11/28/18	0.00	-8.19	270.55	0.03	-0.12	5.43	**-0.03**
Latvia	9/28/04	11/28/18	0.03	0.43	10.10	0.03	-0.45	5.90	**-0.04**
Lithuania	12/16/02	11/28/18	0.05	0.12	20.05	0.02	-0.45	6.00	**-0.05**
Malaysia	1/3/00	11/28/18	0.02	1.50	48.32	0.02	-0.20	6.04	**-0.05**
Mexico	1/3/00	11/28/18	0.04	0.00	5.64	0.04	-0.06	12.34	**-0.14**
Morocco	7/2/10	11/28/18	0.00	0.83	909.56	0.00	-0.49	8.41	0.02
Peru	1/3/00	11/28/18	0.04	-0.41	12.63	0.02	-0.38	6.53	0.07
Philippine	6/26/00	11/28/18	0.02	-0.07	12.44	0.03	-0.68	11.52	**-0.01**
Poland	1/3/00	11/28/18	0.02	-0.32	3.76	0.02	**0.02**	6.28	**-0.15**
Qatar	1/3/00	11/28/18	0.04	-0.50	12.66	0.00	-0.12	4.13	0.05
Romania	5/17/10	11/28/18	0.02	-0.24	11.13	0.01	-0.38	7.81	**-0.15**
Russia	1/3/00	11/28/18	0.04	-0.26	16.66	0.04	**0.56**	16.77	0.02
South Africa	1/3/00	11/28/18	0.03	-0.19	3.63	0.04	**0.08**	4.46	0.01
South Korea	1/3/00	11/28/18	0.01	-0.66	7.15	0.03	-0.56	12.04	**-0.14**
Taiwan	1/3/00	11/28/18	0.00	-0.26	3.77	0.02	-0.12	5.90	**-0.04**
Thailand	1/3/00	11/28/18	0.03	-0.73	11.04	0.03	**0.01**	4.99	**-0.05**
Turkey	1/3/00	11/28/18	0.03	-0.03	8.26	0.07	**8.38**	278.95	**-0.18**
UAE	7/2/01	11/28/18	0.04	-0.17	8.16	0.00	-0.07	3.83	**-0.01**
Vietnam	8/8/08	11/28/18	0.03	-0.24	2.16	0.02	-0.21	6.39	0.00

Table 2: The table provides the summary statistics of the daily logarithmic returns series on domestic stock indices and gold holdings. Data covers the period from Jan 3, 2000, till November 28, 2018, at a daily frequency.

	Stock Market Returns						Gold Returns					
Country	μ	ω	α	γ	β	AIC	μ	ω	α	γ	β	AIC
Argentina	0.110	0.076	0.102	0.418	0.885	4.04	0.058	0.019	0.071	-0.196	0.934	3.01
	(0.024)	(0.016)	(0.011)	(0.066)	(0.014)		(0.013)	(0.004)	(0.008)	(0.079)	(0.007)	
Bahrain	0.007	0.036	0.074	-0.404	0.880	1.12	-0.014	0.013	0.055	-0.144	0.947	2.69
	(0.01)	(0.015)	(0.025)	(0.207)	(0.039)		(0.024)	(0.006)	(0.012)	(0.189)	(0.012)	
Brazil	0.034	0.033	0.062	0.616	0.932	3.77	0.039	0.027	0.082	-0.381	0.919	3.32
	(0.022)	(0.007)	(0.007)	(0.091)	(0.008)		(0.016)	(0.006)	(0.01)	(0.081)	(0.011)	
Bulgaria	0.014	0.074	0.153	-0.056	0.789	2.07	-0.025	0.004	0.042	0.102	0.964	2.55
	(0.013)	(0.025)	(0.03)	(0.092)	(0.05)		(0.017)	(0.002)	(0.008)	(0.161)	(0.007)	
Chile	0.044	0.035	0.122	0.305	0.865	2.43	0.043	0.010	0.048	-0.312	0.955	3.07
	(0.01)	(0.006)	(0.011)	(0.051)	(0.013)		(0.016)	(0.002)	(0.005)	(0.1)	(0.005)	
China	0.041	0.012	0.082	0.162	0.935	3.31	0.023	0.006	0.054	-0.274	0.955	2.67
	(0.014)	(0.003)	(0.009)	(0.056)	(0.007)		(0.011)	(0.001)	(0.005)	(0.083)	(0.004)	
Colombia	0.010	0.042	0.133	0.369	0.850	2.31	0.011	0.011	0.050	-0.005	0.953	3.11
	(0.016)	(0.014)	(0.026)	(0.097)	(0.033)		(0.023)	(0.005)	(0.01)	(0.159)	(0.009)	
Czech Rep	0.046	0.026	0.118	0.286	0.886	2.97	0.018	0.010	0.052	-0.333	0.952	2.80
	(0.012)	(0.004)	(0.01)	(0.048)	(0.01)		(0.012)	(0.002)	(0.006)	(0.1)	(0.006)	
Egypt	0.113	0.063	0.131	0.184	0.859	3.55	0.022	0.021	0.068	-0.263	0.934	2.84
	(0.023)	(0.019)	(0.019)	(0.069)	(0.024)		(0.017)	(0.005)	(0.009)	(0.112)	(0.009)	
Hong Kong	0.018	0.018	0.062	0.629	0.938	3.18	0.032	0.007	0.049	-0.346	0.958	2.70
	(0.015)	(0.003)	(0.006)	(0.085)	(0.006)		(0.012)	(0.001)	(0.005)	(0.086)	(0.004)	
Hungary	0.034	0.028	0.080	0.400	0.918	3.35	0.021	0.009	0.048	-0.479	0.957	2.95
	(0.017)	(0.005)	(0.008)	(0.065)	(0.008)		(0.014)	(0.002)	(0.006)	(0.109)	(0.005)	
India	0.060	0.032	0.110	0.492	0.889	3.13	0.038	0.011	0.060	-0.413	0.945	2.70
	(0.014)	(0.005)	(0.009)	(0.059)	(0.01)		(0.012)	(0.002)	(0.006)	(0.082)	(0.006)	
Indonesia	0.078	0.037	0.116	0.328	0.883	3.08	0.053	0.009	0.060	-0.315	0.948	2.91
	(0.013)	(0.008)	(0.012)	(0.057)	(0.013)		(0.013)	(0.002)	(0.007)	(0.085)	(0.006)	
Israel	-0.007	0.012	0.085	0.336	0.923	2.73	-0.011	0.012	0.063	-0.293	0.942	2.85
	(0.014)	(0.004)	(0.013)	(0.08)	(0.013)		(0.016)	(0.004)	(0.008)	(0.104)	(0.008)	
Jordan	0.034	0.015	0.137	0.015	0.881	1.82	0.005	0.012	0.063	-0.343	0.943	2.78
	(0.009)	(0.004)	(0.019)	(0.061)	(0.017)		(0.017)	(0.004)	(0.009)	(0.112)	(0.008)	
Kenya	0.026	0.203	0.396	0.044	0.479	2.19	0.020	0.005	0.043	-0.174	0.964	2.89
	(0.012)	(0.03)	(0.037)	(0.045)	(0.05)		(0.016)	(0.002)	(0.006)	(0.114)	(0.005)	
Latvia	0.033	0.024	0.108	0.219	0.904	2.79	0.020	0.006	0.055	-0.257	0.953	2.74
	(0.014)	(0.007)	(0.017)	(0.071)	(0.017)		(0.013)	(0.002)	(0.006)	(0.101)	(0.005)	
Lithuania	0.050	0.027	0.199	0.034	0.833	2.12	0.017	0.007	0.053	-0.234	0.954	2.70
	(0.007)	(0.006)	(0.022)	(0.041)	(0.02)		(0.012)	(0.002)	(0.006)	(0.098)	(0.005)	
Malaysia	0.022	0.012	0.098	0.348	0.911	1.98	0.024	0.009	0.057	-0.374	0.950	2.71
	(0.008)	(0.002)	(0.011)	(0.056)	(0.01)		(0.012)	(0.002)	(0.006)	(0.089)	(0.005)	
Mexico	0.038	0.015	0.080	0.545	0.926	2.94	0.032	0.016	0.056	-0.483	0.944	3.01
	(0.014)	(0.003)	(0.008)	(0.07)	(0.007)		(0.014)	(0.003)	(0.006)	(0.098)	(0.006)	
Morocco	-0.015	0.081	0.173	0.038	0.751	2.00	-0.006	0.007	0.051	-0.042	0.955	2.50
	(0.012)	(0.02)	(0.024)	(0.071)	(0.042)		(0.016)	(0.003)	(0.009)	(0.13)	(0.008)	
Peru	0.051	0.040	0.152	0.116	0.851	2.87	0.029	0.008	0.050	-0.402	0.956	2.74
	(0.012)	(0.007)	(0.015)	(0.038)	(0.016)		(0.012)	(0.002)	(0.005)	(0.095)	(0.005)	
Philippine	0.037	0.065	0.129	0.231	0.845	3.01	0.034	0.009	0.056	-0.273	0.949	2.76
	(0.015)	(0.012)	(0.013)	(0.053)	(0.018)		(0.013)	(0.002)	(0.006)	(0.083)	(0.006)	
Poland	0.041	0.016	0.070	0.319	0.932	3.01	0.008	0.013	0.058	-0.459	0.945	2.90
	(0.014)	(0.003)	(0.007)	(0.064)	(0.007)		(0.013)	(0.003)	(0.007)	(0.097)	(0.007)	
Qatar	0.073	0.103	0.275	0.190	0.726	2.62	0.007	0.010	0.058	-0.244	0.949	2.82
	(0.015)	(0.034)	(0.051)	(0.072)	(0.058)		(0.019)	(0.004)	(0.009)	(0.134)	(0.008)	
Romania	0.036	0.053	0.137	0.192	0.836	2.41	-0.006	0.007	0.051	-0.099	0.955	2.65
	(0.016)	(0.014)	(0.022)	(0.078)	(0.029)		(0.017)	(0.003)	(0.009)	(0.137)	(0.008)	
Russia	0.066	0.019	0.098	0.237	0.915	3.71	0.033	0.014	0.070	-0.394	0.937	2.91
	(0.018)	(0.004)	(0.009)	(0.054)	(0.008)		(0.013)	(0.003)	(0.008)	(0.085)	(0.007)	
South Africa	0.034	0.019	0.073	0.713	0.925	2.88	0.033	0.018	0.059	-0.405	0.941	3.21
	(0.013)	(0.003)	(0.008)	(0.087)	(0.008)		(0.016)	(0.004)	(0.007)	(0.095)	(0.008)	
South Korea	0.045	0.012	0.079	0.517	0.931	3.14	0.022	0.011	0.057	-0.411	0.947	2.82
	(0.013)	(0.002)	(0.008)	(0.069)	(0.007)		(0.013)	(0.002)	(0.006)	(0.096)	(0.006)	

Taiwan	0.038	0.008	0.058	0.562	0.949	3.03	0.018	0.006	0.048	-0.283	0.959	2.67
	(0.014)	(0.002)	(0.007)	(0.081)	(0.006)		(0.011)	(0.001)	(0.005)	(0.092)	(0.004)	
Thailand	0.055	0.017	0.110	0.273	0.903	2.96	0.021	0.007	0.052	-0.269	0.954	2.68
	(0.012)	(0.004)	(0.01)	(0.05)	(0.009)		(0.011)	(0.002)	(0.006)	(0.093)	(0.005)	
Turkey	0.084	0.027	0.080	0.342	0.925	3.94	0.042	0.024	0.078	-0.344	0.924	3.14
	(0.022)	(0.006)	(0.009)	(0.062)	(0.009)		(0.014)	(0.005)	(0.009)	(0.08)	(0.01)	
UAE	0.045	0.048	0.234	0.048	0.795	2.44	0.009	0.011	0.061	-0.303	0.946	2.80
	(0.011)	(0.012)	(0.03)	(0.055)	(0.028)		(0.016)	(0.004)	(0.008)	(0.113)	(0.007)	
Vietnam	0.076	0.038	0.154	0.193	0.851	3.10	0.010	0.006	0.050	-0.032	0.958	2.78
	(0.018)	(0.009)	(0.016)	(0.053)	(0.016)		(0.016)	(0.002)	(0.007)	(0.11)	(0.005)	

Table 3: TGARCH(1,1) estimates for stock market and gold returns. Standard errors are given in parenthesis.

Country	Best fit Copula	AIC	λ_L	Conclusion
Argentina	BB8	-306.9	0	Weak Safe haven
Bahrain	Joe	-2662.1	0	Weak Safe haven
Brazil	t	-31.0	+	Not a safe haven
Bulgaria	Frank	-2313.3	0	Weak Safe haven
Chile	Joe	-156.3	0	Weak Safe haven
China	Joe	-540.3	0	Weak Safe haven
Colombia	Frank	-2395.7	0	Weak Safe haven
Czech Rep	t	-45.4	+	Not a safe haven
Egypt	Joe	-2073.5	0	Weak Safe haven
Hong Kong	Joe	-273.0	0	Weak Safe haven
Hungary	t	-59.0	+	Not a safe haven
India	t	-37.9	+	Not a safe haven
Indonesia	t	-42.7	+	Not a safe haven
Israel	Frank	-1283.5	0	Weak Safe haven
Jordan	Joe	-2086.6	0	Weak Safe haven
Kenya	Frank	-1554.7	0	Weak Safe haven
Latvia	Frank	-508.1	0	Weak Safe haven
Lithuania	Gaussian	-214.6	0	Weak Safe haven
Malaysia	t	-42.9	+	Not a safe haven
Mexico	t	-54.8	+	Not a safe haven
Morocco	Joe	-2493.0	0	Weak Safe haven
Peru	BB7	-344.5	+	Not a safe haven
Philippine	t	-47.1	+	Not a safe haven
Poland	t	-51.8	+	Not a safe haven
Qatar	Joe	-2669.7	0	Weak Safe haven
Romania	Frank	-1948.1	0	Weak Safe haven
Russia	Joe	-185.6	0	Weak Safe haven
South Africa	Joe	-179.5	0	Weak Safe haven
South Korea	t	-41.3	+	Not a safe haven
Taiwan	t	-26.4	+	Not a safe haven
Thailand	t	-31.8	+	Not a safe haven
Turkey	t	-200.5	+	Not a safe haven
UAE	Joe	-2168.5	0	Weak Safe haven
Vietnam	Joe	-2128.8	0	Weak Safe haven

Table 4: The best fitting copula functions for gold returns and equity returns are shown.

Country	Tail correlation	Conclusion
Argentina	-0.0001	Strong Safe haven
Bahrain	0.0029	Not a strong safe haven
Bulgaria	-0.0006	Strong Safe haven
Chile	-0.0008	Strong Safe haven
China	-0.0007	Strong Safe haven
Colombia	0.0012	Not a strong safe haven
Egypt	0.0028	Not a strong safe haven
Hong Kong	0.0030	Not a strong safe haven
Israel	0.0037	Not a strong safe haven
Jordan	-0.0028	Strong Safe haven
Kenya	-0.0029	Strong Safe haven
Latvia	-0.0046	Strong Safe haven
Lithuania	0.0699	Not a strong safe haven
Morocco	-0.0005	Strong Safe haven
Qatar	0.0021	Not a strong safe haven
Romania	0.0072	Not a strong safe haven
Russia	0.0027	Not a strong safe haven
South Africa	-0.0029	Strong Safe haven
UAE	0.0021	Not a strong safe haven
Vietnam	0.0007	Not a strong safe haven

Table 5: Correlation between stock and gold returns at 0.1% tail of stock returns.