Gold and Government Bonds as Safe-Haven Assets Against Stock Market Turbulence in China

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Abstract
We examine whether gold and China’s government bonds are safe-haven assets against the turbulence of the Shanghai Stock Exchange Composite Index by employing vine copula models during the 2003 to 2015 period. We find that either bonds or gold can be a weak safe haven but only gold can be a strong safe haven. Our simultaneous analysis advises against a joint safe-haven strategy of gold and bonds, given the high- to low-tail correlation. This result highlights an investment strategy of using a single safe-haven asset against the Chinese stock market turbulences.

Keywords
safe haven, gold, government bonds, asymmetric vine copula

Introduction
Extreme market conditions have reminded investors of the essentialness of risk management. The recent extreme events highlight the demand for tools to hedge the risk related to extremely severe market conditions. Based on Baur and Lucey (2010) and Baur and McDermott (2010), an asset is considered a safe haven when it is unrelated or negatively related to another asset during market turmoil. In this study, we follow their definition to clearly distinguish the role of safe-haven assets.

Conventional wisdom holds that assets such as government bonds and gold are safe havens in bad times in the United States and the European Union (e.g., Baur & Lucey, 2010; Baur & McDermott, 2010; Connolly et al., 2005; Longstaff, 2004). However, there is no consensus about the safe-haven role of these assets in China. Dee et al. (2013) revealed that gold was not a safe haven in China’s capital markets but Gürgün and Unalms (2014), Aroui et al. (2015), and Beckmann et al. (2018) demonstrated that gold performed as a weak safe haven for Chinese stock markets. So far, most studies have only examined the pairwise correlation between stocks and the selected safe-haven asset. To the best of our knowledge, no extant studies have simultaneously considered the extreme dependence among multiple safe-haven assets with respect to the Chinese stock market.

Many skewed/fat-tailed distributions were suggested to interpret the dynamic nature of asset returns (Kollo & Pettere, 2010). Copula functions with skewed/fat-tailed distribution are widely suggested in finance, particularly in the field of risk management (Azzalini & Capitanio, 2003; Christoffersen & Langlois, 2013). However, few models allowed for a thin-tailed distribution. We suggest a multivariate extended skew-$t$ (MEST) copula model (Arellano-Valle & Genton, 2010; Liu et al., 2016), extended to a vine copula construction to examine the joint tail dependence and multivariate tail dependence among the Shanghai Stock Exchange Composite Index, government bonds, and gold for the 2003 to 2015 period. Although past studies, for example, H. G. Min et al. (2016), suggested the U.S. dollar is able to be a safe-haven asset for stocks, the U.S. dollar is not included in our study owing to foreign exchange controls in China.

Empirically, we examine the potential of a safe-haven combination of stocks–bonds–gold from an investor’s perspective. Most prior studies simply combined these data without considering whether investment strategies implied by the study results could be obtained by domestic investors. Empirically, we find that the MEST copula accommodates strong asymmetric tail dependencies among assets. The significant estimates of the shape and extension parameters in the MEST copula indicate the presence of skewed and heavy/thin tails in most Chinese capital markets.

First, we consider only one safe-haven asset in the portfolio and find that government bonds serve, at best, as a weak safe haven against stock market downturns. However,
we find that gold may serve as a strong safe-haven asset under extreme conditions.

Next, we allow a portfolio to include multiple safe-haven assets to verify whether this provides better portfolio diversification. We take two steps to test the portfolio strategy of jointly or independently safe-haven assets. First, we employ the multivariate model to test whether bonds (gold) acts as a strong safe-haven asset when gold (bonds) is in extreme (good or bad) market conditions. By examining the unconditional and conditional joint lower tailed probabilities of stocks, bonds, and gold, we conclude that neither bonds nor gold can be a reliable safe haven; their effectiveness as a safe-haven asset depends on the alternative investment. Second, we apply the vine copula method to estimate the multivariate lower tailed dependence coefficient. The results show that the estimated lower tailed dependence coefficient of the combination of all three assets is larger than that of bonds–stocks and that of gold–stocks, implying that a portfolio including multiple safe havens does not dominate that including a single safe haven.

This study proceeds as follows. Sections “Literature Review” and “The Model” provide the literature review and the model. In the “Empirical Analysis” section, we present the empirical analysis. Section “Concluding Remarks” concludes.

Literature Review

Safe-Haven Effect of Government Bonds and Gold

Both long-term government bonds and gold have been continuously used by international investors to protect from stock market losses and other macroeconomic variables. The long-term government bond is an obvious choice as a safe-haven asset, in that, it offers fixed returns if held to maturity. In contrast, gold has been considered the best asset for long-run investment. (Saad, 2012). The role of gold and bond in investors’ portfolios has been examined in different ways. In this section, we first review existing literature on the safe-haven effects of gold and bonds on stock markets.

A natural candidate for a safe-haven asset against the stock market is the long-term government bond, which shows a negative correlation with stock returns and is considered to have no default risk (Baur & McDermott, 2013; Connolly et al., 2005; Longstaff, 2004). During stock market turbulence, the demand for government-backed assets surges as their liquidity function is supported by governments (Ilmanen, 2003; Kim et al., 2006). Barsky (1989) concluded that comovements of stock and bond markets are state dependent. Fleming et al. (1998) demonstrated that strong linkages exist across stock, bond, and money markets, particularly in terms of volatility spillovers. Pipplack and Straetmans (2010) showed that U.S. Treasury bonds are negatively correlated with financial assets in times of market turbulences.

Review of Nonnormal Copula Function in Financial Application

Multivariate symmetric distributions have emerged in the literature in the recent two decades (Fang et al., 1990). Nevertheless, symmetric distributions cannot capture some features of financial data, such as the skewness of returns. In many cases, assuming asymmetric distributions is more appropriate for representing financial returns (Campbell et al., 1997).

A number of papers incorporate skewed tails in the development of multivariate distributions. For instance, Sahu et al. (2003) centered on skewness properties of multivariate symmetric distributions, whereas Azzalini and Capitanio (2003) studied how to generate a family of nonsymmetric multivariate densities. Arellano-Valle and Genton (2010) proposed the MEST distribution to take into account the asymmetric and heavy/thin-tailed properties. For the relevant development of these distributions in financial studies, see Adcock (2010) and Liu et al. (2016).

In the recent two decades, more studies have begun to construct asymmetric copulas to support financial data. For instance, Demarta and McNeil (2005) suggested a skew-$t$ copula in terms of a Gaussian mixture representation. Kollo and Pettere (2010) proposed a multivariate skew-$t$ copula,
whereas Smith et al. (2012) established skew-\( t \) copulas. Christoffersen et al. (2012) proposed a dynamic asymmetric copula model to describe not only long-term but also short-term dynamic correlation. Christoffersen and Langlois (2013) established a four-factor Capital Asset Pricing Model (CAPM) by applying a dynamic asymmetric copula. González-Pedraza et al. (2015) proposed a conditional skew-\( t \) copula to model returns. However, these models can only account for asymmetry and fat tails in dependence; they are not flexible enough to accommodate various types of distributions and tail properties.

The Model

Vine Copula Structure

Most existing papers on vine copulas use conventional copula functions, for example, Aas et al. (2009), Mendes et al. (2010), and Low et al. (2013), which fail to capture either skewed tails or heavy/thin tails. Liu et al. (2016) construct a multivariate copula model based on Arellano-Valle and Genton (2010) to deal with both skewness and heavy/thin-tail properties, called the MEST copula. It comprises three kinds of parameters to control the degree of freedom, skewness, and heavy/thin-tail property. Owing to its flexibility, we use the bivariate extended skew-\( t \) (BEST) copula for the estimation of each pair copula.

Although an R-vine model provides maximum flexibility, this study only considers the most common vine structures, \( D \)-vine, as our study only includes three assets (Chollete & Czado, 2010). Let \( Y_i \) be a continuous three-dimensional random sample and \( Y_i \) be realized values. From Sklar’s theorem, the multivariate copula density function \( c_{i,2,3}(F(y_1), F(y_2), F(y_3)) \) can be given by \( c_{i,2,3}(F(y_1), F(y_2))c_{i,2,3}(F(y_2), F(y_3)) \), implying there are two levels of trees in the vine structure.

BEST Copula

Suppose \( Y = \{Y_1, Y_2, Y_3\} \) follows a BEST distribution, denoted by \( Y \sim \text{BEST}(\Phi^{(l)}, \theta^{(l)}, \tau^{(l)}, \nu^{(l)}) \) with zero mean. Note that the superscript (1) indicates that the distribution is taken in the first tree. Following Arellano-Valle and Genton (2010), its density function evaluated at \( y_i = \{y_1, y_2, y_3\} \in \mathbb{R}^3 \) is given by:

\[
\begin{align*}
T_1 & \left( \frac{\tau^{(l)}}{\sqrt{1 + \theta^{(l)}\Phi^{(l)}\theta^{(l)}}}; \nu^{(l)} \right) \\
& \left( \left( \frac{\nu^{(l)} + 2}{\nu^{(l)} + \nu^{(l)^{-1}}\Phi^{(l)}\nu^{(l)}} \right)^{1/2} \right) y_i^{(l)} + 2 \right),
\end{align*}
\]

where \( i = 1, 2, 3 \), \( \Phi^{(l)} = \begin{bmatrix} 1 & \rho^{(l)} \\ \rho^{(l)} & 1 \end{bmatrix} \) is the correlation matrix, \( \theta^{(l)} = [\theta^{(l)}_1, \theta^{(l)}_2]^T \in \mathbb{R}^2 \) is a shape parameter, \( \nu^{(l)} \in \mathbb{R} \) is an extension parameter and \( \nu^{(l)} \) is the degree of freedom.

In Equation 1, \( t_2 \left( y_i; \Phi^{(l)}, \nu^{(l)} \right) T_1 \left( \Phi^{(l)} y_i + \tau^{(l)} \right) \) denotes a two-dimensional Student’s \( t \) density function with a correlation matrix \( \Phi^{(l)} \) and the degree of freedom \( \nu^{(l)} \) and \( T_1(\cdot) \) standards for a standard univariate Student’s \( t \) distribution with degrees of freedom \( \nu^{(l)} \). From Sklar’s theorem (1973), the BEST copula \( c_{i,1} \) is

\[
\begin{align*}
\frac{f_{i} (u_{i}^{-1}; \lambda_i, \theta^{(l)}, \tau^{(l)}, \nu^{(l)} + 1)}{f_{i} (u_{i}^{-1}; \lambda_i, \theta^{(l)}, \tau^{(l)}, \nu^{(l)} + 1)} + 2,
\end{align*}
\]

\[
\left( \frac{u_{i}^{-1} \lambda_i, \theta^{(l)}, \tau^{(l)}, \nu^{(l)} + 1}{f_{i} (u_{i}^{-1}; \lambda_i, \theta^{(l)}, \tau^{(l)}, \nu^{(l)} + 1)} + 1\right),
\]

where \( \lambda_i, \tau_i, \) and \( \nu_i \) are shape, extension, and degree of freedom parameters for marginal densities \( f_i(y_i) \). \( u_{i} = F_i(y_i) \) stands for the distribution function of univariate EST for the variable \( i \) and \( i = 1, 2 \) and \( u_{i}^{-1} \) is the inverse of the cumulative distribution function \( F_i \), see Liu et al. (2016) for details.

Equation 2 gives the unconditional BEST copula densities for each pair in the first tree in a D-vine model. The BEST copula functions in the first tree involve the unconditional marginal distribution functions of each variable. However, in the higher tree, the BEST copula functions involve the conditional distribution functions. For example, \( \{F(y_1|y_2), F(y_3|y_2)\} \) are considered in the BEST copula functions in the second tree in a D-vine. Following the same process used for deriving the BEST copula in the first tree, the BEST copula in the second tree in a D-vine follows:

\[
\begin{align*}
& c_{1,3,2}(u_{2,3}^{-1}; \lambda_3, \theta^{(2)}, \tau^{(2)}, \nu^{(2)}), \\
& \lambda_3 \left( \theta^{(2)}, \tau^{(2)} \right), \tau_1 \left( \tau^{(2)} \right), \nu^{(2)} \\
& f_{1} (u_{2,3}^{-1}; \lambda_3, \theta^{(2)}, \tau^{(2)}, \nu^{(2)} + 2) + 1),
\end{align*}
\]

where \( u_{2,3} = F(y_1|y_2) \) and \( u_{2,3} = F(y_3|y_2) \).

When the degree of freedom goes to infinity and one, a BEST distribution reduces to a bivariate skewed normal distribution and the bivariate skewed Cauchy distribution, respectively.

Multivariate Lower Tail Dependence Function of a D-Vine Mode

Liu et al. (2016) gives the lower tail dependence function of the BEST copula model, which takes the form:
where

\[ \tilde{b}_i = \left\{ \begin{array}{c}
  \frac{w_i T_i (-\lambda_i \sqrt{v_i^{(l)} + 1}; v_i^{(l)} + 1)}{w_{i+1} T_{i+1} (-\lambda_{i+1} \sqrt{v_{i+1}^{(l)} + 1}; v_{i+1}^{(l)} + 1)} \sqrt{v_i^{(l)} + 1} \\
  \frac{T_i \left( \tau_i \sqrt{1 + \lambda_i^2}; v_i^{(l)} \right)}{w_{i+1} T_{i+1} (-\lambda_{i+1} \sqrt{v_{i+1}^{(l)} + 1}; v_{i+1}^{(l)} + 1)} \sqrt{v_i^{(l)} + 1} \\
  \frac{w_{i+1} T_{i+1} (-\lambda_{i+1} \sqrt{v_{i+1}^{(l)} + 1}; v_{i+1}^{(l)} + 1)}{w_i T_i (-\lambda_i \sqrt{v_i^{(l)} + 1}; v_i^{(l)} + 1)} \sqrt{v_i^{(l)} + 1} \\
  \frac{T_i \left( \tau_i \sqrt{1 + \lambda_i^2}; v_i^{(l)} \right)}{w_{i+1} T_{i+1} (-\lambda_{i+1} \sqrt{v_{i+1}^{(l)} + 1}; v_{i+1}^{(l)} + 1)} \sqrt{v_i^{(l)} + 1}
\end{array} \right. \]

Chang et al. (2019) show the trivariate lower tail dependence, function which is

\[ b(w_1, w_2, w_3) = \int_{-\infty}^{\infty} C_{13} (t_{12}(w_1|w_2), t_{32}(w_2|v_2)) \, dv_2, \]

where \( C(\cdot) \) follows the BEST copula function and \( t_{12}(w_1|w_2) \) and \( t_{32}(w_3|v_2) \) are lower conditional tail dependence functions. Finally, the trivariate lower tail dependence coefficient can be obtained when \( w_1 = w_2 = w_3 = 1 \).

**Empirical Analysis**

**Data**

Daily data on the Shanghai Stock Exchange Composite stock market index, Shanghai Stock Exchange government bond index, and gold prices are collected from March 04, 2003, to May 29, 2015. The price of gold is measured in Chinese yuan per troy ounce. The return series are constructed by using the log-difference of the asset prices. The paths followed by the stock market returns, government bond returns, and gold returns are depicted in Figure 1. During the 2008 to 2009 crisis period, gold returns are clearly negatively correlated with stock returns, but bond returns are not, implying gold may act as a stronger safe haven than government bonds.

Table 1 provides summary statistics. The averages (in absolute values) are larger than the standard deviations, indicating relatively low volatilities. The returns for all assets are skewed to the left, suggesting the possibility of extremely bad outcomes. All return series also showed excessive kurtosis, ranging from 7.46 to 33.22, denoting heavy tails comparing with the normal distribution. The large values from the Jarque–Bera test strongly reject the assumption of normality of all series distributions.

We conduct the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests for the considered returns. The results indicate that the nonstationary hypothesis is rejected at 1% significance level, which means that all considered returns are stationary.

**Estimation Procedure**

This article applies the canonical maximum likelihood to estimate the MEST copula model. The procedures are presented as follows:

First, we fit each return series with two different models, an AR(\(p\))-GARCH model and an AR(\(p\))-GJR model, in terms of the quasi-maximum likelihood estimator. We select the optimal order of lag and the choice between GARCH and GJR in terms of the Bayesian information criterion.

Based on the residuals and the associated standardized residuals, we can estimate the parameters \( (\Phi, \theta(\lambda), \lambda, \tau, v) \) by maximizing the log-likelihood function of the BEST copula function of Equation 2.

**Estimation of Marginal Distribution and MEST Copula Model**

Table 2 lists the results of the marginal density estimations. The slope parameters are generally significant at 5% significance levels. To check the specification of selected models, we use
Table 1. Descriptive Statistics of Stock, Bond, and Gold Return Series.

| Variables | Mean (in %) | Median (in %) | SD    | Skewness | Kurtosis | J-B test | Pearson | ADF      | PP       |
|-----------|-------------|---------------|-------|----------|----------|----------|---------|----------|----------|
| Stock     | 0.0365      | 0.0551        | 0.0167| -0.2142  | 7.4595   | 2,552.3000*** | —       | -53.191*** | -53.228***|
| Bond      | 3.6534      | 3.5402        | 0.5835| 0.5633   | 2.9118   | 162.4004***  | -0.0529 | -42.628*** | -44.796***|
| Gold      | 0.0381      | 0.0593        | 0.0119| -0.1605  | 9.9143   | 6,092.700***  | 0.0577  | -52.016*** | -52.028***|

Note. This table presents the description for the daily return series of China Shanghai stock market index, 10-year government bond, and gold prices. “SD” and “J-B test” denote the standard deviation and the Jarque–Bera normality test, respectively. “Pearson” denotes the Pearson’s correlation and the partial correlation, respectively. “ADF” and “PP” denote the augmented Dickey–Fuller and Phillips–Perron unit root tests.

***Significance at 1%.
the Q and Lagrange multiplier (LM) tests for serial correlation and autoregressive conditional heteroscedasticity. The Q and LM values fail to reject the null hypothesis both of no serial correlation and of no conditional heteroscedasticity in the residuals at the 5% level.

In Table 3, the estimates of \( \lambda_1 \), \( \lambda_2 \), \( \lambda_3 \), and \( \tau \) are significant, indicating the asymmetry and fat/thin-tailed properties of copula density functions and the suitability of our suggested model.

**Analysis of Single Safe-Haven Effect Strategy**

To verify whether either bonds or gold is a safe haven for stocks, we employ the lower tailed dependence coefficient

\[
\hat{\lambda}_L = \lim_{u \to 0^+} \Pr[F_1(y_1) < u \mid F_2(y_2) < u].
\]

Panel A of Table 3 reports the estimates of \( \hat{\lambda}_L \) for stock–bond and stock–gold pairs. With respect to the observed tail dependencies, 0.01 is used as the cutoff value for verifying a weak safe haven, based on the Basel Accord. The estimates of \( \hat{\lambda}_L \) for stock–bond and stock–gold pairs are less than 0.01 and insignificant at the 5% confidence level. Our results show that both bonds and gold are weak safe-haven assets versus stocks, suggesting that the returns of gold and bonds are not strongly correlated with stock returns in times of stock crashes. Nevertheless, when holding portfolios containing stocks and gold (bonds), investors would hope these alternative assets to perform better when the other part of the portfolio loses money. This property can be examined by the test of strong safe haven. According to the definition, we can identify the strong safe haven property by examining whether there is a positive correlation between stock returns and negative gold returns (negative bond returns). Panel B of Table 3 reports the estimated copula parameters and \( \hat{\lambda}_L \) with negative bond returns and negative gold returns. The estimates of \( \hat{\lambda}_L \) for the stock–gold pair are larger than 0.01 and significant at the 5% confidence level, showing that gold is able to be a strong safe haven for stocks.

During a stock market crisis, the 10-year government bond is at best a weak safe-haven asset for stocks, and gold is not only a strong but also a weak safe-haven asset. The findings are consistent with the results of Baur and McDermott (2013), Bulut and Rizvanoglu (2019), and Lee et al. (2019).

**Conditional Analysis of Safe-Haven Effect of Bond and Gold**

In this section, we examine whether bonds (gold) are a weak safe haven for stocks conditional on extremes in negative returns for gold (bonds). We study the extreme dependence

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**Table 2. Estimation Results of Marginal Functions.**

| Coefficients | Stock AR(2)-GARCH | Bond AR(2)-GARCH | Gold AR(2)-GARCH |
|--------------|-------------------|------------------|------------------|
| \( \alpha \)  | 0.0003*** (0.0001) | 0.0184*** (0.0061) | 0.0005*** (0.0001) |
| \( \beta_1 \) | 0.0162*** (0.0016) | 0.5000*** (0.0397) | 0.0167 (0.0181) |
| \( \beta_p \) | 0.0093 (0.0184) | 0.4951*** (0.0395) | 0.0415*** (0.0151) |
| \( \phi \)   | 9.6995e−08*** (1.1614e−06) | 3.6297e−05*** (1.4013e−05) | 9.0076e−06*** (8.8919e−08) |
| \( \gamma \) | 0.0858*** (0.0052) | 0.2245*** (0.0556) | 0.1036*** (0.0121) |
| \( \delta \) | 0.8724*** (0.0100) | 0.7755*** (0.0507) | 0.8299*** (0.0106) |
| \( Q \)     | 10.7484** [0.0566] | 19.3754 [4.976] | 17.6458 [6.107] |
| LM          | 1.4006 [2366] | 0.6387 [4242] | 3.3519 [0.671] |

Note. This table presents the estimates of the marginal models for returns of the China stock index, government bond, and gold price. Numbers in brackets are \( p \) values and numbers in parentheses are standard deviations. Q stands for Q statistics for testing the hypothesis of no serial correlation. LM stands for ARCH-LM statistics for the hypothesis of no autoregressive conditional heteroscedasticity. LM = Lagrange multiplier. *** *, ** denote significance at 1%, 5%, and 10%, respectively.

**Table 3. Estimation Results of MEST Copula Functions and the Associated Tail Dependence Coefficient.**

| V | \( \lambda_1 \) | \( \lambda_2 \) | \( \lambda_3 \) | \( \tau \) | \( \hat{\lambda}_L \) between stock and bond | \( \hat{\lambda}_L \) between stock and gold |
|---|----------------|----------------|----------------|------|-------------------------------|-------------------------------|
| Panel A: Weak safe-haven analysis | | | | | | |
| 12.5007*** (0.6950) | −6.0000*** (0.0773) | 0.0592*** (0.0119) | 0.0721*** (0.0080) | 18.6888*** (0.7844) | 0.0048* | 0.0050 |
| Panel B: Strong safe-haven analysis | | | | | | |
| 8.0187** (3.1737) | 0.1244*** (0.0077) | 0.0261** (0.0129) | −9.9440*** (0.4233) | 32.4151*** (2.6845) | 0.0000 | 0.0154*** |

Note. Panel A reports the estimates of the MEST copula model for China and the pairwise lower tail dependence coefficient; whereas Panel B reports those with negative gold returns and negative bond yields. Numbers in parentheses are standard deviations. \( \lambda \) are the shape parameters for marginal distribution, \( \tau \) is an extension. Parameter and \( v \) are the degree of freedom. \( \lambda_1 \) stands for the lower tail dependence coefficient. MEST = multivariate extended skew-t. *** *, ** denote significance at 1%, 5%, and 10%, respectively.
of the two pairs of assets: stocks–bonds conditional on the gold market and stocks–gold conditional on the bond market.

First, we consider the conditional joint probability to investigate whether bonds (gold) work as a strong safe-haven asset if gold (bonds) has an extreme poor performance.

For the sake of the probability, we evaluate the joint density of \( y_1 \) and \( y_2 \) markets based on the \( y_3 \) markets, \( f(y_1,y_2 \mid y_3 \in \Delta) \), where \( \Delta \) is a predetermined region of either bond or gold returns. This tail probability can be given by:

\[
P_{\Delta} = \Pr[y_1 < F_3^{-1}(\alpha), y_2 < F_3^{-1}(\alpha) \mid y_3 \in \Delta]
\]

\[
= C(\alpha, \alpha; y_3 \in \Delta), \alpha \in (0,1).
\]

where \( C(\cdot) \) is the distribution function of MEST copula. Particularly, we consider these two scenarios: \( \Delta_1 = \{y_3 : F_3^{-1}(0) \leq y_3 \leq F_3^{-1}(0.05)\} \) and \( \Delta_2 = \{y_3 : F_3^{-1}(0.95) \leq y_3 \leq F_3^{-1}(1)\} \), where \( F_3 \) is the marginal distribution.

If the series of stock and bond returns are perfectly correlated, the joint probability is \( \alpha \). In contrast, if stocks and bonds returns are uncorrelated, the probability equals \( \alpha^2 \). From Table 4, the estimates of the probability show that when gold returns (bonds returns) fall into either the extremely good or extremely bad case, bond returns (gold returns) and stock returns tend to fall into the lower tails of the distribution. These findings imply that neither bonds nor gold is able to be a strong safe-haven asset for stocks conditional on the poor performance of the other alternative investments.

Second, we investigate whether bonds (gold) is a weak safe-haven asset for stocks if assuming the poor gold (bonds) returns. \( x \) and \( y \) are statistically independent conditional on \( z \) if and only if \( \Pr(x < \alpha | z < \alpha) = \Pr(x < \alpha) \Pr(y < \alpha, z < \alpha) \), where \( \alpha \) refers to a given quantile. We examine whether stocks and bonds (gold) are conditional independent to verify whether bonds (gold) are a weak safe-haven asset. For instance, if \( \Pr(y_1 < F_3^{-1}(\alpha) | y_2 < F_3^{-1}(\alpha)) = \Pr(y_2 < F_3^{-1}(\alpha)) \), where \( y_1 \) and \( y_2 \) stand for time series of bond, stock, and gold returns, respectively, then stock and bond are conditional independent.

From the results in Table 5, the absolute difference between the two conditional probabilities for stock–bond and stock–gold pairs is larger than 1%, indicating that stocks and bonds (gold) are not independent conditional on gold (bonds). Thus, we argue that neither bonds nor gold is able to be a weak safe-haven asset conditional on the poor performance of the other alternative investment.

When bond (gold) declines dramatically, stocks and gold (bonds) also decline dramatically. Hence, gold is not a strong safe haven for stocks when bonds perform poorly. Furthermore, the conditional independence analysis indicates that bonds (gold) are no longer treated as a weak safe-haven asset when the alternative investment is included in the portfolio.

Sandoval and Franca (2012) showed that the stock markets have a tendency to have a higher correlation during markets crash. Therefore, the conditional distributions of stocks and gold (bonds) have a tendency to have heavier tails than the unconditional distributions.

### Multivariate Lower Tail Dependence Analysis

Finally, we estimate the multivariate lower tailed dependence coefficient via a D-vine MEST copula method to provide a straightforward insight regarding the multivariate tail dependence among stocks, bonds, and gold. Panel A of Table 6 reports the results of the copula and conditional functions estimation. The estimated \( \lambda \) and \( \xi \) are generally

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**Table 4. Joint Safe-Haven Effects: Conditional Joint Lower Tail Probability.**

|                      | Panel A: Joint lower tail probability between stock and bond conditional on gold (in %) | Panel B: Joint lower tail probability between stock and gold conditional on bond (in %) |
|----------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
|                      | \( \alpha = 1\% \)                                                                 | \( \alpha = 1\% \)                                                                 |
| Gold                 | \( \alpha = 5\% \)                                                                 | \( \alpha = 5\% \)                                                                 |
| 0%-5%                | 0.578                                                                               | 0.568                                                                               |
| 95%-100%             | 0.374                                                                               | 0.389                                                                               |

**Table 5. Joint Safe-Haven Effects: Conditional Independence Test.**

|                      | Panel A: Joint lower tail probability between stocks and bond conditional on gold (in %) | Panel B: Joint lower tail probability between stocks and gold conditional on bond (in %) |
|----------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
|                      | \( \Pr(y_1 < F_3^{-1}(\alpha) | y_2 < F_3^{-1}(\alpha)) \) | \( \Pr(y_1 < F_3^{-1}(\alpha) | y_2 < F_3^{-1}(\alpha)) \) |
|                      | 3.5552                                                                               | 3.4817                                                                               |
| % difference between two probabilities | 15.5355                                                                               | 11.5355                                                                               |

**Note.** This table presents the results of conditional independence test. \( \alpha \) is set to be 0.01. Panel A reports the conditional lower tail probabilities of stock on bond and gold and the conditional tail probabilities of stock on gold, respectively. Panel B reports the conditional lower tail probabilities of stock on bond and gold and the conditional tail probabilities of stock on bond, respectively.
significant, indicating the existence of skewed tail and fat/thin-tail features.

The estimates of $\lambda_1$ for the stock–bond and stock–gold pairs reported in Panel B of Table 3 are 0.0063 and 0.0049, respectively, consistent with those in Panel A of Table 3. The lower tailed dependence coefficient of bonds and gold conditional on the stock market (0.6964) reveals the high tail comovement between government bonds and gold given movements in the stock markets. Finally, the estimated multivariate lower tailed dependence coefficient of bonds, gold, and stocks is 0.0169, which is larger than 1%, confirming that adding both bonds and gold to the portfolio generally cannot provide better safe-haven attributes for equity investors than when adding either bonds or gold separately to the portfolio.

**Correlation With Value-at-Risk (VaR)**

Finally, we investigate the VaR in terms of the MEST copula function. We evaluate the 1% Portfolio value-at-risk (PVaR) in terms of an equally weighted portfolio. We choose the large negative stocks returns (2%, 4%, . . ., 20%) to calculate 1% PVaR. Based on the choices of the stock returns, we can search for the corresponding returns of bonds or gold to obtain a joint probability of 1%. For ease of interpretation, we discuss the average PVaR across different combinations. The average 1% PVaR for stock–bonds, stock–gold, and stock–bonds–gold are −0.0051, −0.0074, and −0.0082, respectively. This implies that, on average, there is a 1% probability so that the daily portfolio loss is larger than 0.51% for stock–bonds pair, 0.74% for stock–gold pair, and 0.24% for stock–bonds–gold pair. That is, if a portfolio contains US$500 in stocks and US$500 in bonds (gold), the PVaR is US$5.1 (US$7.4) on average. Moreover, if a portfolio contains US$333.33 in stocks, US$333.33 in bonds, and US$333.33 in gold, the PVaR is US$8.2 on average. Thus, the average 1% VaR of stock–bonds–gold portfolio is larger than both the average 1% VaRs of stock–bonds portfolio and of stock–gold portfolio. This is consistent with the previous findings in the “Multivariate Lower Tail Dependence Analysis” section.

**Conclusion**

Since the recent stock markets crash, risk management of the Chinese stock market has attracted increasing attention. This study attempts to investigate whether government bonds and gold can serve as safe-haven assets for Chinese stocks. We utilize an MEST copula model as well as the coefficient of tail dependence to verify the tail correlation for stock, bond, and gold markets. Our study finds that bonds and gold are weak safe havens. In addition, gold provides a strong safe-haven ability for stocks.

The occurrence of safe haven in crises times is good news for investors in China because it indicates that there is an asset class to protect investors from market losses during market turmoil. Our empirical analysis shows that either bonds or gold can stabilize the Chinese stock markets because they improve diversification.

When stocks, bonds, and gold are jointly analyzed, we find that including both gold and bonds in a portfolio does not outperform including either gold or bonds in a portfolio. For the sake of diversification, the portfolios should have stocks and one of the studied safe-haven assets, gold and bonds. Although our study complements recent studies on the gold and bonds assets in China, further analysis of joint estimation of safe-haven assets remains necessary.

The MEST copula model provides support of skewed tails or heavy/thin tails for nonnormal returns of stocks, bonds, and gold in China. Moreover, the development of multivariate tail dependence coefficients supports the analysis of how multiple assets crash together when one of them crashes. Our research also implies that investors should consider the tail dependence structure of assets before putting more safe-haven assets in the portfolio to hedge stock market crashes.

**Table 6. Estimation Results of the Vine Copula Model.**

| Panel A: Copula and conditional functions estimation | $c_{1,2}$ | $c_{3,2}$ | $c_{1,3|2}$ |
|---------------------------------------------------|----------|----------|-------------|
| $\nu$                                             | 19.3218*** (0.8934) | 6.9731*** (1.7912) | 16.3361*** (0.8999) |
| $\lambda_1$                                       | 0.2346*** (0.0126) | −6.7319** (2.8915) | −9.2313*** (0.0917) |
| $\tau$                                            | −9.0755*** (0.8921) | 1.2311*** (0.0844) | −8.7753*** (0.0413) |
| $n$                                               | 21.8721*** (5.9932) | 16.7858*** (6.9879) | 25.9317*** (2.2558) |

| Panel B: Estimation results of the lower tail dependence coefficient | $\lambda_{(stock, bond)}$ | $\lambda_{(stock, gold)}$ | $\lambda_{(bond, gold||stock)}$ | $\lambda_{(stock, bond, gold)}$ |
|-----------------------------------------------------------------|-----------------------------|-----------------------------|---------------------------------|---------------------------------|
| $0.0048^*$                                                        | 0.0051                      | 0.7311***                   | 0.0173                          |                                |

Note. $c_{1,2}$, $c_{3,2}$, and $c_{1,3|2}$ denote the copula densities of stock and bond, of stock and gold, and of bond and gold conditional on stock, respectively. Numbers in parentheses are standard deviations. $\lambda$s are the shape parameters for marginal distribution, $\tau$ is an extension parameter, and $\nu$ is the degree of freedom.

***, **, and * denote significance at 1%, 5%, and 10%, respectively.
This is very similar to the modern portfolio theory of Harry Markowitz, which takes correlations and covariances of asset returns into consideration.

Authors' Note
No ethics statement is needed. The article is approved by all authors for publication.

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