Extreme Risk Spillovers Among Gold, Foreign Exchange and Stock Markets: Based on the Method of Granger Causality in Risk

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Abstract
This paper investigates extreme risk spillovers among gold, foreign exchange and stock markets by focusing on the Granger causality in risk. Value at Risk (VaR) is used to measure market risk and a class of kernel-based test statistics is used to examine extreme risk spillovers. The results show that there exist negative extreme risk spillovers between gold and stock markets and both negative spillovers and positive spillovers are found between gold and foreign exchange markets. In addition different spillover effects are found between foreign exchange and Chinese stock market and between foreign exchange and US stock market.

Key words: Extreme risk spillovers, Value at Risk, Stock market, Granger causality in risk, Financial crisis

1. INTRODUCTION

Globalization and liberalization of financial market has strengthened the financial market integration and interdependence, which will increase the likelihood of the risk transmission from one financial market or asset to other markets or assets (Zhou, 2013; Liu, 2014). During the periods of financial crisis, in order to hedge or reduce the risk investors will rebalance their portfolios between the risky financial assets and safer assets, and this ‘flight to quality’ phenomenon results in the price increase of safer assets (Tuysuz, 2013).

In recent years, the global economy is in the midst of slow growth environment with increasing uncertainty. For example, the uncertainty of US monetary policy to raise interest rate leads to the fluctuation of the global financial markets; the slowdown of emerging market and developing economies and the slow recovery of advanced economies weaken the global economic growth momentum. As uncertainty increases, investors tend to shift their assets from high-risk markets to low-risk markets. Under this background, as a safer asset, gold has attracted increasing attention by investors.

In academic literature, whether gold acts as a hedge or a safe haven is well studied by scholars. Increasing evidence has shown that gold can act as a safe haven for stock markets during the periods of crisis (see, e.g., Baur and McDermott, 2010; Ciner et al., 2013; Arouri et al., 2015; Beckmann et al., 2015; Jain and Biswal, 2016). The studies of Capie et al. (2005), Reboredo (2013) and Ciner et al. (2013) has shown that gold can act a hedge against US dollar.

As Choudhry et al. (2015) point out that the most of the former studies ignore the possibility of mutual dependence among various asset classes by adopting a unidirectional approach. In order to bridge this gap, Choudhry et al. (2015) study the bidirectional nonlinear dynamic co-movements among various assets based on nonlinear Granger causality tests.

Based on the studies of Hong et al. (2009) and Du and He (2015), this paper attempts to study the interdependences among gold, foreign exchange and stock markets from the perspective of extreme risk spillovers. The paper focuses on studying the extreme risk spillovers between gold and stock markets, between foreign exchange and stock markets and between gold and foreign exchange markets. For stock markets, Chinese and US stock markets are selected to be studied. For foreign exchange market, US dollar index is the selected. For gold market, the London gold price is selected.

The contribution of this paper is twofold. Firstly, this paper studies the risk spillover effects among gold, foreign exchange and stock markets from the perspective of extreme risk spillovers. In the field of risk management, Value at Risk (VaR) is widely used to measure the extreme downside market risk. In fact, there exist not only downside risk, but also upside risk. In order to capture the upside risk, Du and He (2015) introduce the notion of upside VaR. Former studies mainly focus on the extreme risk spillover effects in stock markets (Hong et al., 2009; Liu, 2014), in international REIT markets (Zhou, 2013), in world gold markets (Wang et al., 2014) and between crude oil and stock markets (Du and He, 2015). In this paper, we extend the study of extreme risk spillovers to gold and foreign exchange markets. Secondly, we also study the direction of risk spillovers by implementing the method of Hong et al. (2009) to construct two test statistics which can test both the one-way Granger causality in risk and two-way Granger causality in risk including instantaneous risk spillovers. Based on these test statistics, we can study the transmission of the extreme risk among different markets.
The remainder of this article is organized as follows. Section 2 is the literature review. The methodology is described in Section 3. Section 4 presents the sample data and discusses the empirical results. The conclusion is presented in Section 5.

2. LITERATURE REVIEW

This paper mainly adds to the following two strands of literature. The first strand focuses on the relationship between gold and stock markets. Baur and McDermott (2010) study the relationship between gold and stock markets by testing the safe haven effect. The results indicate that gold is a safe haven for most stock markets in developed countries, and can act as a strong safe haven during the peak of the recent financial crisis. However, the situation is quite different for emerging stock markets. Gold is not a safe haven for most of emerging stock markets and a weak safe haven for some emerging stock markets.

Beckmann et al. (2015) study the gold’s function of a hedge or a safe haven by augmenting the model of Baur and Lucey (2010) to smooth transition regression with two extreme regimes. The results indicate that gold is both a hedge and a safe haven for stock markets. Gold can serve as a safe haven during the extreme financial markets.

Using a VAR–GARCH framework, Arouiri et al. (2015) investigate the relationship between world gold prices and Chinese stock returns from the insight for hedging and diversification strategies. They find that gold can serve as a safe haven for Chinese stock market during the recent global financial crisis.

Some studies focus on the nonlinear relationship between gold and stock markets (Choudhry et al., 2015; Jain and Biswal, 2016). For example, Choudhry et al. (2015) apply the nonlinear Granger causality test to test the dynamic relationship between gold and stock markets during the global financial crisis. Their results show that gold is not a safe haven during the financial crisis period. However, gold can be used as a hedge in stable financial conditions. By using DCC-GARCH model and nonlinear causality tests, Jain and Biswal (2016) study the dynamic linkages among oil price, gold price, exchange rate, and stock market in India.

The second strand of literature focuses on the relationship between gold and foreign exchange markets (Capie et al., 2005; Joy, 2011; Ciner et al., 2013; Reboredo, 2013). In an early study, Capie et al. (2005) examine the hedge function gold against dollar. They find that the ability that gold serves as a dollar hedge is time-varying and highly depends on unpredictable political attitudes and events.

Using daily data from the US the UK markets, Ciner et al. (2013) investigate dynamic linkages between oil, gold, currency, bond and stock markets. The results show that gold plays the role of a monetary asset to act as a safe haven against exchange rates during extreme price movements.

Reboredo (2013) uses copulas model to examine the role of gold as a safe haven or hedge against the US dollar. The results indicate that gold can act as hedge against USD rate movements and can act as an effective safe haven against extreme USD rate movements.

3. METHODOLOGY

3.1 Extreme risk measurement

In academic literature, Value at Risk (VaR) is a popular measurement of extreme risk. The conventional concept of VaR refers to downside market risk. In fact, there exist not only downside risk but also upside risk in the financial markets. In order to measure the upside risk, Du and He (2015) introduce the notion of upside VaR. In this paper, we use both the upside VaR and downside VaR, denoted by $V_{i}(up)$ and $V_{i}(down)$, respectively. For a given time series of returns $Y_{i}$, at the confidence level of $100(1-\alpha)\%$, the upside VaR and downside VaR are written as:

$$P(Y_{i} > V_{i}(up) | I_{t-1}) = \alpha,\quad (1)$$
$$P(Y_{i} < -V_{i}(down) | I_{t-1}) = \alpha.\quad (2)$$

where $I_{t-1} = \{Y_{t-1}, Y_{t-2}, \ldots\}$ is the information set available at time $t-1$. Mathematically, the upside VaR and downside VaR are the right $\alpha$-quantile and left $\alpha$-quantile of the returns, respectively.

In order to estimate VaR, this paper employ GJR-GARCH model which can capture the characteristics of financial returns, such as volatility clustering, fat tails, skewness and leverage effects (Glosten et al. 1993; Hung et al., 2008; Du & He, 2015). For a given time series of returns $Y_{i}$, the GJR-GARCH model takes the following form:

$$Y_{i} = c + \sum_{j=1}^{p} \phi_{j} Y_{t-j} + \epsilon_{i},\quad (3)$$
$$\epsilon_{i} = \sqrt{h_{i}} z_{i},\quad (4)$$
\[ h_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i e_{t-i}^2 + \gamma e_{t-i} d_{t-i} + \sum_{j=1}^{n} \beta_j h_{t-j}, \]  
(5)

\[ z_t \sim m.d.s.(0,1) \text{ with conditional CDF } F(.). \]  
(6)

where Eq.(3) and Eq.(5) are the conditional mean and variance equations, respectively. Let \( \mu_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} \), then \( \mu_t \) and \( h_t \) are the conditional mean and variance of \( Y_t \) given \( I_{t-1} \), respectively. Eq. (4) defines the standardized error \( z_t \) and in Eq. (6), the standardized residual has a conditional distribution with mean zero and variance one.

In the conditional variance equation, indicator \( d_{t-i} = 1 \) when \( e_{t-i} < 0 \), denoting bad news; otherwise \( d_{t-i} = 0 \) and denotes good news. The coefficient \( \gamma \) is used to measure the difference between the effects of good news and bad news on the conditional variance, namely, the leverage effects.

As efficient estimation of VaR depends highly on the conditional distribution for the standardized error (Du and He, 2015), attention should be paid to the selection of the appropriate distribution. In this paper, three kinds of distribution for the standardized error are considered to estimate the VaR accurately: Student's t distribution, generalized error distribution (GED) and skewed t distribution. In this paper, the skewed t distribution proposed by Hansen (1994) is used. This distribution has two parameters to be estimated: the degrees of freedom parameter \( 2 < \eta < \infty \) and the skewness parameter \( -1 < \lambda < 1 \). The freedom degrees parameter controls the tail thickness and the skewness parameter controls the asymmetry. In fact, skewed t distribution covers several distribution. For example, when \( \lambda = 0 \), the skewed t distribution can be rewritten as standardized Student's t distribution. When \( \lambda = 0 \) and \( \eta = \infty \), the standardized normal distribution can be obtained. Taking these characteristics of skewed t distribution into consideration, it has been widely used to describe financial returns series (Jondeau & Rockinger, 2003; Hong et al., 2009; Wen et al., 2012; Patton, 2013).

From Eq. (3)-Eq. (6), we can obtained the upside VaR and downside VaR of time series \( Y_t \):

\[ V_t(\text{up}) = \mu_t + \sqrt{h_t} Z_{\alpha}, \]  
(7)

\[ V_t(\text{down}) = -\mu_t - \sqrt{h_t} Z_{\alpha}. \]  
(8)

where \( Z_{\alpha} \) is the left-tailed critical value of the standardized innovation at level \( \alpha \) and \( Z_{1-\alpha} \) is the upper \( \alpha \)-quantile.

Following the study of Du and He (2015), the method proposed by Kupiec (1995) is used to test the accuracy of the VaR model for calculating extreme market risks. Under the null hypothesis, the test statistic LR follows \( \chi^2(1) \) distribution asymptotically. For a given significance level, if LR is larger than the critical value, the null hypothesis of correct specification of the VaR model should be rejected, indicating inaccuracy of the VaR model.

### 3.2 Granger causality in risk

Based on the study of Du and He (2015), we consider four types risk spillovers between different markets, namely, downside, upside, down-to-up and up-to-down risk spillovers. The downside risk spillover and upside risk spillover are two types of positive risk spillover effects between two financial markets and the down-to-up risk spillover and up-to-down risk spillovers are two types of negative spillover effects.

For two different markets \( \{ Y_{1t} \} \) and \( \{ Y_{2t} \} \), the downside risk indicator and upside risk indicator functions are defined as:

\[ Z_{\text{h,up}} = I(Y_{1t} > V_{1t}(\text{up})), \quad l = 1, 2. \]  
(9)

\[ Z_{\text{h,down}} = I(Y_{1t} < -V_{1t}(\text{down})), \quad l = 1, 2. \]  
(10)

where \( I(\bullet) \) is an indicator function and \( l \) represents the markets 1 or 2. When the market return exceeds VaR (larger than the upside VaR or less than the downside VaR) the risk indicator \( Z_{\text{h}} \) takes value of 1 and otherwise takes value of 0.

For four types risk spillovers, the tests for Granger causality risk from market 1 to market 2 are stated as:

**Null Hypothesis 1:** There is no one-way Granger causality in downside risk from market 2 to market 1.

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1 The results indicate that skewed t distribution is the most accurate, which is supported by Du and He (2015).
$H_0 : E(Z_{t,down} \mid I_{(t-1).down}) = E(Z_{t,down} \mid I_{(t-1).down})$. 

Against

$H_1 : E(Z_{t,down} \mid I_{(t-1).down}) \neq E(Z_{t,down} \mid I_{(t-1).down})$.

where $I_{(t-1).down} = (I_{(t-1).down}^{1}, I_{2(t-1).down}^{1})$. $I_{(t-1).down}^{1}$ and $I_{2(t-1).down}^{1}$ represent the information set of downside risk available at time $(t-1)$.

**Null Hypothesis 2:** There is no one-way Granger causality in upside risk from market 2 to market 1

$H_0 : E(Z_{t,up} \mid I_{(t-1).up}) = E(Z_{t,up} \mid I_{(t-1).up})$.

Against

$H_1 : E(Z_{t,up} \mid I_{(t-1).up}) \neq E(Z_{t,up} \mid I_{(t-1).up})$.

where $I_{(t-1).up} = (I_{(t-1).up}^{1}, I_{2(t-1).up}^{1})$. $I_{(t-1).up}^{1}$ and $I_{2(t-1).up}^{1}$ are the information set of upside risk available at time $(t-1)$.

**Null Hypothesis 3:** There is no one-way Granger causality in down-to-up risk from market 2 to market 1

$H_0 : E(Z_{t,up} \mid I_{(t-1).up}) = E(Z_{t,up} \mid I_{(t-1).up})$.

Against

$H_1 : E(Z_{t,up} \mid I_{(t-1).up}) \neq E(Z_{t,up} \mid I_{(t-1).up})$.

**Null Hypothesis 4:** There is no one-way Granger causality in up-to-down risk from market 2 to market 1

$H_0 : E(Z_{t,down} \mid I_{(t-1).down}) = E(Z_{t,down} \mid I_{(t-1).down})$.

Against

$H_1 : E(Z_{t,down} \mid I_{(t-1).down}) \neq E(Z_{t,down} \mid I_{(t-1).down})$.

### 3.3. Test statistics

In order to test the Granger causality in risk between different markets, Hong et al. (2009) propose a class of kernel-based statistics.

For two estimated series of risk indicators $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$, Hong et al. (2009) define the sample cross-covariance function between these two risk indicators as follows:

$$\hat{C}(j) = \sum_{t=1}^{T-j} \hat{Z}_{1,t} \hat{Z}_{2,t+j}$$

(11)

where $j$ is the lag order and $\tilde{\alpha}_t = T^{-1} \sum_{t=1}^{T} \hat{Z}_{1,t} \hat{Z}_{2,t}$ is the sample cross-correlation function between $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$.

The test statistic for one-way Granger causality in risk from market 2 to market 1 is:

$$Q_1 (M) = \left( T \sum_{j=1}^{T-j} k^2 (j/M) \hat{\rho}^2 (j) - C_{12} (M) \right) D_{12} (M)^{1/2},$$

(13)

The test statistic for two-way Granger causality in risk including instantaneous risk spillovers between two markets is:

$$Q_2 (M) = \left( T \sum_{j=1}^{T-j} k^2 (j/M) \hat{\rho}^2 (j) - C_{22} (M) \right) D_{22} (M)^{1/2},$$

(14)
where \( k(\bullet) \) is a kernel function which can take several forms. In this paper, we select the Daniell kernel:
\[
k(x) = \sin(\pi x)(\pi x)
\]
by minimizing
\[
\int_0^\infty k^4(z)dz.
\]
\( M \) is the largest lag order. \( C_{1T}(\bullet), C_{2T}(\bullet), D_{1T}(\bullet) \) and \( D_{2T}(\bullet) \) are the centering and standardized constants defined as:
\begin{align}
C_{1T}(M) &= \sum_{j=1}^{T-1}(1 - j/T)k^2(j/M), \\
D_{1T}(M) &= 2\sum_{j=1}^{T-1}(1 - j/T)(1 - (j+1)/T)k^4(j/M), \\
C_{2T}(M) &= \sum_{|j|\leq M}(1 - |j|/T)k^2(j/M), \\
D_{2T}(M) &= 2[1 + \hat{\rho}^2(0)]\sum_{|j|\leq M}(1 - |j|/T)(1 - (|j|+1)/T)k^4(j/M).
\end{align}

Under the null hypothesis, \( Q_1(M) \) and \( Q_2(M) \) follow an asymptotically standard normal distribution.

4. EMPIRICAL RESULTS AND DISCUSSIONS

4.1 Data
In the paper, we choose Shanghai Composite Index (SH), S&P 500 Index (SP), London Gold Price (LGP) and US Dollar Index (USD) to represent Chinese stock market, US stock market, gold market and foreign exchange market. Daily data are derived from the Wind Database and cover the time period from January 1, 2005 to July 12, 2016. Returns for different markets are obtained as the first difference in the natural logarithm of the daily closing price. In order to solve the non-synchronous trading problem, the daily returns of gold market, US stock market and foreign exchange market are lagged one day to match the current returns of Chinese stock market. After matching the data from different markets, we obtain totally 2706 observations.

Figure 1 presents the daily returns of the stock, gold and foreign exchange market indices. During the full sample period, the global financial market has witnessed several crisis events including the global finance crisis induced by the US subprime mortgage crisis starting in July–August 2007, the European debt crisis and the stock market turbulence in China starting in June 2015. Due to these crisis events, the global financial market becomes more volatile, especially during the period 2007-2009 and 2015-2016. The descriptive statistics are presented in Table 1. For the stock markets, as one of emerging market, Chinese stock market is more volatile with higher returns than US stock market, which is supported by many empirical studies. During the whole sample, both the mean and standard deviation of Chinese stock market are around twice of US stock markets. For the gold market, the mean of returns is relative high with lower volatility compared to the stock markets. For the foreign exchange market, the mean and standard deviation of the returns are the lowest. In general, for all the markets, the skewness is below 0 and kurtosis is above 3, indicating that we cannot assume the return distribution to be normal. In addition, the Jarque–Bera test also rejects the normality.

Table 1. Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>J-B</th>
</tr>
</thead>
<tbody>
<tr>
<td>SH</td>
<td>0.0316</td>
<td>3.1022</td>
<td>-0.5159</td>
<td>6.7232</td>
<td>1682.9836***</td>
</tr>
<tr>
<td>SP</td>
<td>0.0159</td>
<td>1.5580</td>
<td>-0.2043</td>
<td>13.5775</td>
<td>12633.6385***</td>
</tr>
<tr>
<td>LGP</td>
<td>0.0316</td>
<td>1.5031</td>
<td>-0.3394</td>
<td>8.8443</td>
<td>3903.0779***</td>
</tr>
<tr>
<td>USD</td>
<td>0.0034</td>
<td>0.2696</td>
<td>-0.1744</td>
<td>5.1424</td>
<td>531.2248***</td>
</tr>
</tbody>
</table>

Note: This table provides the summary statistics of the returns in various markets. SH is the Shanghai Composite Index, SP is the S&P 500 Index, LGP is the London Gold Price and USD is the US Dollar Index. J–B is the Jarque–Bera test for normality.
Estimation of VaR

In order to test the extreme risk spillovers across markets, the upside VaR and downside VaR need to be estimated. As mentioned above, the distribution of daily returns is not normal and will display the characteristics of volatility clustering, fat tails, skewness and leverage effect. In order to capture these characteristics, the Student’s t distribution, generalized error distribution (GED) and skewed t distribution together with GJR-GARCH model are used to estimate the upside and downside risk. After comparing the results of the three distributions, we find that skewed t distribution is the most accurate one.

The estimated results of the GJR-GARCH model with skewed t distribution are presented in Table 2. First, for all the time series, the coefficients of lagged conditional variance, $\beta_1$, are significant at the 1% level, which indicating the presence of volatility clustering. Second, there is a significant leverage effect, captured by coefficient $\gamma$, in the gold and foreign exchange markets but not in the stock markets. The coefficients of leverage effects are negative for the gold and foreign exchange markets, indicating that good news has stronger impact than bad news. Third, the asymmetric parameters, $\lambda$, are all blow 0 at the 5% significance level except for that of the foreign exchange market, indicating that the time series is left skewed. Last, the freedom degrees $\eta$ are all above 4 at the 1% significance level which indicates again that returns have the characteristics of fat tails.

After estimating the GJR-GARCH model, the upside and downside VaR are calculated at the 5% significance level for all returns. The results are presented in Table 3. Following the study of Du and He (2015), we calculate the failure rate to test the accuracy of the VaR model. The failure rate is the ratio of failure days and sample size. As presented in Table 3, the failure rate is around 5% which indicates that the GJR-GARCH model based on skewed t distribution can estimate the VaR efficiently. Due to the estimation of VaR dependent on the standardized error conditional distribution, we also consider the estimation accuracy of Student’s distribution and generalized error distribution. The results indicate that the skewed t distribution is more accurate than Student’s distribution and generalized error distribution. In the following section, we will use the GJR-GARCH model based on skewed t distribution to estimate the series of downside VaR and upside VaR and then to investigate the extreme risk spillovers across different markets.

<table>
<thead>
<tr>
<th>Table 2. Estimation results of GJR-GARCH model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean equation</td>
</tr>
<tr>
<td>$c$</td>
</tr>
<tr>
<td>$\phi_1$</td>
</tr>
<tr>
<td>$\phi_2$</td>
</tr>
<tr>
<td>$\phi_3$</td>
</tr>
</tbody>
</table>
### Table 3. VaR estimation based on skewed t distribution

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.dev.</th>
<th>Failure time</th>
<th>Failure rate</th>
<th>LR statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SH</td>
<td>2.6741</td>
<td>1.0189</td>
<td>141</td>
<td>0.0521</td>
<td>0.2495</td>
</tr>
<tr>
<td></td>
<td>2.5766</td>
<td>0.9457</td>
<td>133</td>
<td>0.0492</td>
<td>0.0414</td>
</tr>
<tr>
<td>SP</td>
<td>1.8363</td>
<td>1.1853</td>
<td>149</td>
<td>0.0551</td>
<td>1.4158</td>
</tr>
<tr>
<td></td>
<td>1.6113</td>
<td>1.0617</td>
<td>135</td>
<td>0.0499</td>
<td>0.0007</td>
</tr>
<tr>
<td>LGP</td>
<td>1.8816</td>
<td>0.6320</td>
<td>144</td>
<td>0.0532</td>
<td>0.5773</td>
</tr>
<tr>
<td></td>
<td>1.8374</td>
<td>0.5923</td>
<td>127</td>
<td>0.0469</td>
<td>0.5427</td>
</tr>
<tr>
<td>USD</td>
<td>0.8143</td>
<td>0.2530</td>
<td>137</td>
<td>0.0506</td>
<td>0.0224</td>
</tr>
<tr>
<td></td>
<td>0.8083</td>
<td>0.2484</td>
<td>142</td>
<td>0.0525</td>
<td>0.3439</td>
</tr>
</tbody>
</table>

Note: the critical values of LR statistics at the 1%, 5% and 10% significance levels are 6.635, 3.841 and 2.706, respectively.

#### 4.3. Empirical results of extreme risk spillovers

In this section, we calculate the test statistics for one-way and two-way Granger causality in risk, respectively. In order to present the extreme risk spillovers across markets more intuitively, we plot the dynamics of extreme risk spillovers at different levels of M. For a given pair of markets, statistic $Q_1$ measures the one-way extreme risk spillovers from market w2 to market 1, statistic $Q_{-1}$ measures the one-way extreme risk spillovers from market 1 to market 2 and statistic $Q_2$ measures the two-way extreme risk spillovers including the instantaneous extreme risk spillovers between market 1 and market 2.

The extreme risk spillovers in the two causality directions between Chinese stock market and gold market are presented in Figure 2. In general, there exist negative extreme spillover effects between Chinese stock market and gold market. For the down-to-up risk spillovers, statistic $Q_1$ becomes significant after 5 days and keeps significant at the 5% significance level. It indicates that the extreme upside risk of gold market is transmitted into Chinese stock market gradually and Chinese stock market is exposed to extreme downside risk. Compared to $Q_1$, the statistic $Q_{-1}$ is not significant during the whole period, indicating that there exists not one-way down-to-up risk spillovers from Chinese stock market to gold market. For the two-way risk spillover, statistic $Q_2$ becomes significant at the 5% significance level after 15 days, indicating that, there exists instantaneously negative spillovers between Chinese stock market and gold market.

\[
\begin{array}{cccccc}
\text{Variance equation} & \alpha_0 & 0.0226^{**} & 0.0222^{***} & 0.0099^{**} & 0.0005 \\
\alpha_1 & 0.0556^{***} & 0.0000 & 0.0635^{***} & 0.0469^{***} \\
\beta_1 & 0.9392^{***} & 0.8752^{***} & 0.9511^{***} & 0.9629^{***} \\
\gamma & 0.0007 & 0.2188 & -0.0358^{***} & -0.0207^{**} \\
\lambda & -0.0736^{***} & -0.1929^{***} & -0.0671^{**} & -0.0179 \\
\eta & 4.9792^{***} & 7.5910^{***} & 5.1585^{***} & 9.4984^{***} \\
\end{array}
\]

Note: Parameters are estimated by the GJR-GARCH model with skewed t distribution. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.
Figure 2. Extreme risk spillovers between Chinese stock market and gold market

Figure 3 presents the extreme risk spillovers in the two causality directions between Chinese stock market and foreign exchange market. In general, there also exist negative extreme spillover effects between Chinese stock market and foreign exchange market. For the down-to-up extreme risk spillovers, $Q_{i}$ is significant within 15 days at the 5% significance level, which indicates that the extreme upside risk of foreign exchange market (US Dollar Index) is transmitted to Chinese stock market quickly and Chinese stock market is exposed to extreme downside risk. These down-to-up risk spillovers will diminish. $Q_{-i}$ is not significant during the whole period, indicating that there exists not one-way down-to-up risk spillovers from Chinese stock market to foreign exchange market. For the two-way risk spillover, statistic $Q_{1}$ is significant at the 5% significance level within 5 days, indicating that, there exists instantly negative spillovers between Chinese stock market and foreign exchange market.

Figure 3. Extreme risk spillovers between Chinese stock market and foreign exchange market

Figure 4 presents the extreme risk spillovers between US stock market and gold market. In general, there also exist negative extreme spillover effects between US stock market and gold market. For the down-to-up extreme risk spillovers, $Q_{i}$ is significant within 10 days at the 5% significance level, which indicates that the extreme upside risk of gold market is transmitted to US stock market quickly and US stock market is exposed to extreme downside risk. These down-to-up risk spillovers will diminish after 10 days. $Q_{-i}$ is not significant
during the whole period, indicating that there exists not one-way down-to-up risk spillovers from US stock market to gold market. For the two-way risk spillover, statistic $Q_i$ is significant within 10 days, indicating that, there exists instantaneously negative spillovers between US stock market and gold market.

Figure 4. Extreme risk spillovers between US stock market and gold market

Figure 5 presents the extreme risk spillovers between US stock market and foreign exchange market. In general, there also exist positive extreme spillover effects between US stock market and foreign exchange market. For the upside extreme risk spillovers, $Q_i$ is not significant indicating that there exists no instantaneously spillovers between US stock market and foreign exchange market.
For the downside risk spillovers, the extreme risk spillovers between gold market and foreign exchange market show the following patterns: in the short-term, there are downside risk spillovers from the foreign exchange market to gold market. These spillovers will diminish and then emerge as the lag order $M$ increases. In addition, in the short-term, there exist instantaneously spillovers between gold market and foreign exchange market.

For the upside risk spillovers, the patterns of extreme risk spillovers are as follows: in the short-term, there are not downside risk spillovers from the foreign exchange market to gold market. After several days, the upside extreme risk is transmitted from gold market to foreign exchange market. There also exist instantaneously upside spillovers between gold market and foreign exchange market.

For the up-to-down risk spillovers, the patterns of extreme risk spillovers are as follows: in the short-term, there are up-to-down risk spillovers from the gold market to foreign exchange market. There also exist instantaneously spillovers between gold market and foreign exchange market. As the lag order $M$ increases, both one-way up-to-down and instantaneously risk spillovers will diminish.

5. CONCLUSION

During the turmoil period of global financial market, gold is widely considered as a safer asset. Former studies have used different methods to investigate market risk. In this paper, we contribute to the literature by extending the studies of Hong et al. (2009) and Du and He (2015) to examine the interactions across gold, foreign exchange and stock markets from the perspective of extreme risk spillovers. First, we estimate the time series of downside VaR and upside VaR by using the GJR-GARCH model based on skewed t distribution. Second, we calculate the time series of risk indicators for downside risk and upside risk. Last, we construct two test statistics of one-way Granger causality in risk and two-way Granger causality in risk to test extreme risk spillover effects between gold and stock markets, between foreign exchange and stock markets and between gold and foreign exchange markets.

The results show that there are extreme risk spillover effects across gold, foreign exchange and stock markets. First, there are negative extreme risk spillover effects between gold market and Chinese stock market and between gold market and US stock market, namely, the up-to-down risk spillovers from gold market to stock markets. However, there is difference between Chinese stock market and US stock market. The upside extreme risk of gold market is transmitted to US stock market more quickly than to Chinese stock market. Second, the spillover effects between foreign exchange market and Chinese stock market and between foreign exchange market and US stock market are different. On the one hand, there are negative down-to-up risk spillovers between Chinese stock market and foreign exchange market. On the other hand, there are positive up-to-up risk spillovers between US stock market and foreign exchange market. Last, the extreme risk spillover effects between foreign exchange market and gold market are complicate, including downside risk spillovers and up-to-down risk spillovers in the short-term and upside risk spillovers in the long-term.
Our findings have important implications for policy maker and international investors. Due to the negative the up-to-down risk spillovers between gold market and Chinese stock market, when the gold price increase extremely, Chinese stock market is exposed to extreme downside risk. For investors, they should adjust the proportion of stock assets in investment portfolios to spread the risk. For policy maker, they can use this relationship between gold market and Chinese stock market to establish risk warning mechanism.

Due to the negative the down-to-up risk spillovers between Chinese stock market and gold market, when the extreme downside risk appears in Chinese stock market, the US dollar will increase dramatically. Taking this relationship into consideration, international investors can buy the US dollar to hedge against Chinese stock market risk. For policy maker, they should pay much attention to capital outflow during the turmoil period of stock market.

REFERENCES


