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Understanding the Nexus Between Emerging Stock Market Volatility and Gold Price Shocks

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Abstract. This study investigates the contagion and spillover effects of gold price shocks on the volatility of the Asian emerging stock markets. Gold prices' positive and negative shocks are quantified, and the Vector Autoregressive (VAR) and Copula approaches are employed to measure the spillover and contagion effects between gold price shocks and stock volatilities. Several Copula functions are considered, and the best-fit one is used to explain the correlation or the contagion effect, while the Granger causality test and VAR model are used to examine the casual and spillover effects, respectively. The study's findings show that there is some evidence indicating the volatility spillover, causality, and contagion between gold price shocks and stock volatility.

Keywords: Copulas · Contagion · Gold price shocks · Spillover effects · VAR

1 Introduction

Emerging stock markets have become increasingly integrated with the global economy in the last few decades. They are in the developing economies that have rapid economic growth, and income per capita per year greater than 15,000 US dollars. The countries where emerging stock markets are operating contain 80% of the world's population, and the size of their combined economy covers 20% of the world economy. It is well known that the stock market is important in the development of emerging economies as the businesses could issue their shares to get money from public investors. Thus, stock markets have been considered a reflection of the economic performance of emerging countries. Many investors have considered this market an alternative, which could provide an excellent opportunity for a higher profit. Although emerging stock markets can offer higher gains to investors due to rapid domestic economic growth, they also expose investors to a greater investment risk due to price volatility, economic and financial uncertainty, and an ongoing global economic slowdown [33]. This indicates that emerging stock markets are as well exposed to various shocks. To solve and mitigate the risk in the stock market, especially during an extreme market downturn, Nguyen et al. [24] and Pastpipatkul, Yamaka, and Sriboonchitta [28] suggested investing in the gold market. Gold is considered a reliable investment and a safe haven commodity that mitigates macroeconomic risk. Therefore, investigating the interconnection between gold price

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shocks and the stock market is crucial because this relationship is a relevant reference source for portfolio management and hedging strategies. The relationship between gold prices and stock returns is of significant interest to many scholars in both literature and empirical fields.

Theoretically, there is an inverse relationship between stock market returns and gold prices. There have been circumstances where stock market returns rise and gold prices fall. Gold prices may also rise in sympathy with the fall in stock prices. The reason lies in the perception of investors in the market. Investors who expect a bearish market generally take positions for their investment in gold futures. To reduce the stock market risk, many investors consider gold as the hedging in their portfolios. Gold is a valuable and extremely liquid metal and is classified as a product and a financial asset. Gold has also played an important role as a precious metal with significant portfolio diversification properties [10]. Investors prefer to reconstruct their investment portfolios by replacing some of their stock holdings with gold to protect the losses. Even though there are many empirical papers on stock exchange volatility have been conducted around the globe, few studies have been done on gold return volatility, i.e., the response of gold returns and volatility to public information arrival [18] and the influences of macroeconomic variables on gold returns and volatility [32].

A few studies have shown the impacts of gold price shocks and stock market volatility. However, most of the previous studies have focused on either the co-volatility or stock price and gold price relation. Therefore, this study attempts to provide a new perspective on the stock-gold nexus by identifying gold price shocks by decomposing gold return into positive and negative changes. Then, the relationship between the emerging stock markets and gold price shocks is investigated in various aspects, namely causality, spillover effect, and the risk contagion effect, using the Granger causality test, vector autoregression (VAR) model, and Copula model, respectively. In finance, the terms spillover, contagion, and causality are commonly used interchangeably. The definitions of these three words and their difference are explained in some writings ([14]; Xu [34]; Maneejuk [19]).

The following three aspects mainly reflect the overall contribution of this paper. First, this study applies the Granger causality test and VAR model to examine the causality and spillover effect between gold price shocks and emerging stock markets. It is unclear if emerging stock volatility is being anticipated by gold price shocks or if gold price shocks are just a consequence of the emerging stock volatility. To disentangle these effects, a Granger causality analysis of the stock volatility and different lags and leads of gold price shocks would be very informative. Second, I evaluate the spillover effect between the gold price shocks and emerging stock markets. This spillover can happen in both good and bad times and is not only related to a crisis period. Third, the Copula model is used to describe the nonlinear and asymmetric dependency structure as well as the lower tail coefficients, which can effectively depict the risk of contagion. Using tail coefficients to measure risk contagion from gold price shocks in different emerging markets is also an innovative approach compared with previous studies. It will help the government to provide economic policies from a more macro perspective and investors to make diversified investments with less risk.

This study is organized as follows. Section 2 provides a review of the related study (literature review). Section 3 presents data and methodology. Section 4 presents empirical results and discussion. Section 5 concludes the study.

2 Literature Review

In recent years, emerging stock markets have shown substantial growth due to the high capital inflows [4]. However, the emerging stock markets are exposed to global news and events that lead to a risky and uncertain events. The investments in gold are regarded as an inflation hedge, store of value, a source of wealth, and a safe haven asset for stock markets during periods of stock market troubles [2, 3].

Following the rapid financialization, the Granger causality, spillover effect, and contagion effect between gold and stock markets have been empirically tested. As for the causality and spillover effect, the most famous and common method to test the causality between two variables is the Granger causality test proposed by Granger [13], and the Vector Autoregressive (VAR) model can be used to detect the linear causality and causal effect between variables. Mishra, Das, and Mishra [22] attempted to investigate the causality and causal effect between gold prices and stock market returns in India and provided evidence of feedback causality between them during 1991–2009. Notably, the gold prices Granger-caused stock market returns, and stock market returns also Granger-caused the gold prices in India during the sample period. Similar to the work of Bhunia and Das [6], they provided support for feedback causality between the selected variables. Their results indicated that the co-movement of gold prices and stock prices is high even during the global financial crisis and after that. However, Hussin et al. [23] that studied the relationship between gold price and the Islamic stock market in Malaysia revealed that gold price is not a valid variable for predicting changes in Islamic stock prices. Choudhry, Hassan, and Shabi [9] investigated co-movements between gold returns and stock market volatility during the global financial crisis in 2007–2008 for the UK, the USA, and Japan. They found that gold may not perform well as a safe haven during the financial crisis period due to the weak bidirectional interdependence between gold returns and stock market volatility. However, gold may be used as a hedge against stock market returns and volatility in the stable financial conditions.

In the VAR framework, Raza, Jawad, Tiwari, and Shahbaz [30] investigated the asymmetric effect of gold prices, oil prices, and their related volatility on emerging stock markets, using monthly data from January 2008 to June 2015. The results showed that gold prices have a negative effect on the stock markets of Mexico, Malaysia, Thailand, Chile, and Indonesia. Additionally, Mensi et al. [21] studied the correlations and volatility spillovers between the S&P 500 and commodity price indices for energy, food, and gold by using a VAR-GARCH model over the period 2000 to 2011, and the results showed a significant transmission in many S&P500 and commodity pairs and found that the highest conditional correlations are the S&P500-gold and the S&P 500-WTI pairs. Hood and Malik [15] studied the role of gold volatility as hedge and safe haven of the US stock market and found that gold is a weak hedge against the US stock market.

As for the measurement of contagion risk, the most classical method is based on the correlation coefficient (Pearson [29]), which only describes a static linear correlation between the variables. Thus, Engle [12] introduced the Dynamic Conditional

Correlation-GARCH model to measure the time-varying correlation between the variables. Later, this model has been receiving increasing interest for researchers and practitioners. Chen and Wang [8] used DCC-GARCH to examine China's dynamic relationships between gold and stock markets. They found that gold acts as a safe haven for only market downturns, while gold does not offer a good risk hedging in market upturns. Basher and Sadorsky [1] considered various DCC-GARCH-type models, namely DCC-GARCH, GO-GARCH, and ADCC-GARCH, to investigate the dynamic correlation. In general, they revealed that gold has a positive correlation with emerging market returns. Thus, gold might not be good hedging for emerging stock markets.

Recently, the DCC-GARCH performance has been questioned by many researchers as there is evidence that the dependencies between financial variables are nonlinear and asymmetric. Therefore, the Copula method has been introduced to measure the contagion or co-movement between two or more variables. Copula was firstly introduced by Sklar [31] and further developed and described by Joe [16]. This model has been widely used to examine the contagion effects between gold and stock. Do, McAleer, and Sriboonchitta [11] studied the impact of gold on the volatility of the emerging ASEAN stock market. Nguyen et al. [24], Pastpipatkul, Yamaka, and Sriboonchitta [26], Pastpipatkul et al. [27] and Beckmann, Berger, and Czudaj [5] used different Copula functions to test the correlation between gold and stock.

Through summarizing the previous literature, there are many methods for testing causality, measuring spillover effects, and quantifying risk contagion, and each method has its own advantages and disadvantages. This study investigates the causality using the Granger causality test. In addition, the VAR model and Copula model are used to explore the spillover effect and contagion effect, respectively. Furthermore, with respect to the impact of gold price on the stock market, all the above studies used either gold price or gold return as a proxy, which may not yield the desired results. In fact, there might be an asymmetric impact from positive and negative gold price shocks on the emerging stock market. Hence, it is of interest to find out whether the output shocks of gold price have different impacts on stock volatility in emerging economies.

3 Data and Methodology

3.1 Data

This study uses weekly time series of gold prices and ten emerging stock indexes of Korea (KOR), Thailand (TH), China (CN), Indonesia (ID), India (IND), Vietnam (VN), Philippines (PH), Saudi Arabia (SA), Qatar (QA) and Hong Kong (HK) throughout 1 January 2001, to 31 December 2018. All information every Friday of the week is taken. For some weeks that the market was closed on Friday, the information of Thursday was taken instead. All stock indexes and gold prices are collected from www.investing.com. Returns of gold and stocks are calculated by taking the first difference of the natural logarithm.

Table 1. Descriptive statistics of daily stock market returns and gold prices.

Variable	Mean	Std.Dev	Skewness	Kurtosis	ADF
RGold	0.0033	0.2470	−0.1998	4.5683	−31.1167***
RCN	0.0008	0.0335	−0.0423	5.6511	−27.9771***
RIND	0.0028	0.0298	−0.2767	6.0163	−18.6378***
RID	0.0033	0.0296	−0.6408	7.6383	−31.6757***
RKR	0.0019	0.0301	−0.3639	8.2530	−32.9096***
RHK	0.0010	0.0294	−0.0679	5.5274	−30.4016***
RPH	0.0022	0.0278	−0.1281	7.7969	−31.8466***
RSA	0.0019	0.0339	−0.9987	9.1291	−28.9613***
RQA	0.0028	0.0333	−0.1224	8.3156	−28.4976***
RTH	0.0023	0.0273	−0.9961	10.6266	−12.6105***
RVN	0.0023	0.0398	−0.0702	6.8271	−17.4981***

Notes: ADF is the Augmented Dickey-Fuller unit root test. The null hypothesis is that the variable includes a unit root, and the alternative is that the variable does not include a unit root meaning the variable is stationary. *** indicates decisive evidence of rejecting the null hypothesis.

Table 1 presents the descriptive statistics of the weekly returns of gold and ten stock markets. It can be seen that the gold price and Indonesian stock return show the highest average return (0.0033), followed by India's stock return and Qatar's stock return, respectively. Gold price has the highest standard derivation (0.2470), followed by Vietnam's and Saudi Arabia's stock returns. This indicates that gold return has enormous fluctuations and is riskier than the emerging stock markets' returns. Negative skewness and high kurtosis values are observed in all market and gold returns, indicating fat tails in the return distributions and non-normality of the data series. The Augmented Dickey-Fuller (ADF) test is employed to examine the stationarity of the data series, and the result indicates that all stock market returns and gold prices are stationary.

3.2 Methodology

In order to establish the causality, spillover effect, and risk contagion effect between positive and negative gold price shocks; and emerging stock market volatilities, the study employs a rich set of quantitative techniques such as the Granger causality, VAR model, and various Copula functions. Prior to examining the linkages between the variables, the simple GARCH (1,1) model is used to quantify the conditional variance or volatility of the stock market. Then, the Granger causality test is employed to examine the lead-lag relationship between gold price shocks and stock market volatility. Finally, the VAR and Copula models are used to investigate the spillover effect and contagion effect, respectively.

3.2.1 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

In this study, GARCH(1, 1) is used to estimate the volatility of ten emerging stock market returns. Let $R_{i,t}$ and $\sigma_{i,t}$ be the return and conditional volatility of stock i at time t, respectively. The GARCH(1, 1) for stock i can be written as

$$R_{i,t} = \mu_i + \varepsilon_{i,t}, \tag{1}$$

where μ_i is the constant parameter of the mean equation for stock i. $\varepsilon_{i,t}$ is the error term which can be decomposed as follows:

$$\varepsilon_{i,t} = \sqrt{\sigma}_{i,t} z_{i,t}, \tag{2}$$

where $\sigma_{i,t} = E(\varepsilon^2_{i,t}|\psi_{i,t-1})$ is the conditional variance of the error and $z_t \sim skewed - t(0,1,df,\gamma)$ is the standardized residual following the skewed-t distribution. df and γ are degree of freedom and skewness parameters, respectively. $\psi_{i,t-1}$ is the information set of stock i available at time $t-1$. According to Bollerslev [7], the conditional variance can be predicted by the lagged conditional variance and the square of the error term in the mean equation. In this study, I consider using GARCH (1, 1) to model the volatility as one lag order can sufficiently capture the volatility clustering of the stock market returns (Oh and Patton [25]). Thus, the conditional variance equation can be written as

$$\sigma_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \beta_i \sigma_{i,t-1}, \tag{3}$$

where $\alpha_{i,0} > 0$, $\alpha_{i,1} > 0$, $\beta_i > 0$ and $\alpha_i + \beta_i \leq 1$.

3.2.2 Granger Causality Test

According to Granger [13], the Granger causality is a statistical hypothesis test for determining whether one time-series is useful in forecasting another. Note that the causality between positive and negative gold price shocks; and emerging stock market volatilities is examined. Thus, the specific testing equations for this study can be presented as follows:

$$\sigma_{i,t} = \sum_{p=1}^{P} \phi_p \sigma_{i,t-p} + \sum_{p=1}^{P} \delta_p g_{t-p} + u_{i,t}, \tag{4}$$

$$g_t = \sum_{p=1}^{P} \omega_p g_{t-p} + \sum_{p=1}^{P} \eta_p \sigma_{i,t-p} + v_{i,t}, \tag{5}$$

where g_t is gold return which is decomposed as the positive and negative shocks ($g_t^+ = max(\Delta RGOLD, 0)$ and $g_t^- = min(\Delta RGOLD, 0)$). To test the causality between stock volatility and gold price shocks in Eqs. 4–5, we set the null hypothesis of no causality as $H_0 : \delta_1 = \delta_2 = ... = \delta_p = 0$ ($H_0 : \eta_1 = \eta_2 = ... = \eta_p = 0$), while the alternative hypothesis is that H_0 is not true. To test this hypothesis, the F-statistic is used.

3.2.3 Vector Autoregressive Model (VAR)

The VAR model for each pair i is formulated as follows:

$$\begin{bmatrix} g_t^+ \\ z_{i,t} \end{bmatrix} = A_{0,i}^+ + \sum_{p=1}^{P} A_{i,p}^+ \begin{bmatrix} g_{t-p}^+ \\ z_{i,t-p} \end{bmatrix} + e_{i,t}^+, \tag{6}$$

$$\begin{bmatrix} g_t^- \\ z_{i,t} \end{bmatrix} = A_{0,i}^+ + \sum_{p=1}^{P} A_{i,p}^- \begin{bmatrix} g_{t-p}^- \\ z_{i,t-p} \end{bmatrix} + e_{i,t}^-, \tag{7}$$

where $A_{i,p}^-$ and $A_{i,p}^+$ are the autoregressive coefficient or spillover effect between stock i and $g_t = (g_t^-, g_t^+)$. $A_{0,i}^-$ and $A_{0,i}^+$ are vectors of the constant term, $e_{i,t}^+$ and $e_{i,t}^-$ are error terms which are assumed to follow the normal distribution with mean zero and variance $\sum$. To select the optimal lag order of a VAR(p) model in Eqs. (6–7), the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are employed, and the best lag is obtained at the lowest AIC and BIC.

3.2.4 Copula Approaches

The correlation between gold price shocks and emerging stock market volatilities are measured by the Copula model. Following Sklar's theorem (Sklar [31]), two continuous marginals can be joined by Copula function $C(\cdot)$. Thus, a two-dimensional joint distribution function $H(x, y)$ can be defined as

$$H(x, y) = C(F_1(x), F_2(y)), \tag{8}$$

where $F_x(x)$ and $F_y(y)$ are the cumulative marginal distribution of random variables x and y, respectively. If $F_x(x)$ and $F_y(y)$ are continuous, the Copula function associated with $H(\cdot)$ is unique and can be computed by

$$C(u, v) = H(F_1^{-1}(u), F_2^{-1}(v)), \tag{9}$$

where $F^{-1}(\cdot)$ is the inverse function. u and v are uniform $[0, 1]$ variables, where $u = F_x(x)$ and $v = F_y(y)$. This study aims to find the correlation between the gold price shocks and emerging stock market volatilities; thus, the joint distribution of $u = F_z(z_{i,t})$ and $v^+ = F_v(g_t^+/sd(g_t^+))$, and the joint distribution of $u = F_z(z_{i,t})$ and $v^- = F_v(g_t^-/sd(g_t^-))$ are

$$H(u, v^+) = H(F_z(z_{i,t}), F_v(v^+)), \tag{10}$$

$$H(u, v^-) = H(F_z(z_{i,t}), F_v(v^-)), \tag{11}$$

Note that $sd()$ is standard deviation. There are various Copula functions proposed to join the marginal distributions, and the selection of Copula function type is important. In this paper, five Copulas are considered to capture different patterns of dependence between stock market volatility and gold price shocks. Copula functions commonly used in research are Gaussian, Student-t, Gumbel, Clayton, and Frank. Also, AIC is used as the measure for selecting the best-fit Copula function [17]. The Copula specifications are presented in Table 2.

Table 2. Copula functions

Copula	Function	Parameter
Gaussian	$C^G(u,v\|\theta) = \Phi\left[\Phi^{-1}(u), \Phi^{-1}(v)\right].$	$\theta = [-1,1]$
Student-t	$C^S(u,v\|\theta) = T_\theta\left[t_\theta^{-1}(u), t_\theta^{-1}(v)\right].$	$\theta = [-1,1]$
Gumbel	$C^{Gu}(\mathrm{u,v}\,\|\,\theta_{Gu,t}) = \exp\left(-\left((-\ln(\mathrm{u}))^\theta + (-\ln(\mathrm{v}))^\theta\right)\right)^{1/\theta}$	$\theta = [1,\infty]$
Clayton	$C^{Cl}(u,v\|\theta) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}.$	$\theta = [0,\infty]$
Frank	$C^{Fr}(u,v\|\theta) = -\frac{1}{\theta} log\left[1 + \frac{(exp(-\theta u)-1)(exp(-\theta v)-1)}{exp(-\theta)-1}\right].$	$\theta = [-\infty,\infty]$

Notes: $2 < v \leq 30$ is the degree of freedom of Student-t Copula. D is (Debye function).

4 Empirical Results and Discussion

The series of results are provided in the following sections.

4.1 GARCH Model Results

Table 3. Estimates from GARCH (1, 1) for the 10 stock markets.

Parameter Estimation	μ_i	$\alpha_{0,i}$	$\alpha_{1,i}$	β_i	Log-likelihood	Q(10) MBF	ARCH-LM(1)
CN	0.0003	<0.0001*	0.1231***	0.8604***	1903.939	0.2280	0.8993
	(0.0008)	(<0.0001)	(0.0279)	(0.0284)			
IND	0.0033***	<0.0001	0.0987***	0.8895***	2022.767	0.4269	0.6320
	(0.0004)	(<0.0001)	(0.0231)	(0.0262)			
ID	0.0034***	<0.0001	0.1243***	0.8481***	2003.342	0.0792	0.9815
	(0.0008)	(<0.0001)	(0.0326)	(0.0429)			
KR	0.0016*	<0.0001*	0.1286***	0.8567***	2044.873	0.5249	0.6271
	(0.0007)	(<0.0001)	(0.0295)	(0.0344)			
HK	0.0019*	<0.0001*	0.0855***	0.8927***	2013.785	0.7588	0.8403
	(0.0008)	(<0.0001)	(0.0205)	(0.0248)			
PH	0.0028***	<0.0001	0.1081**	0.8568***	2033.291	0.4216	0.6623
	(0.0008)	(<0.0001)	(0.0344)	(0.0488)			
SA	0.0029***	<0.0001***	0.3271***	0.6348***	1972.510	0.0060	0.9464
	(0.0007)	(<0.0001)	(0.0490)	(0.0409)			
QA	0.0024**	<0.0001**	0.2589***	0.6832***	1960.371	0.1001	0.2883
	(0.0008)	(<0.0001)	(0.0578)	(0.0670)			
TH	0.0019**	<0.0001	0.0803***	0.9145***	2070.848	0.5220	0.3001
	(0.0007)	(<0.0001)	(0.0192)	(0.0199)			
VN	0.0002	<0.0001**	0.3461***	0.6741***	1861.425	0.4001	0.4539
	(0.0008)	(<0.0001)	(0.0634)	(0.0517)			

Notes: *, **, and *** stand for strong, very strong, and decisive evidence, respectively. ( ) denotes the standard error.

This section presents the estimation results of the GARCH(1, 1) conditional volatility models for ten emerging stock markets. First, the estimation from the GARCH(1, 1) model is presented in Table 3. All the coefficients in the variance equations, i.e., the unconditional volatility ($\alpha_{0,i}$), the ARCH effect ($\alpha_{1,i}$), and the GARCH effect (β_i) are positive with decisive evidence, indicating that all stock market indices exhibit high volatility persistence. Then, the goodness-of-fit is conducted to test whether the obtained standardized residuals have no autocorrelation and heteroscedasticity. The Ljung-Box Q-statistic at lag 10 and ARCH Lagrange Multiplier (LM) test at lag 1 are used for these proposes. According to the Minimum Bayes factor (MBF) ([20]), there is no autocorrelation and heteroscedasticity of the standardized residuals.

4.2 Estimates of Causality Using Granger Causality

Table 4. Granger causality test for the relationship between gold price shock and stock market return.

	$Stock \rightarrow PGS$		$PGS \rightarrow Stock$		$Stock \rightarrow NGS$		$NGS \rightarrow Stock$	
	MBF-value	Causality	MBF-value	Causality	MBF-value	Causality	MBF-value	Causality
CN	0.3433	No	0.8734	No	0.2093	No	0.3494	No
IND	0.4455	No	0.3394	No	0.0022	Yes	0.6303	No
ID	0.4467	No	0.2094	No	0.0222	Yes	0.2299	No
KR	0.6695	No	0.4033	No	0.0330	Yes	0.4985	No
HK	0.3325	No	0.4983	No	0.0000	Yes	0.3940	No
PH	0.6094	No	0.3098	No	0.2934	No	0.3440	No
SA	0.4950	No	0.5903	No	0.4093	No	0.3904	No
QA	1.0000	No	0.399	No	0.3003	No	0.7445	No
TH	1.0000	No	0.3094	No	0.0203	Yes	0.0000	Yes
VN	0.2343	No	0.5093	No	0.0333	Yes	0.4009	No

Note: *PGS* and *NGS* are, respectively, positive gold price shock and negative gold price shock.

The results of Granger causality tests are presented in Table 4. $Stock \rightarrow PGS$ indicates that the stock market volatility Granger causes a positive gold price shock, whereas $PGS \rightarrow Stock$ indicates the positive gold price shock Granger causes stock market volatility. Likewise, $Stock \rightarrow NGS$ and $NGS \rightarrow Stock$ present the Granger causalities between negative gold price shock and stock market volatility. The results of causal relationships between the gold price shocks and the emerging stock market volatilities can be summarized as follows. (1) There is no Granger causality between positive gold price shock and the emerging stock market volatilities. (2) Considering the relationship between negative gold price shock and the emerging stock market volatilities, the unilateral Granger causality is found from stock market volatility to negative gold price for the cases of Indonesia, India, Korea, Hongkong, and Vietnam. (3) The bilateral Granger causality is observed between negative gold price shock and Thai stock market volatility.

4.3 Estimates of Spillover Effect Using the VAR Model

Table 5. VAR model estimation.

POSITIVE GOLD PRICE SHOCKS				NEGATIVE GOLD PRICE SHOCKS			
VARIABLE	$A_{0,i}^{+}$	g_{t-1}^{+}	$z_{i,t-1}$	VARIABLE	$A_{0,i}^{-}$	g_{t-p}^{-}	$z_{i,t-1}$
g_{CN}^{+}	0.0101***	0.0336	0.0005	g_{CN}^{-}	−0.0083***	0.0139	0.0006
	(0.0005)	(0.0331)	(0.0004)		(0.0005)	(0.0331)	(0.0004)
z^{CN}	−0.0041	1.5859	0.0757*	z^{CN}	0.0413	3.3872	0.0729*
	(0.0405)	(2.2543)	(0.0331)		(0.0379)	(2.2254)	(0.0331)
g_{IND}^{+}	0.0101***	0.0358	0.0002	g_{IND}^{-}	−0.0084***	0.0075	0.0011*
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0332)	(0.0004)
z^{IND}	0.0012	−2.2356	0.0698*	z^{IND}	−0.0137	1.0004	0.0670*
	(0.0406)	(2.2560)	(0.0329)		(0.0381)	(2.2466)	(0.0332)
g_{ID}^{+}	0.0100***	0.0369	−0.0001	g_{ID}^{-}	−0.0084***	0.0068	0.0010*
	(0.0005)	(0.0331)	(0.0004)		(0.0005)	(0.0333)	(0.0004)
z^{ID}	−0.0438	3.5885	−0.0225	z^{ID}	0.0239	3.5506	−0.0274
	(0.0407)	(2.2641)	(0.0330)		(0.0382)	(2.2567)	(0.0334)
g_{KR}^{+}	0.0101***	0.0364	0.0001	g_{KR}^{-}	−0.0084***	0.0102	0.0011*
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0331)	(0.0004)
z^{KR}	0.0111	−1.6421	−0.0510	z^{KR}	−0.0048	0.1435	−0.0506
	(0.0407)	(2.2595)	(0.0330)		(0.0381)	(2.2409)	(0.0332)
g_{HK}^{+}	0.0100***	0.03764	−0.0005	g_{HK}^{-}	−0.0084***	0.0067	0.0010*
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0333)	(0.0004)
z^{HK}	−0.0511	1.7848	0.0003	z^{HK}	−0.0083	2.8504	−0.0050
	(0.0408)	(2.2645)	(0.0331)		(0.0382)	(2.2586)	(0.0335)
g_{PH}^{+}	0.0101***	0.0359	0.0002	g_{PH}^{-}	−0.0083***	0.0141	0.0003
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0334)	(0.0004)
z^{PH}	2.5433	−0.0167	−0.0536	z^{PH}	−0.0099	2.0052	−0.0201
	(2.2691)	(0.0330)	(0.0409)		(0.0383)	(2.2624)	(0.0333)
g_{SA}^{+}	0.0101***	0.0367	0.0003	g_{SA}^{-}	−0.0083***	0.0171	0.0006
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0330)	(0.0004)
z^{SA}	−0.0352	1.0363	0.1050**	z^{SA}	−0.0158	1.0041**	0.1045
	(0.0404)	(2.2450)	(0.0329)		(0.0379)	(2.2158)	(0.0329)
g_{QA}^{+}	0.0101***	0.0360	−0.0001	g_{QA}^{-}	−0.0083***	0.0177	0.0004
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0330)	(0.0004)
z^{QA}	0.0353	−2.2508	0.1475***	z^{QA}	−0.0031	−1.7436	0.1486***
	(0.0402)	(2.2319)	(0.0327)		(0.0376)	(2.2022)	(0.0327)
g_{TH}^{+}	0.0101***	0.0362	0.000	g_{TH}^{-}	−0.0084***	0.0102	0.0009*
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0332)	(0.0004)
z^{TH}	−0.0077	0.9451	0.0064	z^{TH}	0.0441	4.9338*	−0.0014
	(0.0406)	(2.2594)	(0.0329)		(0.0381)	(2.2377)	(0.0330)
g_{VN}^{+}	0.0100***	0.0359	0.0004	g_{VN}^{-}	−0.0083***	0.0173	0.0008
	(0.0005)	(0.0330)	(0.0004)		(0.0005)	(0.0330)	(0.0004)
z^{VN}	0.0102	1.1367	0.2052***	z^{VN}	0.0374	1.7845	0.2051***
	(0.0398)	(2.2093)	(0.0324)		(0.0373)	(2.1800)	(0.0324)

Notes: *, **, and *** stand for strong, very strong, and decisive evidence, respectively. The parenthesis ( ) denotes the standard error.

The spillover effects between positive/negative gold price shocks and the emerging stock markets are reported in Table 5. The results show strong evidence of positive spillover effects of adverse gold price shocks on Saudi Arabian stocks with a value of 1.0041 and on Thai stocks with a value of 4.9338. For other pairs, there is no evidence supporting the spillover effect between gold price shocks and stock market volatility. Therefore, this study concludes that the spillover effects between stock market and gold price shocks for emerging stock markets are quite weak; specifically, emerging stock market volatilities do not react to gold shocks, except for the cases of Thai and Saudi Arabian financial markets.

4.4 Estimation Results of Copula

The estimates of dependence between gold price shocks (*PGS* and *NGS*) and ten emerging stock market volatilities are provided in Table 6. Five static Copula functions (Gaussian, Student-t, Clayton, Gumbel, and Frank) are also compared using the AIC. The best model is presented in bold number.

Table 6. Estimated Copula parameters and their corresponding AICs

COPULA		CN	IND	ID	KR	HK	PH	SA	QA	TH	VN
GAUSSIAN	θ	0.10	0.01	0.06	−0.04	0.02	0.00	−0.04	−0.02	0.04	0.04
		(0.01)	(0.18)	(0.19)	(0.13)	(0.20)	(0.19)	(0.04)	(−0.01)	(0.14)	(−0.01)
	AIC	−2.50	1.97	0.48	1.39	1.83	2.00	1.14	**1.70**	1.07	1.36
		(−2.62)	(−12.77)	(−14.24)	(−5.17)	(−18.07)	(−14.45)	**(1.32)**	(1.97)	**(−6.53)**	**(1.93)**
STUDENT-T	θ	0.10	0.03	0.07	−0.01	0.03	0.03	−0.02	−0.02	0.11	0.04
		(0.11)	(0.16)	(0.16)	(0.10)	(0.19)	(0.17)	(0.02)	(0.00)	(0.14)	(−0.01)
	AIC	0.42	**−4.19**	2.73	2.16	0.26	2.21	3.41	5.54	v4.85	7.40
		(−1.04)	(−12.98)	(−17.23)	(−5.35)	(−18.29)	(−16.10)	(2.65)	(2.72)	(−6.10)	(5.77)
CLAYTON	θ	0.08	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.05
		(0.08)	(0.12)	(0.12)	(0.09)	(0.15)	(0.13)	(0)	(0.01)	(0.07)	(0)
	AIC	−0.07	2.00	1.96	2.00	2.00	1.97	2.01	2.00	2.00	1.06
		(−3.38)	**(−14.38)**	**(−17.96)**	**(−8.08)**	**(−19.44)**	**(−18.31)**	(2.00)	**(1.78)**	(−5.24)	(2.01)
GUMBEL	θ	1.02	1.03	1.02	1.00	1.03	1.00	1.01	1.01	1.05	1.00
		(1.05)	(1.12)	(1.13)	(1.10)	(1.13)	(1.11)	(3.35)	(1.00)	(1.11)	(0)
	AIC	0.50	−0.61	1.58	2.01	**−1.44**	2.01	2.01	2.00	−1.20	2.02
		(−0.12)	(−8.98)	(−10.44)	(−5.53)	(−11.63)	(−8.00)	**(0.51)**	(2.00)	(−7.18)	(2.00)
FRANK	θ	0.82	0.32	0.90	0.28	0.35	0.51	0.14	−0.16	0.94	0.44
		(1.06)	(0.93)	(1.21)	(0.42)	(1.19)	(1.23)	(−0.15)	(0.11)	(0.87)	(−0.07)
	AIC	**−4.97**	0.82	**−5.10**	**1.16**	0.53	**−0.84**	1.84	1.76	**−6.93**	**0.08**
		(−6.49)	(−6.10)	(−7.30)	(0.64)	(−12.02)	(−10.38)	(1.89)	(1.93)	(−3.52)	(1.97)

Notes: The parenthesis () presents the dependence parameter and AIC of negative gold price shock- stock market volatility nexus. The bold number indicates the best-fit Copula function.

According to Table 6, the Frank Copula is the most appropriate function for joining the positive gold price shock and stock markets of China, Indonesia, Korea, Philippines, Thailand, and Vietnam. The Gaussian Copula is an appropriate function for joining positive gold price shocks and Saudi Arabian and Qatar markets. For the dependence between negative gold price shock and emerging stock markets, Clayton is the best-fit Copula function for paring adverse gold price shocks and Indian, Indonesian, Korean, Hong Kong, and Philippines markets, while Gumbel is the best-fit Copula for joining negative gold price shock and Saudi Arabian and Thai markets. The best-fit Copulas are then reported in Table 7.

Overall, the dependence parameters of negative gold price shock and stock-market pairs are mostly higher than the positive price shock and stock-market pairs. Among all pairs of gold price shocks and stock market, the result of Kendall's tau reveals that the negative price shock and Saudi Arabian market pair presents the highest degree of correlation, while the lowest correlation is found in the case of negative price shock and Vietnam's market pair. Considering the tail dependence, the upper tail dependence is found in the cases of Hongkong-PGS, Saudi Arabia-NGS, and Thailand-NGS pairs. It is quite interesting that the negative price shock performs a high correlation with Saudi Arabian and Thai markets during the bullish regime, implying that the large drop in the gold price could decrease the volatilities of Saudi Arabian and Thai markets during the market upturn regime. Therefore, the investors of these two countries should be aware of the negative shock of gold prices. Regarding the lower tail dependence, which reflects the degree of contagion, it is found that there exists a weak degree of contagion between negative gold price shock and Hong Kong stock market volatility. This is another interesting result as both forms of gold price shocks have presented a degree of tail dependence on Hong Kong. This indicates that Hong Kong stock return volatility is quite sensitive to the gold price shocks during extreme events.

Table 7. Dependence measure between gold price shocks and stock return

MARKET	SELECTED COPULA	DEPENDENCE PARAMETER	KENDALL'S TAU	UPPER TAIL	LOWER TAIL
CH	Frank (Frank)	0.82 (1.06)	0.09 (0.12)	0 (0)	0 (0)
IND	Student-t (Clayton)	0.03 (0.12)	0.02 (0.06)	0 (0)	0 (0)
ID	Frank (Clayton)	0.90 (0.12)	0.10 (0.06)	0 (0)	0 (0)
KR	Frank (Clayton)	0.28 (0.09)	0.03 (0.04)	0 (0)	0 (0)
HK	Gumbel (Clayton)	1.03 (0.15)	0.03 (0.07)	0.04 (0)	0 (0.01)
PH	Frank (Clayton)	0.51 (0.13)	0.06 (0.06)	0 (0)	0 (0)
SA	Gaussian (Gumbel)	−0.04 (−3.35)	−0.03 (−0.34)	0 (0.22)	0 (0)
QA	Gaussian (Gaussian)	−0.02 (0.04)	−0.02 (0.03)	0 (0)	0 (0)
TH	Frank (Gumbel)	0.94 (1.11)	0.10 (0.10)	0 (0.13)	0 (0)
VN	Frank (Gaussian)	0.44 (−0.01)	0.05 (−0.01)	0 (0)	0 (0)

Notes: The parentheses ( ) denotes the result of negative gold price shock and stock market volatility.

5 Conclusion

This study aims to examine the causality, spillover, and correlation effects between gold price shocks and ten Asian emerging stock markets. Three econometric approaches, namely the Granger causality test, VAR, and Copula, are conducted to achieve this research goal. These methods reveal three key findings. First, the Granger causality test reveals weak evidence supporting the causality relation between stock volatility and positive gold price shock. However, some slight evidence shows that six out of ten emerging stock markets can be viewed as the predictor of the negative price shock, while only Thai stock is predicted by negative price shock. Second, the VAR estimation results also revealed a weak spillover between stock and gold price shocks. Third, several Copula functions are compared, and the best-fit Copula is used to reveal the degree of dependence as well as tail dependence. The results show that the correlation between stock return and gold price shock is not so high. Likewise, the degree of tail dependence is observed in some pairs. Finally, results from this investigation reveal some robust similarities in such a way that there is a low degree in the stock-gold price nexus in many perspectives.

For the further study, more linkage dimensions, such as quantile to quantile correlation and dynamic conditional correlation, are suggested in order to confirm the relationship between gold price shocks and stock markets.

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