On the co-movements among gold and other financial markets: a multivariate time-varying asymmetric approach

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Abstract

The analysis of time varying correlation between gold price and financial market in the context of international investments has been well researched in the literature in last few years. In this paper we study the interdependence of three financial markets and the gold price. We adopt a multivariate asymmetric dynamic conditional correlation EGARCH framework, during the period spanning from January 5, 1995 until May 30, 2017. The empirical results suggest asymmetric responses in correlations among gold market and financial market. We find that asymmetric dynamic correlations exhibit substantial time variation even in similar market tensions for same pairs of assets. Our findings imply that investors and fund managers should take into account the asymmetric dependence structure, which depends on the upside or downside of the market.

Keywords A-DCC model · Gold market · Exchange market · Stock market and asymmetries

JEL classification C13 · C22 · C32 · C52 · C53 · G15

1 Introduction

The dynamic relationships between gold and other financial market have attracted a special attention from both practitioners and academics. A strong relationship between

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them would have important implications for international capital budgeting decisions and economic policies because negative shocks affecting one market may be transmitted quickly to another through contagious effects. This issue has become more critical with the occurrence of recent black swan events such as the US 2007 subprime crisis.

A common and pronounced finding presented in recent finance literature is that asset returns exhibit asymmetric dependence, that is, financial markets behaves differently between tranquil and extreme conditions. The presence of asymmetries in financial markets casts doubt on the benefit of portfolio diversification and the effectiveness of risk management.

Gold is a strategic resource that is largely used in national security and in various national economic activities. Large fluctuations in the gold market lead to increased price volatility. The latter imposes challenges on market participants such as consumers and producers and affects price stabilization policies, who often try to predict the future price of gold.

The empirical evidence on the gold – financial markets relationships has been document by numerous studies, for example, Longin and Solnik (2001) and Ang and Chen (2002) examine asymmetry in stock returns using exceedance correlation (see Ang and Bekaert (2002)). Campbell et al. (2008) reject the normality in the distribution of financial asset returns. Number of studies evaluate the function of gold as a hedge or safe haven asset (Hillier et al. 2006; Baur and Lucey 2010; Baur and McDermott 2010; Qadan and Yagil 2012; Hood and Malik 2013; Miyazaki and Hamori 2013). On the other hand, several studies show that gold has strengthened linkages with other financial assets owing to the financialization of commodities (Domanski and Heath 2007; Baur 2011; Tang and Xiong 2012; Silvennoinen and Thorp 2013; Miyazaki and Hamori 2014).

In emerging markets, which attract global institutional investors, prior studies provide evidence of significant interactions between gold and equity prices and their volatilities (e.g., Wang et al. 2010, and Arouri et al. 2015, for China; Jain and Biswal 2016, for India; Raza et al. 2016, for emerging markets; Kumar 2014). Some other studies document hedge and/or safe-haven properties of gold for stock markets (see, among others, Arouri et al. 2015, for China; Gurgun and Unalmis 2014, for emerging markets).

To examine the interaction between gold and stock market, some econometric methods are used. For example, Bekiros et al. (2017) use a GARCH-based copula methodology and a wavelet approach to studies the hedging and diversification roles of gold for BRICS stock markets. Results indicate the evidence of two-way causality linkages, suggesting that gold behaves more like equities. In the other hand, Sarwar (2017) considers the links between the implied volatilities of US stock markets and the gold, the author disregards the relationships in large emerging markets.

Recently, Sarwar and Khan (2017) use a GARCH models and the Granger causality test, and they indicates that intensified US market uncertainty reduces emerging market returns in Latin America and increases the variance of returns. Bouri et al. (2017a) find the presence of nonlinearity and significant co-integration in the interaction between the implied volatilities of gold, crude oil and Indian equities. Bouri et al. (2017b) examine the short- and long-term causality between the implied volatility of gold and that of India and China. The authors show evidence of a feedback effect. Yang and Zhou (2017) identify the significant impact of quantitative easing on the implied volatility spillovers across US Treasury bonds commodities and developed stock market indices.

In the context of asymmetric effect and time varying, Kang et al. (2016) show that the dynamic correlations among BRICS markets and commodities (oil and gold) are time varying and sensitive to major economic and financial events. Some studies consider the effect of the global financial crisis. For example, Xu and Hamori (2012) use the cross-correlation function approach and indicate that the volatility linkages between the US and BRIC stock markets have significantly eased after the GFC. In addition, Mensi et al. (2014) use a quantile regression approach and find that the BRICS stock markets exhibit dependence on the US equities, gold markets and crude oil, and that dependence is affected by the global financial crisis (GFC).

The main objective of this work is to explore the asymmetric dynamics in the correlations among gold and other financial markets, as this remains under explored in empirical research. Furthermore, it would be interesting to conduct an empirical analysis on how the dependence structures of the gold and financial market changed particularly at the different phases of financial markets, the subprime mortgage turmoil and the global financial crisis. Two major contributions on this topic are made in the present study. First, we investigate the asymmetric behavior of dynamic correlations among gold and financial market by employing the multivariate asymmetric DCC (A-DCC) model put forward by Cappiello et al. (2006). The A-DCC model allows for conditional asymmetries in covariance and correlation dynamics, thereby enabling to examine the presence of asymmetric responses in correlations during periods of negative shocks. Second, we evaluate how the selected period of crises influenced the estimated DCCs among the currency markets.

This article is organized as follows. In the next section, we briefly review the methodology to test for asymmetry in the correlation. Section 3 describes the data and Section 4 presents our empirical results. Section 5 concludes.

2 Econometric methodology

To investigate the dynamics of the correlations between gold and other financial markets namely, S&P500 index (SPX), the Bank of America Merrill Lynch U.S. Corp. Master Total Return Index (CMBI), and the trade weighted U.S. dollar index against major currencies (USDI), we use the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006). This approach generalizes the DCC model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation dynamics. In this paper, we adopt the following three step approach (see also Kenourgios et al. (2011), Toyoshima et al. (2012), Samitas and Tsakalos (2013) and Toyoshima and Hamori (2013)). In the first step, we estimate the conditional variances of gold and financial market returns using an autoregressive- asymmetric exponential generalized autoregressive conditional heteroscedasticity (AR(m)–EGARCH(p, q)) model¹. For a more detailed analysis, we use the following equations:

¹ See Nelson (1991).

$$r_t = \mu_0 + \sum_{i=1}^m \mu_i r_{t-i} + \varepsilon_t \quad (1)$$

$$\ln(h_t) = \omega + \sum_{i=1}^q [\alpha_i |z_{t-i}| + \gamma_i z_{t-i}] + \sum_{i=1}^p \beta_i \ln(h_{t-i}) \quad (2)$$

where r_t indicates gold returns and financial market return, ε_t is the error term, h_t is the conditional volatility, and $z_t = \varepsilon_t / \sqrt{h_t}$ is the standardized residual.

The EGARCH model has several advantages over the pure GARCH specification. First, since $\ln(h_t)$ is modelled, then even if the parameters are negative, h_t will be positive. There is thus no need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ_i will be negative. Note that a negative value of γ_i means that negative residuals tend to produce higher variances in the immediate future.

We assume that the random variable z_t has a student distribution (see Bollerslev (1987)) with $\nu > 2$ degrees of freedom with a density given by:

$$D(z_t, \nu) = \frac{\Gamma\left(\nu + \frac{1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right) \sqrt{\pi(\nu-2)}} \left(1 + \frac{z_t^2}{\nu-2}\right)^{-\frac{\nu+1}{2}} \quad (3)$$

Where $\Gamma(\nu)$ is the gamma function and ν is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $\nu > 4$, the conditional kurtosis equals $3(\nu-2)/(\nu-4)$, which exceeds the normal value of three. For large values of ν , its density converges to that of the standard normal.

The log form of the $EGARCH(p, q)$ model ensures the positivity of the conditional variance, without the need to constrain the parameters of the model. The term z_{t-i} indicates the asymmetric effect of positive and negative shocks. If $\gamma_i > 0$, then $z_{t-i} = \varepsilon_{t-i} / \sigma_{t-i}$ is positive. The term $\sum_{i=1}^p \beta_i$ measures the persistence of shocks to the conditional variance.

The conditional mean equation (Eq. 1) is specified as an autoregressive process of order m . The optimal lag length m for each asset return series is given by the Schwartz-Bayesian Information Criterion (SBIC). (Eq. 2). represents the conditional variance and is specified as and $EGARCH(p, q)$ process. The optimal lag lengths p and q are determined by employing the SBIC criterion.

From Eq. 2, we first obtain the conditional volatilities and then recover the conditional correlations. The conditional covariance matrix is then defined as follows:

$$H_t = D_t R_t D_t \quad (4)$$

where the diagonal matrix D_t is the conditional standard deviation obtained from Eq. 2. The matrix of the standardized residuals Z_t is used to estimate the parameters of the Asymmetric dynamic conditional correlation (A-DCC) model developed by Cappiello et al. (2006). The AG-DCC model is given as

$$Q_t = (\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G) + A' Z_{t-1} Z_{t-1}' A + B' Q_{t-1} B + G' \eta_{t-1} \eta_{t-1}' G \quad (5)$$

where $\bar{Q}$ and $\bar{N} = E(\eta_t \eta_t')$ are the unconditional correlation matrices of Z_t and η_t . $\eta_t = I[Z_t < 0] \circ Z_t$, $I[\cdot]$ is an indicator function such that $I = 1$ if $Z_t < 0$ and $I = 0$ if $Z_t \geq 0$, while " $\circ$ " is the Hadamard product.

The A-DCC (1,1) model is identified as a special case of the AG-DCC(1,1) model if the matrices A , B and G are replaced by the scalars a_1 , b_1 and g_1 . Cappiello et al. (2006) show that Q_t is positive definite with a probability of one if $(\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G)$ is positive definite. The next step consists in computing the correlation matrix R_t from the following equation:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (6)$$

Where $Q_t^* = \sqrt{q_{ii,t}}$ is a diagonal matrix with a square root of the i th diagonal element of Q_t on its i th diagonal position.

3 Data description

The data comprises daily gold PM fixing (Gold) released by the London Bullion Market Association and the S&P500 index (SPX), the Bank of America Merrill Lynch U.S. Corp. Master Total Return Index (CMBI), and the trade weighted U.S. dollar index against major currencies (USDI), respectively. For each currency, the continuously compounded return is computed as: $r_t = 100 * \ln\left(\frac{p_t}{p_{t-1}}\right)$ for $t = 1, 2, \dots, T$, where p_t is the price on day t . The sample covers a period from January 05, 1995 until May 30, 2017, leading to a sample size of 8213 observations. SPX is from DataStream. CMBI and USDI are from the Federal Reserve Economic Database of the St. Louis FED.

To examine the time variation of correlation dynamics, we split the sample into three subsample periods: the first period is 5 January 1995–10 September 2001; the second is 11 September 2001–August 7, 2007; and the third is 8 August 2007–30 May 2017. Each subsample is characterized by different phases of financial markets and virtually corresponds to the moderation era until the collapse of the dot-com bubble and terrorist attacks (subsample 1); the asset price, especially housing, boom era until the subprime mortgage turmoil (subsample 2); and the global financial crisis era to present (subsample 3).

Table 1 reports the descriptive statistics for our data set per subsample period. In the whole sample and the subsample one, the SPX exhibits the largest positive mean return, thereby suggesting that the stock price is most significantly. In addition, the standard deviation or volatility of SPX is the highest over the sample period. The higher levels of Skewness for each return series indicate that extreme variations tend to occur more frequently for these currencies. Besides, there exist fat tails in the return distribution according to the high values of kurtosis for all returns. To accommodate the existence of "fat tails", we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality assumption at the 1% level for all for all gold and financial markets.

Table 1 Descriptive statistics for gold and other financial markets returns

	Whole sample(5 January 1995–30 May 2017)		subsample 1 (5 January 1995–10 September 2001)		subsample 2 (11 September 2001–7 August 2007)		subsample 3 (8 August 2007–30 May 2017)	
	GOLD	SPX	GOLD	SPX	GOLD	SPX	GOLD	SPX
Mean	0.0145	0.02031	-0.0131	0.0354	0.0419	0.0139	0.0169	0.0138
Maximum	8.8872	10.957	8.8872	4.9887	6.6762	5.5744	8.6250	10.957
Minimum	-9.8206	-9.4695	-5.1049	-7.1127	-7.5740	-5.0468	-9.8206	-9.4695
Standard deviation	0.8924	0.9824	0.6647	0.9249	0.8881	0.8425	1.0195	1.0914
LB-Q(20)	37.9915*	108.893*	40.3439*	36.6837*	27.2929	16.7099	26.6279	114.929*
(p value)	0.0088	0.0000	0.0045	0.0127	0.1272	0.6717	0.146	0.0000
LB-Q(20)	693.045*	5823.35*	230.712*	271.476*	146.87*	1207.46*	312.508*	3157.59*
(p value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Skewness	-0.0897*	-0.2777*	1.7865*	-0.2877*	-0.543*	0.1259*	-0.276*	-0.3727*
(p value)	0.0008	0.0000	0.0000	0.0000	0.0000	0.0168	0.0000	0.0000
Excess Kurtosis	11.421*	13.404*	27.718*	6.8126*	7.0836*	5.9653*	9.0800*	16.145*
(p value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jarque-Bera	44646*	61592*	79440*	4754.1*	4615.9*	3203.9*	12465*	39347*
(p value) observations	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	GOLD	CMBI	GOLD	CMBI	GOLD	CMBI	GOLD	CMBI
Maximum	0.0145	0.0174	-0.0131	0.0232	0.0419	0.0146	0.0169	0.0152
Minimum	8.8872	1.966	8.8872	1.1599	6.6762	1.0173	8.625	1.966
Standard deviation	-9.8206	-2.3055	-5.1049	-1.8019	-7.574	-1.2164	-9.8206	-2.3055
LB-Q(20)	0.8924	0.2603	0.6647	0.2544	0.8881	0.2428	1.0195	0.2739
(p value)	37.9915*	56.1932*	40.3439*	46.6847*	27.2929	35.3046*	26.6279	51.3243*
LB-Q(20)	0.0088	0.0000	0.0045	0.0006	0.1272	0.0185	0.146	0.0001
(p value)	693.045*	1123.38*	230.712*	94.663*	146.87*	268.865*	312.508*	847*
Skewness	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(p value)	-0.0897*	-0.3849*	1.7865*	-0.368*	-0.543*	-0.2272*	-0.2767*	-0.4551*

Table 1 (continued)

Whole sample (5 January 1995–30 May 2017)				subsample 1 (5 January 1995–10 September 2001)		subsample 2 (11 September 2001–7 August 2007)		subsample 3 (8 August 2007–30 May 2017)	
	GOLD	SPX	GOLD	SPX	GOLD	SPX	GOLD	SPX	GOLD
(p value)	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Excess Kurtosis	11.421*	4.7604*	27.718*	4.4032*	7.0836*	2.8404*	9.0800*	5.5044*	0.0000
(p value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jarque-Bera	44646*	7957.6*	79440*	2027*	4615.9*	743.69*	12465*	4688.6*	0.0000
(p value) observations	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	GOLD	SPX	GOLD	USDI	GOLD	USDI	GOLD	USDI	GOLD
Maximum	0.0145	0.0003	-0.0131	0.0084	0.0419	-0.0153	0.0169	0.0043	0.0043
Minimum	8.8872	2.4833	8.8872	1.7175	6.6762	1.4806	8.625	2.4833	8.625
Standard deviation	-9.8206	-4.1073	-5.1049	-2.4077	-7.574	-1.3553	-9.8206	-4.1073	-9.8206
LB-Q(20)	0.8924	0.3688	0.6647	0.3054	0.8881	0.3539	1.0195	0.4137	1.0195
(p value)	37.9915*	16.4121	40.3439*	22.7147	27.2929	27.5864	26.6279	21.6219	26.6279
LB-Q(20)	0.0088	0.6907	0.0045	0.303	0.1272	0.1195	0.1460	0.3613	0.1460
(p value)	693.045*	843.412*	230.712*	187.5*	146.87*	265.137*	312.508*	349.684*	312.508*
Skewness	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(p value)	-0.0897*	-0.3304*	1.7865*	-0.439*	-0.543*	0.0736	-0.2767*	-0.4404*	-0.2767*
Excess Kurtosis	0.0008	0.0000	0.0000	0.0000	0.0000	0.1622	0.0000	0.0000	0.0000
(p value)	11.421*	6.6779*	27.718*	5.1266*	7.0836*	1.9656*	9.0800*	7.6981*	9.0800*
Jarque-Bera	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(p value) observations	44646*	15410*	79440*	2751.6*	4615.9*	349.19*	12465*	9043*	12465*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

gold and financial market returns are in daily frequency. Observations for all series in the whole sample period are 8213. Numbers in parentheses are p values. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. $LB(20)$ and $LB^2(20)$ are the 20th order Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively

The gold exhibits the largest positive mean return in subsample two, thereby suggesting that the gold return is most significantly. In addition, the standard deviation or volatility of gold is the highest over the subsample two. The higher levels of Skewness for each return series indicate that extreme variations tend to occur more frequently for these currencies. Besides, there exist fat tails in the return distribution according to the high values of kurtosis for gold and stock returns. To accommodate the existence of “fat tails”, we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality assumption at the 1% level for all for all gold and financial markets.

In subsample 3, gold exhibits the largest positive mean return in subsample three; thereby suggesting that the gold return is most significantly. In addition, the standard deviation or volatility of stock return (SPX) is the highest over the subsample three. The higher levels of Skewness for each return series indicate that extreme variations tend to occur more frequently for these currencies. Besides, there exist fat tails in the return distribution according to the high values of kurtosis for stock returns. To accommodate the existence of “fat tails”, we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality assumption at the 1% level for all for all gold and financial markets.

4 Tests for sign and size bias

Engle and Ng (1993) propose a set of tests for asymmetry in volatility, known as sign and size bias tests. The Engle and Ng tests should thus be used to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. In practice, the Engle-Ng tests are usually applied to the residuals of a GARCH fit to the returns data.

Define S_{t-1}^- as an indicator dummy variable such as:

$$S_{t-1}^- = \begin{cases} 1 & \text{if } \hat{z}_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

The test for sign bias is based on the significance or otherwise of ϕ_1 in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \nu_t \quad (8)$$

where ν_t is an independent and identically distributed error term. If positive and negative shocks to $\hat{z}_{t-1}$ impact differently upon the conditional variance, then ϕ_1 will be statistically significant.

It could also be the case that the magnitude or size of the shock will affect whether the response of volatility to shocks is symmetric or not. In this case, a negative size bias test would be conducted, based on a regression where S_{t-1}^- is used as a slope dummy variable. Negative size bias is argued to be present if ϕ_1 is statistically significant in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- z_{t-1} + \nu_t \quad (9)$$

Finally, we define $S_{t-1}^+ = 1 - S_{t-1}^-$, so that S_{t-1}^+ picks out the observations with positive innovations. Engle and Ng (1993) propose a joint test for sign and size bias based on the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- z_{t-1} + \phi_3 S_{t-1}^+ z_{t-1} + \nu_t \quad (10)$$

Significance of ϕ_1 indicates the presence of sign bias, where positive and negative shocks have differing impacts upon future volatility, compared with the symmetric response required by the standard GARCH formulation. However, the significance of ϕ_2 or ϕ_3 would suggest the presence of size bias, where not only the sign but the magnitude of the shock is important. A joint test statistic is formulated in the standard fashion by calculating TR^2 from regression (10), which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

Table 2 reports the results of Engle-Ng tests. First, in the whole period, the individual regression results show that the residuals of the symmetric GARCH model for the RGOLD and RSPX series do not suffer from negative size bias and exhibit sign and positive size bias. Second, for the RCMBI and RUSDI series, the individual regression results show that the residuals of the symmetric GARCH model exhibit negative size bias and do not suffer from sign positive size bias. Finally, the $\chi^2(3)$ joint test statistics for GOLD, SPX, CMBI, and USDI have p values of 0.0262, 0.0000, 0.0836, and 0.0296, respectively, demonstrating a very rejection of the null of no asymmetries. The results overall would thus suggest motivation for estimating an asymmetric volatility model for these particular series.

In the subsample one, the individual regression results show that the residuals of the symmetric GARCH model for the RGOLD and RSPX series do not suffer from sign and negative size bias and exhibit positive size bias. For the RCMBI, the individual regression results show that the residuals of the symmetric GARCH model exhibit sign bias and do not suffer from negative and positive size bias. For the RUSDI, the individual regression results show that the residuals of the symmetric GARCH model do not suffer from sign, negative and positive size bias.

In the subsample two, the individual regression results show that the residuals of the symmetric GARCH model for the RGOLD and RSPX series do not suffer from positive size bias and exhibit sign and negative size bias. For the RCMBI, the individual regression results show that the residuals of the symmetric GARCH model exhibit positive size bias and do not suffer from sign and negative size bias. For the RUSDI, the individual regression results show that the residuals of the symmetric GARCH model do not suffer from sign and positive size bias and exhibit negative size bias.

Finally, in the subsample three, the individual regression results show that the residuals of the symmetric GARCH model for the RGOLD and RSPX series do not suffer from negative and positive size bias and exhibit sign bias. For the RCMBI and RUSDI, the individual regression results show that the residuals of the symmetric GARCH model exhibit negative size bias and do not suffer from sign and positive size bias.

Table 2 Tests for sign and size bias for gold and other financial market return series

Variables	GOLD			SPX			CMBI			USDI		
	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif
Whole sample(5 January 1995–30 May, 2017)												
ϕ_0	0.7919*	0.078	0.0000	0.9777*	0.0654	0.0000	0.9367*	0.0545	0.0000	1.0094*	0.0549	0.0000
ϕ_1	0.2285	0.105	0.0296	0.1968**	0.084	0.0191	0.1122	0.0753	0.1362	0.0732	0.0748	0.3278
ϕ_2	-0.0468	0.0721	0.5163	0.0556	0.0508	0.2735	-0.106***	0.0498	0.0938	0.1002**	0.051	0.0494
ϕ_3	0.1934*	0.0762	0.0112	-0.1874*	0.0686	0.0063	0.0147	0.0569	0.7953	-0.0280	0.0547	0.6082
$\chi^2(3)$	9.2448**	—	0.0262	35.9877*	—	0.0000	14.8429***	—	0.0836	14.3124**	—	0.0296
subsample 1 (5 January 1995–10 September 2001)												
ϕ_0	0.9065*	0.144	0.0000	0.9732*	0.1170	0.0000	0.8014*	0.1144	0.0000	0.9605*	0.1056	0.0000
ϕ_1	-0.1700	0.2098	0.4179	0.1357	0.1525	0.3738	0.3424**	0.1516	0.0240	-0.0224	0.1421	0.8745
ϕ_2	-0.0615	0.1611	0.7023	-0.0895	0.0934	0.3378	0.1023	0.0985	0.2991	-0.1159	0.0933	0.2144
ϕ_3	0.4403*	0.1376	0.0013	-0.247**	0.1249	0.0473	0.1600	0.1157	0.1672	0.0187	0.1078	0.8616
$\chi^2(3)$	18.343*	—	0.0003	19.7906*	—	0.0001	15.0995***	—	0.0646	11.8233*	—	0.0098
subsample 2 (11 September 2001–7 August 2007)												
ϕ_0	0.8141*	0.1233	0.0000	0.6541*	0.1031	0.0000	1.0258*	0.0918	0.0000	1.0502*	0.0792	0.0000
ϕ_1	0.5784*	0.1635	0.0004	0.5984*	0.1835	0.0006	0.0193	0.1324	0.8841	0.0627	0.1211	0.6044
ϕ_2	0.2313**	0.1047	0.0273	0.2117**	0.1042	0.0275	0.0120	0.0899	0.8936	0.1688***	0.0887	0.0571
ϕ_3	-0.0178	0.1243	0.8858	-0.0148	0.1147	0.8457	-0.1615**	0.0969	0.0257	-0.0429	0.0819	0.6003
$\chi^2(3)$	19.691*	—	0.0001	17.671*	—	0.0002	10.8478**	—	0.0380	14.2539**	—	0.0353
subsample 3 ((8 August 2007–30 May 2017)												
ϕ_0	1.0357*	0.1036	0.0000	1.0457*	0.1138	0.0000	0.9878*	0.0789	0.0000	1.0545*	0.0875	0.0000
ϕ_1	-0.0425	0.1382	0.7582	-0.0438	0.1252	0.7572	-0.0103	0.11	0.9252	0.0614	0.1197	0.6082
ϕ_2	-0.170**	0.0899	0.0588	-0.182**	0.0959	0.0687	-0.1963***	0.0724	0.0837	0.1681**	0.0834	0.0439
ϕ_3	-0.210**	0.1055	0.0462	-0.280**	0.1533	0.0362	-0.0565	0.0839	0.5003	-0.0724	0.0859	0.3994
$\chi^2(3)$	13.409*	—	0.0038	11.4591*	—	0.0069	14.5776***	—	0.0754	14.773**	—	0.0891

The superscripts *, **, and *** denote the level significance at 1%, 5%, and 10%, respectively

5 Empirical results

5.1 AR-EGARCH specification

The first step of this specification is to estimate the univariate $AR(m) - EGARCH(p, q)$ models for each gold and financial market return series.² Table 3 reports the estimates for the $AR(m) - EGARCH(p, q)$ model. The $EGARCH(1, 1)$ model is chosen for all returns. All the parameters of the EGARCH model are statistically significant at the 1% significance level or better for all variables in different period of crises. Table 3 also reports the estimates of the parameter β , which measures the degree of volatility persistence. In the whole period, we find that β for GOLD, SPX, CMBI and USDI returns is 0.9953, 0.9867, 0.9923 and 0.9953, respectively. In the subsample 1, we find that β for GOLD, SPX, CMBI and USDI returns is 0.9792, 0.9786, 0.9761 and 0.9887, respectively. In the subsample 2, we find that β for GOLD, SPX, CMBI and USDI returns is 0.9948, 0.9922, 0.9958 and 1.0010, respectively.

Finally, in the subsample 3, we find that β for GOLD, SPX, CMBI and USDI returns is 0.9949, 0.9900, 0.9944 and 0.9970, respectively. From these estimates, we could infer that the persistence in shocks to volatility is relatively large.

Table 3 also depicts the diagnostics of the empirical findings of the AR – EGARCH model. $LB - Q(20)$ and $LB - Q^2(20)$ are the Ljung-Box test statistics for the null hypothesis that there is no serial correlation up to order 20 for standardized and squared standardized residuals, respectively. As shown in the table, both statistics are not above 1%, 5% and 10% in all cases. The null hypothesis of no autocorrelation up to order 20 for squared standardized residuals is accepted.

5.2 Asymmetric DCC results

To assess our empirical results and gain further insight into the dynamic correlation structure of gold and other financial markets, we use the Asymmetric Dynamic Conditional Correlation (A-DCC) model developed by Cappiello et al. (2006) in a bivariate framework. Following a first stage approach similar to the DCC model (see Engle (2002)), the univariate EGARCH standardized residuals are used as inputs into the A-DCC estimation process. The estimated parameters a_1 and b_1 in the DCC model capture the effects of lagged standardized shocks, $Z_{t-1}Z'_{t-1}$, and lagged dynamic conditional correlations, Q_{t-1} , on current dynamic conditional correlations, respectively.

The statistical significance of these correlations in each gold price and financial market pair indicates the presence of dynamic correlations. The evaluation of asymmetric correlation responses to negative stock returns is inspected through the parameter g_1 . The A-DCC model nests the standard DCC model when the parameter g_1 is set to equal to zero.

The second step is to estimate the A-DCC model. We use this methodology to test the correlation among the selected returns. Therefore, the outcome views the relationship between the gold price and the other financial markets. Moreover, the subperiods

² Prior to estimating the univariate $AR(m) - EGARCH(p, q)$ models, we verify that the null hypothesis of stationarity in the return series of gold prices and financial market could not be rejected using the KPSS test.

Table 3 AR(0)-EGARCH(1,1) results

	GOLD			SPX			CMBI			USDI		
	Coefficient	StdError	p value	Coefficient	StdError	p value	Coefficient	StdError	p value	Coefficient	StdError	p value
Whole sample(5 January 1995–30 May 2017)												
μ_0	0.0155**	0.0086	0.0725	0.0446*	0.0089	0.0000	0.0298*	0.0034	0.0000	0.0069	0.0046	0.1320
ω	-0.0766*	0.0078	0.0000	-0.0854*	0.0081	0.0000	-0.0796*	0.0112	0.0000	-0.0715*	0.008	0.0000
α	0.1103*	0.0114	0.0000	0.1111*	0.0112	0.0000	0.0797*	0.0104	0.0000	0.0848*	0.009	0.0000
β	0.9953*	0.0015	0.0000	0.9867*	0.0022	0.0000	0.9923*	0.0022	0.0000	0.9953*	0.0016	0.0000
γ	0.028*	0.0084	0.0009	-0.1389*	0.0101	0.0000	-0.0057	0.0057	0.3171	0.0037	0.0056	0.5023
Student-t parameter (ι)	3.8830*	0.2257	0.0000	5.0309*	0.3732	0.0000	7.7046*	6921	0.0000	6.6289*	0.5768	0.0000
Log likelihood	-7660.6157	—	—	-1012.806	—	—	-2910.0478	—	—	-2211.047	—	—
$LB-Q(20)$	16.1262	—	0.7087	18.4127	—	0.5586	15.2204	—	0.9200	17.2228	—	0.5501
$LB-Q^2(20)$	26.9641	—	0.1148	22.5897	—	0.1436	28.3659	—	0.1835	36.2287	—	0.2404
subsample 1 (5 January 1995–10 September 2001)												
μ_0	-0.0180**	0.0095	0.0575	0.0619*	0.0189	0.0010	0.0390*	0.0063	0.0000	0.0216*	0.0065	0.0009
ω	-0.1647*	0.0285	0.0000	-0.0929*	0.0152	0.0000	-0.1172*	0.0322	0.0002	-0.0976*	0.0259	0.0001
α	0.2327*	0.0427	0.0000	0.1190*	0.0196	0.0000	0.0799*	0.0196	0.0000	0.1026*	0.0238	0.0000
β	0.9792*	0.0078	0.0000	0.9786*	0.0053	0.0000	0.9761*	0.0102	0.0000	0.9887*	0.0059	0.0000
γ	0.0483***	0.0265	0.0684	-0.1317*	0.0184	0.0000	-0.0064	0.0133	0.6323	0.0084	0.0122	0.4873
Student-t parameter (ι)	3.1885*	0.2807	0.0000	6.9949*	1.1727	0.0000	5.7323*	0.7628	0.0000	4.8921*	0.6179	0.0000
Log likelihood	-2372.4597	—	—	-300.5348	—	—	-577.5165	—	—	-669.5847	—	—
$LB-Q(20)$	14.2584	—	0.5867	17.3352	—	0.5201	17.2336	—	0.3958	12.2228	—	0.8801
$LB-Q^2(20)$	21.2227	—	0.1407	28.3342	—	0.2013	29.0350	—	0.1426	22.3304	—	0.1433
subsample 2 (11 September 2001–7 August 2007)												
μ_0	0.0957*	0.0239	0.0000	0.0298***	0.017	0.0804	0.0215*	0.0062	0.0005	-0.0302*	0.0002	0.0000

Table 3 (continued)

	GOLD			SPX			CMBI			USDI		
	Coefficient	StdError	p value	Coefficient	StdError	p value	Coefficient	StdError	p value	Coefficient	StdError	p value
ω	-0.0332*	0.0104	0.0014	-0.0475*	0.0109	0.0000	-0.0493*	0.0177	0.0054	0.0077*	0.0001	0.0000
α	0.0480*	0.0143	0.0008	0.0558*	0.0136	0.0000	0.0498*	0.0153	0.0011	-0.0073*	0.0008	0.0000
β	0.9948*	0.0026	0.0000	0.9922*	0.0025	0.0000	0.9958*	0.0035	0.0000	1.0010*	0.0007	0.0000
γ	0.0599*	0.0133	0.0000	-0.1042*	0.0139	0.0000	-0.0031	0.0082	0.7074	-0.0405*	0.0021	0.0000
Student-t parameter (ι)	5.0381*	0.7283	0.0000	9.1202*	1.7535	0.0000	10.6884*	2.6757	0.0000	29.2699*	0.4168	0.0000
Log likelihood	-2126.6641	—	—	-1886.674	—	—	-199.4922	—	—	-772.7456	—	—
$LB - \hat{Q}(20)$	15.5527	—	0.1457	14.2287	—	0.1201	12.3028	—	0.1104	18.3952	—	0.1705
$LB - \hat{Q}^2(20)$	28.3020	—	0.2241	27.3590	—	0.5847	33.3583	—	0.5729	39.2862	—	0.4201
subsample 3 (8 August 2007–30 May 2017)												
μ_0	0.0418**	0.0175	0.0169	0.0415*	0.0097	0.0000	0.0266*	0.0052	0.0000	0.0122**	0.0068	0.0736
ω	-0.0622*	0.0089	0.0000	-0.0721*	0.0111	0.0000	-0.0794*	0.0149	0.0000	-0.0639*	0.0116	0.0000
α	0.0899*	0.0133	0.0000	0.1014*	0.0173	0.0000	0.0855*	0.0145	0.0000	0.0799*	0.0139	0.0000
β	0.9949*	0.0025	0.0000	0.9900*	0.0026	0.0000	0.9944*	0.0026	0.0000	0.9970*	0.002	0.0000
γ	0.0103	0.0101	0.3086	-0.1903*	0.0201	0.0000	-0.0140***	0.0082	0.0868	0.0203*	0.0073	0.0056
Student-t parameter (ι)	4.1955*	0.3799	0.0000	3.3672*	0.2923	0.0000	9.3624	1.5875	0.0000	6.3131*	0.7662	0.0000
Log likelihood	-3805.2545	—	—	-3365.342	—	—	-500.4312	—	—	-1525.356	—	—
$LB - \hat{Q}(20)$	12.0358	—	0.1704	14.0025	—	0.1738	12.5573	—	0.1142	17.2228	—	0.1732
$LB - \hat{Q}^2(20)$	25.0214	—	0.5124	28.2410	—	0.4432	30.2224	—	0.2904	39.2503	—	0.4501

$r_t = \mu_0 + \varepsilon_t$ and $\ln(h_t) = \omega + \alpha \ln(r_{t-1}) + \beta \ln(h_{t-1})$, where r_t represents gold returns and financial market returns, ε_t is the error term, h_t is the conditional volatility and $\sigma_t = \varepsilon_t / \sigma_t$ is the standardized residual. $LB - \hat{Q}(20)$ and $LB - \hat{Q}^2(20)$ are the Ljung-Box statistics with 20 lags for the standardized and squared standardized residuals, respectively. The superscripts *, **, and *** denote the level significance at 1%, 5%, and 10%, respectively

help us to obtain the required findings. Table 4 reports the empirical results for the whole sample period and the three subsample periods. The estimate on the parameter of standardized residuals (a_1) is statistically significant at the 1% level. The parameter of innovation in the dynamics of the conditional correlation matrix (b_1) is statistically significant at the 1% level for all return series. Moreover, the estimate on the parameter of the asymmetry term (g_1) is only significant. Table 4 shows the empirical findings by subperiod. First, we show that the estimate on the parameter of the asymmetry term (g_1) is statistically significant for gold and financial market returns for all subperiods. Second, we find that while the g_1 coefficient for samples 1, 2 and 3 is statistically significant at conventional levels, it is positive and statistically significant at the 1%

Table 4 Asymmetric DCC results (Whole sample and subsample analysis)

	Symmetric DCC			Asymmetric DCC		
	coefficient	Std.Error	p value	coefficient	Std.Error	p value
Whole sample(5 January 1995–30 May 2017)						
a_1	0.1277*	0.0047	0.0000	0.1277*	0.0046	0.0000
b_1	0.9897*	0.0008	0.0000	0.9897*	0.0008	0.0000
g_1	—	—	—	0.1235*	0.0031	0.0003
Log likelihood	−18,919.0079	—	—	−18,919.0079	—	—
BIC	38,063.61595	—	—	38,072.29288	—	—
subsample 1 (5 January 1995–10 September 2001)						
a_1	0.1236*	0.0101	0.0000	0.1236*	0.0108	0.0000
b_1	0.9884*	0.0023	0.0000	0.9884*	0.0023	0.0000
g_1	—	—	—	0.1722*	0.0048	0.0001
Log likelihood	−5013.2033	—	—	−5013.2033	—	—
BIC	10,220.43914	—	—	10,227.90192	—	—
subsample 2 (11 September 2001–7 August 2007)						
a_1	0.1263*	0.0097	0.0000	0.0021*	0.0101	0.0000
b_1	0.9883*	0.0021	0.0000	0.9883*	0.0021	0.0000
g_1	—	—	—	0.1428*	0.0149	0.0004
Log likelihood	−4714.582	—	—	−4714.582	—	—
BIC	9619.9919	—	—	9627.3314	—	—
subsample 3 ((8 August 2007–30 May 2017)						
a_1	0.1394*	0.0082	0.0000	0.1394*	0.0078	0.0000
b_1	0.9867*	0.0019	0.0000	0.9867*	0.0018	0.0000
g_1	—	—	—	0.2156*	0.0228	0.0000
Log likelihood	−9062.2241	—	—	−9062.2241	—	—
BIC	18,328.7124	—	—	18,336.5687	—	—

$Q_t = (1 - a_1 - b_1)\bar{Q} - g_1\bar{N} + a_1Z_{t-1}Z'_{t-1} + b_1Q_{t-1} + g_1\eta_{t-1}\eta'_{t-1}$ where Q_t is the conditional covariance matrix between the standardized residuals; Z_t is the matrix of the standardized residuals; $\bar{Q}$ and $\bar{N}$ are the unconditional correlation matrices of Z_t ; $\eta_t = I[Z_t < 0] \cdot Z_t$ and $I_t[\cdot]$ is a $k \times 1$ indicator function such as $I = 1$ if $Z_t < 0$ and $I = 0$ if $Z_t \geq 0$, while " $\cdot$ " is the Hadamard product. The superscripts *, ** and *** denote the level significance at 10%, 5% and 1%, respectively

level for the three subsample. This result suggests that the interdependent relationship between gold and financial market has grown during the different period of crises.

Figures 1, 2, 3 and 4 plots the estimated DCCs between each pair of the gold and financial market prices. First, the time path of the DCC series fluctuates over the sample period for all pairs, thereby suggesting that the assumption of constant correlations may not be appropriate. This result is generally in line with empirical studies such as Perez-Rodriguez (2006) and Tamakoshi and Hamori (2014). Second, Figures shows that the correlation decreases numerically if a large negative shock hits the gold and U.S. dollar markets simultaneously. Therefore, to some extent, gold plays a role in hedging against depreciation of the U.S. dollar. Generally, gold price increases in response to decreases in the U.S. dollar because investors demand gold to store value or to compensate for losses, and vice versa. This inverse correlation has already been pointed out in many previous studies (e.g. Hammoudeh et al. 2009; Bhar and Hammoudeh 2011).

6 Conclusion

While time varying correlations of gold price and financial market have seen voluminous research, relatively little attention has been given to the dynamics of correlations within a market.

In this paper, we analyze the dynamic conditional correlation between three financial market namely SPX, CMBI and USDI and gold price using the Asymmetric Dynamic Conditional Correlation (A-DCC) model developed by Cappiello et al. (2006). We also use an AR-EGARCH model for statistical analysis of the time-varying correlations by considering the major financial and economic events relative to the terrorist attacks, the

Fig. 1 Dynamic conditional correlations between each gold price and financial market pair. (a) The DCC between the GOLD and SPX. (b) The DCC between the GOLD and CMBI. (c) The DCC between the GOLD and USDI. (d) The DCC between the USDI and CMBI. (e) The DCC between the USDI and SPX. (f) The DCC between the CMBI and SPX. (Whole sample: January 5, 1995, to May 30, 2017)

Fig. 2 Dynamic conditional correlations between each gold price and financial market pair. (a) The DCC between the GOLD and SPX. (b) The DCC between the GOLD and CMBI. (c) The DCC between the GOLD and USDI. (d) The DCC between the USDI and CMBI. (e) The DCC between the USDI and SPX. (f) The DCC between the CMBI and SPX. (Subsample 1: January 5, 1995, to September 10, 2001)

subprime mortgage turmoil and the global financial crisis. The A-DCC model allows for conditional asymmetries in covariance and correlation dynamics, thereby enabling to examine the presence of asymmetric responses in correlations during periods of negative shocks. We then extended the above univariate GARCH models to a bivariate

Fig. 3 Dynamic conditional correlations between each gold price and financial market pair. (a) The DCC between the GOLD and SPX. (b) The DCC between the GOLD and CMBI. (c) The DCC between the GOLD and USDI. (d) The DCC between the USDI and CMBI. (e) The DCC between the USDI and SPX. (f) The DCC between the CMBI and SPX. (Subsample 2: September 11, 2001, to August 7, 2007)

Fig. 4 Dynamic conditional correlations between each gold price and financial market pair. (a) The DCC between the GOLD and SPX. (b) The DCC between the GOLD and CMBI. (c) The DCC between the GOLD and USDI. (d) The DCC between the USDI and CMBI. (e) The DCC between the USDI and SPX. (f) The DCC between the CMBI and SPX. (Subsample 3: Aout 8, 2007, to May 30, 2017)

framework with dynamic conditional correlation parameterization in order to investigate the interaction between gold price and other financial markets.

Our empirical results indicate that gold and financial market exhibit asymmetry in the conditional variances. Therefore, the results point to the importance of applying an appropriately flexible modeling framework to accurately evaluate the interaction between gold price and financial market co-movements. The conditional correlation among the gold and the three financial market exhibits higher dependency when it is driven by negative innovations to changes than it is by positive innovations. we find that correlations display substantial time variation for all pairs even when similar market conditions emerge. Our findings suggest that investors should take into consideration the asymmetric dependence structure, which depends on the upside or downside of the market, to control risk exposure reasonably.

Our empirical findings seem to be important to researchers and practitioners and especially to active investors and portfolio managers who include in their portfolios equities from the gold and other financial markets. The findings lead to important implications from investors' and policy makers' perspective. They are of great relevance for financial decisions of international investors on managing their risk exposures to gold price and financial market fluctuations and on taking advantages of potential diversification opportunities that may arise due to lowered dependence among financial market and gold. The increase of gold and other financial market linkages during crisis periods implies a decrease of portfolio diversification benefits, since holding a portfolio with diverse currencies is less subject to systematic risk. Moreover, this correlations' behavior may be considered as evidence of non-cooperative monetary policies around the world and highlight the need for some form of policy coordination among central banks. Finally, the different patterns of dynamic linkages among gold price and other financial market may influence transnational trade flows and the activities of multinational corporations, as they create uncertainty with regard to exports and imports.

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