Resources Policy 49 (2016) 290–301

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets

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ARTICLE INFO

Article history:
Received 10 April 2016
Received in revised form
25 June 2016
Accepted 28 June 2016

Keywords:
Gold prices
Oil prices
Stock prices
Nonlinear ARDL

ABSTRACT

This paper examines the asymmetric impact of gold prices, oil prices and their associated volatilities on stock markets of emerging economies. Monthly data are used for the period January 2008 till June 2015. The nonlinear ARDL approach is applied in order to find short-run and long-run asymmetries. The empirical results indicate that gold prices have a positive impact on stock market prices of large emerging BRICS economies and a negative impact on the stock markets of Mexico, Malaysia, Thailand, Chile and Indonesia. Oil prices have a negative impact on stock markets of all emerging economies. Gold and oil volatilities have a negative impact on stock markets of all emerging economies in both the short- and the long-run. The results indicate that the stock markets in the emerging economies are more vulnerable to bad news and events that result in uncertain economic conditions.

1. Introduction

Since the last few decades, the stock markets of emerging economies have shown rapid growth in terms of value and volume, creating investment opportunities and significant capital inflows have also been witnessed from developed to emerging markets (Beckmann et al., 2015). However, the stock markets of emerging economies are vulnerable to the global news and events resulting in a volatile and uncertain environment. Historical fluctuations in the crude oil prices show that the world will enter into the era of high oil price volatility in the near future. Ji (2012) argues that the global financial crisis of 2007-08 has disturbed the crude oil market mechanism and the synchronized casualty between crude oil prices and equity market has strengthened after the crisis period.

The investments in gold are regarded as an inflation hedge, store of value, mean of exchange, a source of wealth and a safe haven asset for stock markets during the periods of stock market troubleness (Baur and Lucey, 2010). Gold investment gives the sense of certainty to the investors during financial downturns and can be considered as an alternative and attractive investment due to simplicity of gold market (Baur and McDermott, 2010). Moreover, gold is also a good instrument of inflationary hedge because of its positive correlation with inflation (Bampinas and Panagiotidis, 2015). The investment in gold can at least retains its purchasing power during the periods of high inflation (Goodman, 1956). Gold can also be viewed as a portfolio diversifier because of its low correlation with other assets and therefore lowers the overall portfolio risk (Ciner et al., 2013). Notably, the central banks also retain gold for diversification purposes and to safeguard from economic uncertainties (Chen and Lin, 2014; Ciner et al., 2013; Kaufmann and Winters, 1989; Kumar, 2014).

Despite the role of gold investments in portfolio diversification and hedging, volatility in gold prices has a negative impact on stock markets. Lower volatility in gold prices indicates safe investment conditions (Baur, 2012). It is therefore important to understand the volatility behavior of gold markets for making hedging decisions (Ewing and Malik, 2013). The increased volatility of gold prices is an alert for the investors and exposes them to risk which in turn enhances investors' interest to understand the reaction of stock markets to the gold price volatility (Tully and Lucey, 2007).

The stock markets are impacted by various interrelated economic factors and a complex connection between these factors. However, macroeconomic variables such as gold prices, crude oil prices and their volatilities have a more profound impact on stock

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http://dx.doi.org/10.1016/j.resourpol.2016.06.011
0301-4207/

prices. Previous studies on this topic (Beckmann and Czudaj, 2013; Kanjilal and Ghosh, 2014; Shahbaz et al., 2014; Wang et al., 2011) have mainly analyzed the stock, gold and oil linkages in a linear setting. Anoruo (2011) argues that one basic shortcoming of linear modeling is that it assumes that time series are linear while in real times they are non-linear. Gao et al. (2012; 2015) argue that prior studies have paid little attention on the existing nonlinearities between oil, gold and stock nexuses. Prior studies have also examined the volatility relationships in a linear setting (Arouri et al., 2011a, b; Chang et al., 2010; Hammoudeh and Yuan, 2008; Lin et al., 2014; Sadorsky, 2014) and found that commodities volatilities can explain the stock prices. Moreover, significant volatility transmission is also witnessed from commodities to stock markets.

We argue that analyses of the relationship between the variables in a nonlinear setting have at least two important reasons: (1) a time series can have hidden cointegration if positive and negative components of a series are cointegrated (Granger and Yoon, 2002) and (b) asymmetry and structural breaks (e.g. major credit events, and bankruptcy etc.) are types of nonlinearities that affect the market dynamics, especially when the sample period is marked with the financial crises e.g. global financial crises of 2007-08. To achieve these purposes, we employ the nonlinear ARDL (NARDL) approach which allows testing the long-run and short-run asymmetries. In the presence of asymmetries, the dynamic multipliers quantify the respective responses of the stock markets to positive and negative changes in each of the explanatory variables by taking positive and negative partial sum decompositions of these variables. Moreover, unlike the standard cointegration techniques, this method permits time series to have different orders of integration (Shin et al., 2014).

Our findings show that gold prices, oil prices and their associated volatilities have a non-linear impact on the emerging stock markets in both short and long-run. Gold prices have a positive impact on the emerging BRICS stock markets and a negative impact on stock prices of Mexico, Malaysia, Thailand, Chile and Indonesian markets. Oil prices have a negative impact on all emerging stock markets. Moreover, gold and oil price volatilities negatively impact emerging stock markets in both short and long-run.

We organize the rest of the study as follows. Section 2 provides a review of the related literature. Section 3 presents the methodology. Section 4 discusses the data used and empirical findings and Section 5 concludes the study.

2. Related literature

There is widespread evidence in prior literature emphasizing the importance of nonlinear modeling. For instance, Lee and Lin (2012) depict that macroeconomic variables are impacted by the structural breaks and oil and gold prices follow a nonlinear pattern. On the other hand, Naifar and Al Dohaiman (2013) document that linear models fail to detect the existing nonlinearities in the relationship between stocks, oil and gold prices. Bildirici and Turkmen (2015) find that the explanatory power of nonlinear models is higher than the linear models. Anoruo (2011) examines the testing procedure of linear and non-linear models and states that one basic shortcoming of linear modeling is that it fails to capture the asymmetry in variables' behavior over time. Furthermore, Gao et al. (2012, 2015) argue that prior studies paid little attention on oil-gold-stock nexuses under nonlinear specifications. Notably, positive and negative oil price shocks have a different impact on the economies (Gao et al., 2014) and these nonlinearities also impact the stock markets (Huang et al., 2015; Manimaran et al., 2009). An et al. (2014), Ma et al. (2013) and Vacha and Barunik (2012) suggest that the nonlinear relationship between commodity and stock prices is mainly due to the operations of various market agents with heterogeneous expectations and beliefs.

Several studies have examined the cointegration between commodities and stock prices due to their irreplaceable role in the economy. Oil and gold are the two highly liquid commodities and are synchronized in their movements (Tiwari and Sahadudheen, 2015). However, a series of crises, e.g., economic crisis of 1970, ERM Crisis, OPEC decisions in 1994, Russian Crisis in 1997, Asian financial crisis in 1998 and global financial crisis in 2007-09 have encouraged the investors to evaluate the alternate investment assets for diversification during economic downturns. Narayan and Sharma (2011) suggest that gold has emerged as a desirable asset to safeguard portfolios during turmoil market conditions because of its low correlation with stocks. Arouri et al. (2015) conclude that the volatilities of oil and gold differ during the periods of extreme market declines and therefore investors prefer gold investments due to its safe haven properties. Furthermore, profitable trading strategies can be devised with the investment in gold (Daskalaki and Skiadopoulos, 2011).

Chan et al. (2011) utilize MSIAH specification to collectively examine the return distributions of stocks, T-bills, gold, oil and other real assets. They document that oil prices are positively correlated with other assets during turmoil market conditions. During the flight to quality, investors prefer assets other than oil for diversification and protection against losses due to their low correlation with each other. Morana (2013) also documents that during bad financial conditions, the correlation between oil prices and stock markets increases. Chen et al. (2014) with similar results argue that financial shocks have increased the oil price volatility over the period. These findings invite researcher to further investigate the role of financial conditions while linking the stock and commodity prices. The introduction of commodity indices has not only increased the financizaliation of commodities, but the volatility in these markets as well, which is finally transmitted to financial markets (Delatte and Lopez, 2013).

In the existing energy literature, GARCH models are widely used to model the asset volatilities. For instance, Chang et al. (2010) employ the CCC-GARCH to study the volatility spillover from oil and gasoline spot prices in their respective futures. Arouri et al. (2011a, b) utilize a bivariate GARCH model to determine the volatility transmission and spillovers effects from oil to stock markets. Arouri et al. (2012) apply a VAR-GARCH model to account for volatility spillovers between crude oil and stock returns. Lin et al. (2014) investigate the volatility dynamics between oil and stock markets of Ghana and Nigeria using VAR-GARCH and DCC-GARCH. The volatility dynamics of oil, wheat, copper and emerging markets are examined by Sadorsky (2014a, b) using MGARC-DCC models.

More recently, Basher and Sadorsky (2016) utilize DCC, ADCC and GO-GARCH models to examine the conditional correlation between gold, oil and the price index presenting emerging stock markets. Notably, volatility estimation utilizing GARCH-type models for a large data set is a challenging task due to the curse of dimensionality i.e., tradeoff between feasibility and generality. The estimations through multivariate GARCH models, e.g., BEKK allow parameters to grow rapidly and other specifications such as DCC, CCC and GO-GARCH only capture the time varying correlation, but fail to capture the spillover and transmission effects between commodities volatilities and stock prices. Contrary to previous studies where the volatility is estimated through GARCH-type models, we use oil and gold price volatilities readily tradable at the Chicago Board Options Exchange to determine the nonlinear impact of prices and volatilities on emerging stock market.

3. Methodology

The aim of this study is to examine the nonlinear (asymmetric) short- and long-run impact of gold prices (GP), oil prices (OP) and their associated volatilities (GV and OV, respectively) on the emerging stock prices (SP) and therefore the primary model takes the following functional from:

$$SP = f(GP^{+}, GP^{-}, OP^{+}, OP^{-}, GV^{+}, GV^{-}, OV^{+}, OV^{-}) \tag{1}$$

The nonlinear ARDL (hereafter, NARDL) bound testing approach developed by Shin et al. (2014) is applied to estimate short- and long-run dynamics. The bound testing approach provides robust empirical results even for the small sample sizes (Ghatak and Siddiki, 2001; Narayan and Narayan, 2005; Pesaran et al., 2001) and can be applied regardless of the order of integration with the exception that the series is integrated with the maximum order of one. The order of integration can be verified using unit root tests. Further, when the time series are noted to have cointegration using their positive and negative components (Granger and Yoon, 2002), the case of nonlinear cointegration is implied. Some possible reasons of nonlinearity include, inter alia, noise traders, nonlinear transaction cost, asymmetric adjustment process and/or extreme volatility. The latter becomes highly plausible when the sample has major shocks such as the global financial crisis of 2007-08.

The NARDL framework allows modeling asymmetric cointegration using positive and negative partial sum decompositions and detecting the asymmetric effects both in the short- and long-run. It also allows the joint analysis of the issues of non-stationarity and nonlinearity in the context of an unrestricted error correction model. The nonlinear cointegrating regression (Shin et al., 2014) is specified as:[1]

$$y_t = \beta^{+}x_t^{+} + \beta^{-}x_t^{-} + \mu_t, \tag{2}$$

where $\beta^{+}$and β^{-} are the long term parameters of $kx1$ vector of regressors x_t, decomposed as:

$$x_t = x_0 + x_t^{+} + x_t^{-} \tag{3}$$

where x_t^{+} (x_t^{-}) are the partial sums of positive (negative) change in x_t as follows:

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} \max(\Delta x_j, 0) \tag{4}$$

$$x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} \min(\Delta x_j, 0) \tag{5}$$

The NARDL(p, q) form of the Eq. (3), in the form of asymmetric error correction model (AECM) can be specified as:

$$\Delta y_t = \rho y_{t-1} + \theta^{+}x_{t-1}^{+} + \theta^{-}x_{t-1}^{-} + \sum_{j=1}^{p-1} \varphi_j \Delta y_{t-j} + \sum_{j=0}^{q} \left(\pi_j^{+} \Delta x_{t-j}^{+} + \pi_j^{-} \Delta x_{j-t}^{-}\right) + \varepsilon_t \tag{6}$$

where $\theta^{+} = -\rho\beta^{+}$ and $\theta^{-} = -\rho\beta^{-}$. In nonlinear framework, the first two steps to ascertain cointegration between the variables are same as in linear ARDL bound testing procedure i.e. estimating Eq. (6) using OLS and conducting the joint null ($\rho = \theta^{+} = \theta^{-} = 0$) hypothesis test. However, in NARDL, the Wald test is used to examine the long-run ($\theta^{+} = \theta^{-}$) and short-run ($\pi^{+} = \pi^{-}$) asymmetries in the relationship. Finally, the asymmetric cumulative dynamic multiplier effect of a unit change in x_t^{+} and x_t^{-} on y_t is examined respectively as follows:

$$m_h^{+} = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^{+}},\ m_h^{-} = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^{-}}, h=0,1,2,\ \ldots\ldots \tag{7}$$

where as $h \to \infty$, the $m_h^{+} \to \beta^{+}$and $m_h^{-} \to \beta^{-}$. Recall that β^{+} and β^{-} are the asymmetric long-run coefficients and here can be calculates as $\beta^{+} = -\theta^{+}/\rho$ and $\beta^{-} = -\theta^{-}/\rho$, respectively.

4. Data and findings

Monthly data on the top ten (based on market capitalization and traded volume) emerging stock markets, namely China, India, Brazil, Russia, South Africa, Mexico, Malaysia, Thailand, Chile and Indonesia, Brent crude oil prices, Gold (Bullion LBM U$/troy ounce) prices, crude oil volatility (OVX) index and gold volatility[2] (GVZ) index is used from January 2008 to June 2015[3]. All the data are extracted from Thomson Reuters DataStream, stock indices are denominated in local currencies and gold, oil prices and their volatiles are in US dollar[4]. The effect of exchange-rate showed that the common currency denomination (both stock indices and commodities) generally increases the co-movement in all market conditions (Baur and McDermott, 2010). Moreover, the common currency denomination introduces a common feature in the data which yields a strong co-integration as compared to a case in which local currency stock indices are used (Arouri et al., 2015). The descriptive statistics of return series are reported in Table 1. Although we use price series of the variables for econometric analysis, we report statistical properties of returns because the later are generally of interest from investment point of view. Monthly average returns of China, Brazil and Russian stock markets are negative while the average returns are positive for another seven stock markets. Standard deviations are highest for Russian stock returns among others. Monthly average gold price returns are higher than oil price returns. Daskalaki and Skiadopoulos (2011) and Jensen et al. (2000) also report that gold price returns are higher in comparison to the returns of other commodities. The Jarque-Bera test of normality rejects the null hypothesis for all return series at the 1% level of significance and states that the returns are not normally distributed.[5]

Table 2 displays the pairwise unconditional correlation of emerging stock market prices with gold prices, oil prices, gold volatility and oil volatility. The Chinese stock market has a negative correlation with gold and oil prices. All other emerging stock markets are positively correlated (significant at conventional levels) with gold and oil prices. The emerging stock markets, except China, show a significant negative correlation with volatility indices (both gold and oil). Moreover, the pairwise correlations are considerably higher between gold volatility and emerging stock markets compared to the correlations between oil volatility and emerging stock markets.

The stationarity of the time series is examined through

[1] For a more extensive derivation of the model see Shin et al. (2014).

[2] The gold volatility index is in U.S dollars and is readily traded at Chicago Board Option Exchange.

[3] The start date of our data is dictated by its availability. The data of crude oil volatility (OVX) is only available from January 2008 so we have chosen it to facilitate comparative analysis.

[4] If the dollar loses value relative to other currencies, this will cause the dollar denominated nominal value of non-US stock markets to rise. A falling dollar is also likely to cause a rise in the nominal dollar price of gold (Baur and McDermott, 2010; Arouri et al., 2015).

[5] Notably, the raw price series data is also non-normal and therefore we transformed all the time series into natural logarithmic form to achieve normality. Results of the Jarque-Bera test for the price series are available from author on request.

Table 1
Descriptive statistics of emerging stock markets and selected variables.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB-Stats
Panel A: price series							
China	-0.0385	18.7598	-28.2353	8.4452	-0.7949	4.6639	19.860***
India	0.5154	29.59	-31.7886	7.5843	-0.4813	7.8219	90.663***
Brazil	-0.0544	14.4537	-28.4988	6.7699	-0.7118	5.1808	25.433***
Russia	-0.6982	26.6842	-44.9138	11.4245	-0.6906	4.9883	21.980***
South Africa	0.8399	11.5893	-15.0311	4.7977	-0.4132	4.221	8.151***
Mexico	0.5023	10.9541	-19.6668	5.0311	-0.7072	5.2059	25.749***
Malaysia	0.1965	12.7032	-16.5142	3.7585	-0.7827	7.5046	85.281***
Thailand	0.8079	13.082	-35.9188	6.7679	-2.0095	11.3749	323.589***
Chile	0.4467	13.948	-9.5503	4.0676	0.2752	3.604	2.5042***
Indonesia	0.7343	18.3412	-37.7193	6.914	-1.9131	12.605	400.859***
Gold price	0.3207	13.026	-19.0951	5.9441	-0.5023	3.6777	5.5071***
Gold volatility	-0.2948	48.3573	-30.5953	15.1814	0.6296	3.5004	6.885***
Oil price	-0.3293	26.2966	-45.5615	10.6597	-0.9757	6.2805	54.638***
Oil volatility	0.2344	34.94	-39.2519	13.4973	0.0719	3.0352	0.0821***

Note: JB-stats stand for Jarque-Bera test of normality.
*** Indicate that null hypothesis of normality is rejected at 1% level of significance.

Table 2
Unconditional correlation of emerging stock markets with independent variables.

	Gold price	Gold volatility	Oil price	Oil volatility
China	-0.2765***	0.0049	-0.1995***	0.2041***
	(-12.716)	(-0.2156)	(-9.001)	(9.2143)
India	0.4145***	-0.7886***	0.2632***	-0.5838***
	(20.1362)	(-56.687)	(12.061)	(-31.787)
Brazil	0.3387***	-0.3277***	0.4870***	-0.3301***
	(15.912)	(-15.333)	(24.646)	(-15.457)
Russia	0.3519***	-0.3687***	0.8171***	-0.4332***
	(16.619)	(-17.531)	(62.645)	(-21.243)
South Africa	0.4732***	-0.8621***	0.3598***	-0.6663***
	(23.744)	(-75.212)	(17.047)	(-39.499)
Mexico	0.7197***	-0.8716***	0.5252***	-0.7255***
	(45.823)	(-78.599)	(27.278)	(-46.604)
Malaysia	0.6772***	-0.8696***	0.5207***	-0.7670***
	(40.685)	(-77.852)	(26.963)	(-52.842)
Thailand	0.6777***	-0.8652***	0.5049***	-0.7099***
	(40.734)	(-76.261)	(25.853)	(-44.554)
Chile	0.8761***	-0.6148***	0.5004***	-0.5780***
	(80.333)	(-34.454)	(25.549)	(-31.308)
Indonesia	0.7348***	-0.8358***	0.4946***	-0.7010***
	(47.882)	(-67.295)	(25.157)	(-43.447)

Note: The values in () are the t statistics.
*** Indicate significance at 1% level.

Table 4
Bounds test for nonlinear specifications.

Market	$FPSS_{Nonlinear}$	t_{BDM}
China	5.165***	-3.530***
India	7.220***	-3.076**
Brazil	11.428***	-3.646***
Russia	18.423***	-5.587***
South Africa	8.468***	-4.237***
Mexico	11.363***	-7.017***
Malaysia	9.507***	-3.227**
Thailand	12.753***	-3.252**
Chile	6.659***	-3.812***
Indonesia	7.884***	-5.449***

Note: The exact specification of the asymmetric ARDL model is presented analytically in Table 5.
99% upper (lower) bound with $k=4$ is 5.06 (3.74).
95% upper (lower) bound with $k=6$ is 4.43 (3.15).
** Indicates significance at 5% level.
*** Indicates significance of bound test at 1% level.

Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) unit root tests and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationary test. The results summarized in Table 3 suggest that all examined variables are non-stationary in levels while they become stationary when their first difference (with intercept and trend) form

Table 3
Results of unit root tests.

Series	ADF		PP		KPSS	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
China	-2.4558	-43.618***	-2.5247	-43.732***	0.7503***	0.6868
India	-0.8921	-41.013***	-0.8139	-41.049***	3.2293***	0.3355
Brazil	-2.1251	-45.794***	-2.3900	-46.230***	0.5345**	0.0531
Russia	-2.1569	-38.944***	-2.0839	-38.924***	0.4767**	0.1087
South Africa	-0.4884	-43.204***	-0.3137	-43.471***	5.0237***	0.1569
Mexico	-1.2673	-40.913***	-1.0430	-40.872***	4.4095***	0.0731
Malaysia	-0.6927	-40.077***	-0.7210	-40.202***	4.5610***	0.2532
Thailand	-0.4539	-42.789***	-0.4948	-42.789***	4.7991***	0.2061
Chile	-1.5779	-37.106***	-1.4761	-36.876***	2.9236***	0.1787
Indonesia	-0.6325	-23.139***	-0.6250	-39.421***	4.6738***	0.1745
Gold price	-1.8553	-44.196***	-1.8491	-44.205***	2.8848***	0.2919
Gold volatility	-2.3062	-49.680***	-2.4708	-51.436***	3.4264***	0.0402
Oil price	-1.2222	-42.482***	-1.3420	-42.528***	0.8518***	0.1643
Oil volatility	-2.3200	-28.599***	-2.2623	-53.034***	2.3577***	0.0552

Note: ADF, PP and KPSS are the empirical statistics of the Augmented Dickey–Fuller (1979), and the Phillips–Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test, respectively.

Table 5
Dynamic asymmetric estimation of stock price adjustments.

Variable	a). China		b). India		c). Brazil		d). Russia		e). South Africa	
	Coef.	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**
Constant	2.364***	(0.697)	0.972**	(0.415)	1.589***	(0.629)	1.305**	(0.549)	3.238***	(0.760)
SP_{t-1}	−0.300***	(0.085)	−0.104**	(0.050)	−0.149***	(0.056)	−0.193***	(0.074)	−0.314***	(0.074)
GP^{+}_{t-1}	0.085	(0.169)	0.729***	(0.146)	0.325***	(0.106)	−0.075	(0.140)	0.180**	(0.080)
GP^{-}_{t-1}	0.182	(0.169)	0.208*	(0.119)	−0.002	(0.106)	−0.114	(0.133)	0.118	(0.072)
GV^{+}_{t-1}	−0.301***	(0.102)	−0.193***	(0.066)	−0.145**	(0.064)	−0.087	(0.075)	−0.153***	(0.044)
GV^{-}_{t-1}	0.033	(0.085)	−0.001	(0.065)	0.025	(0.052)	−0.057	(0.075)	−0.066	(0.043)
OP^{+}_{t-1}	−0.126	(0.097)	−0.579***	(0.111)	−0.141*	(0.075)	0.190	(0.130)	−0.177***	(0.054)
OP^{-}_{t-1}	−0.185***	(0.052)	−0.165***	(0.043)	−0.112***	(0.031)	−0.069	(0.069)	−0.033	(0.028)
OV^{+}_{t-1}	0.190**	(0.072)	0.006	(0.039)	0.018	(0.030)	0.054	(0.042)	0.058**	(0.025)
OV^{-}_{t-1}	−0.141	(0.102)	−0.165**	(0.073)	−0.020	(0.064)	0.164*	(0.086)	−0.111***	(0.046)
ΔSP_{t-1}							−0.403***	(0.081)		
ΔGP^{+}_{t}			0.776***	(0.192)	0.535***	(0.153)			0.403***	(0.118)
ΔGP^{-}_{t-2}							0.490***	(0.184)		
ΔGV^{+}_{t}	−0.261***	(0.08)	−0.339***	(0.058)	−0.325***	(0.048)	−0.507***	(0.068)	−0.229***	(0.036)
ΔGV^{+}_{t-2}					0.152***	(0.063)			0.181***	(0.047)
ΔGV^{+}_{t-3}			0.262***	(0.083)						
ΔGV^{-}_{t-1}			0.375***	(0.096)						
ΔGV^{-}_{t-2}			0.313***	(0.088)						
ΔOP^{+}_{t}							0.762***	(0.153)		
ΔOP^{+}_{t-1}			0.430***	(0.141)						
ΔOP^{+}_{t-2}			0.503***	(0.125)						
ΔOP^{+}_{t-3}							−0.519***	(0.150)		
ΔOP^{-}_{t-1}							0.632***	(0.117)		
ΔOP^{-}_{t-2}					0.235***	(0.096)	0.380***	(0.132)	0.260***	(0.070)
ΔOP^{-}_{t-3}			0.478***	(0.125)			0.654***	(0.137)		
ΔOV^{-}_{t}					−0.161***	(0.061)				
ΔOV^{-}_{t-1}									0.159***	(0.043)
ΔOV^{-}_{t-3}			−0.146**	(0.072)						
L^{+}_{GP}	0.283		7.004*		2.186**		−0.391		0.574**	
L^{-}_{GP}	0.605		1.999		−0.015		−0.593		0.374*	
W_{GP}	0.146	[0.703]	2.187	[0.144]	2.461	[0.121]	0.035	[0.851]	0.297	[0.587]
L^{+}_{GV}	−1.003***		−1.852**		−0.971**		−0.453		−0.488**	
L^{-}_{GV}	0.109		−0.009		0.165		−0.294		−0.210	
W_{GV}	9.163	[0.003]	3.509	[0.066]	4.696	[0.034]	0.095	[0.759]	2.572	[0.093]
L^{+}_{OP}	−0.418		−5.564*		−0.948		0.988*		−0.564**	
L^{-}_{OP}	−0.616***		−1.585**		−0.755**		−0.360		−0.105	
W_{OP}	0.572	[0.452]	3.076	[0.084]	0.197	[0.658]	6.033	[0.017]	9.067	[0.004]
L^{+}_{OV}	0.631***		0.061		0.118		0.279		0.186**	
L^{-}_{OV}	−0.469*		−1.589**		−0.136		0.854		−0.352**	
W_{OV}	13.45	[0.000]	4.197	[0.045]	0.310	[0.579]	0.890	[0.349]	12.900	[0.001]
$Adj-R^2$	0.323		0.587		0.651		0.779		0.552	
χ^2_{NORM}	2.459	[0.292]	1.663	[0.441]	1.675	[0.433]	1.055	[0.590]	0.933	[0.627]
χ^2_{SC}	0.837	[0.567]	1.085	[0.366]	1.457	[0.155]	0.520	[0.907]	2.126	[0.031]
χ^2_{HET}	0.288	[0.587]	1.576	[0.208]	5.103	[0.027]	0.004	[0.949]	2.772	[0.097]
χ^2_{FF}	6.125	[0.015]	0.001	[0.972]	0.001	[0.976]	0.405	[0.527]	0.666	[0.417]

Variable	f). Mexico		g). Malaysia		h). Thailand		i). Chile		j). Indonesia	
	Coef.	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**	**Coef.**	**S.E**
Constant	4.269***	(0.618)	1.466***	(0.453)	1.542***	(0.449)	1.541***	(0.544)	3.213***	(0.582)
SP_{t-1}	−0.424***	(0.060)	−0.209***	(0.065)	−0.218***	(0.067)	−0.159***	(0.057)	−0.410***	(0.075)
GP^{+}_{t-1}	0.016	(0.075)	0.117*	(0.061)	0.209**	(0.098)	0.136*	(0.073)	0.277***	(0.107)
GP^{-}_{t-1}	0.189**	(0.076)	0.043	(0.057)	0.487***	(0.121)	0.182**	(0.087)	0.569***	(0.137)
GV^{+}_{t-1}	−0.092**	(0.043)	−0.030	(0.031)	−0.062	(0.050)	−0.070*	(0.037)	−0.100*	(0.060)
GV^{-}_{t-1}	−0.107***	(0.044)	0.041	(0.030)	0.035	(0.057)	0.018	(0.043)	0.011	(0.056)
OP^{+}_{t-1}	0.030	(0.052)	−0.017	(0.044)	−0.176***	(0.062)	−0.058	(0.049)	−0.141*	(0.077)
OP^{-}_{t-1}	−0.048**	(0.024)	−0.034*	(0.019)	−0.072**	(0.032)	−0.067***	(0.024)	−0.115***	(0.033)
OV^{+}_{t-1}	0.007	(0.021)	−0.021	(0.018)	−0.028	(0.030)	−0.025	(0.022)	−0.118***	(0.038)
OV^{-}_{t-1}	−0.039	(0.042)	−0.069**	(0.033)	−0.294***	(0.058)	−0.110***	(0.042)	−0.377***	(0.079)
ΔSP_{t-1}	0.173***	(0.072)								
ΔSP_{t-2}					−0.208***	(0.076)				
ΔGP^{-}_{t}	0.239***	(0.094)			0.552***	(0.137)	0.249***	(0.101)	0.635***	(0.149)
ΔGV^{+}_{t}			−0.202***	(0.029)	−0.311***	(0.050)				
ΔGV^{+}_{t-2}	0.145***	(0.045)								

Table 5 (*continued*)

ΔGV^{-}_{t}	-0.292^{***}	(0.049)								
ΔGV^{-}_{t-1}							-0.164^{***}	(0.049)		
ΔGV^{-}_{t-2}	-0.134^{***}	(0.048)					-0.189^{***}	(0.058)		
ΔGV^{-}_{t-3}	-0.120^{***}	(0.044)							-0.220^{***}	(0.068)
ΔOP^{+}_{t-3}	-0.191^{**}	(0.079)								
ΔOP^{-}_{t-1}									0.262^{***}	(0.102)
ΔOP^{-}_{t-3}	0.195^{***}	(0.071)								
ΔOV^{+}_{t}									-0.212^{***}	(0.059)
ΔOV^{+}_{t-1}							0.129^{***}	(0.043)	0.306^{***}	(0.074)
ΔOV^{+}_{t-2}									0.275^{***}	(0.063)
ΔOV^{+}_{t-3}									0.208^{***}	(0.072)
ΔOV^{-}_{t}					-0.159^{***}	(0.058)	-0.188^{***}	(0.047)	-0.226^{***}	(0.073)
L^{+}_{GP}	0.038		0.559^{*}		0.958^{*}		0.850		0.676^{**}	
L^{-}_{GP}	0.447^{***}		0.206		2.230^{***}		1.141^{***}		1.388^{***}	
W_{GP}	2.913	[0.093]	0.675	[0.414]	3.920	[0.052]	0.176	[0.675]	3.551	[0.064]
L^{+}_{GV}	-0.216^{**}		-0.141		-0.282		-0.437^{*}		-0.243^{*}	
L^{-}_{GV}	-0.252^{***}		0.195		0.161		0.114		0.028	
W_{GV}	0.090	[0.741]	2.615	[0.091]	1.422	[0.237]	2.072	[0.154]	2.296	[0.135]
L^{+}_{OP}	0.072		-0.082		-0.807^{**}		-0.364		-0.343^{*}	
L^{-}_{OP}	-0.113^{*}		-0.162		-0.330		-0.420^{**}		-0.280^{***}	
W_{OP}	3.291	[0.074]	0.197	[0.658]	3.786	[0.055]	0.041	[0.839]	0.131	[0.718]
L^{+}_{OV}	0.016		-0.102		-0.127		-0.156		-0.288^{***}	
L^{-}_{OV}	-0.093		-0.332^{**}		-1.347^{***}		-0.691^{**}		-0.920^{***}	
W_{OV}	1.039	[0.312]	1.653	[0.203]	12.34	[0.001]	2.834	[0.097]	12.86	[0.001]
Adj- R^2	0.689		0.530		0.640		0.480		0.612	
χ^2_{NORM}	0.288	[0.866]	0.808	[0.668]	0.951	[0.622]	2.349	[0.309]	1.965	[0.374]
χ^2_{SC}	2.848	[0.005]	1.901	[0.063]	1.018	[0.421]	0.864	[0.565]	3.187	[0.003]
χ^2_{HET}	1.275	[0.257]	0.190	[0.659]	1.800	[0.179]	0.253	[0.611]	0.880	[0.345]
χ^2_{FF}	2.851	[0.096]	6.460	[0.013]	10.145	[0.002]	0.547	[0.462]	8.436	[0.005]

Note: The superscript "+" and "-" denote positive and negative cumulative sums, respectively.

L^{+} and L^{-} are the estimated long-run coefficients associated with positive and negative changes, respectively, defined by $\hat{\beta} = -\hat{\theta}/\hat{\rho}$

χ^2_{SC}, χ^2_{FF}, χ^2_{HET}, and χ^2_{NORM} denote LM tests for serial correlation, normality, functional form and Heteroscedasticity, respectively.

W_{LR} represents the Wald test for the null of long-run symmetry for respective variable.

Value in [] are p-values. S.E stands for standard errors.

* Indicate significance at 10% level, respectively.

** Indicate significance at 5% level, respectively.

*** Indicate significance at 1% level, respectively.

is used. It is worth noting that when the variables are at least integrated of order one i.e. I(I), the NARDL technique gives the fair results compared to the other cointegration techniques (Fousekis et al., 2016). Therefore, we can proceed with testing of cointegration in a nonlinear framework.

The existence of long-run asymmetric relationship emerging stock markets, gold prices, oil prices, gold price volatility and oil price volatility is ascertained using the bound testing procedure on Eq. (1). The empirical estimates of nonlinear specifications are summarized in Table 4. F_{PSS} denotes the *F*-statistic proposed by Pesaran et al. (2001) for testing the null hypothesis of no cointegration, while t_{BDM} is the *t*-statistic proposed by Banerjee et al. (1998) for testing the null of no long-run relationship. Both tests confirm the presence of nonlinear long-run relationship between stock markets and the explanatory variables.

After confirmation of cointegration among the variables, we proceed with the findings of the short-run asymmetric impact of gold prices, crude oil price and their associated volatilities on the emerging stock markets. The results summarized in the upper panel of Table 5 show that previous month shocks in stock prices have significant negative impact on the future stock prices. For gold prices, it seems that positive and negative previous month shocks have significant positive impact on prices of emerging stock markets. However, the previous month positive shocks in gold prices have more pronounced effects on stock prices of emerging markets. This finding suggests that the increase in gold prices increases the stock prices in the short-run (Baur and McDermott, 2010). In case of crude oil, both positive and negative previous month shocks have negative impact on the emerging stock markets in short-run.

The positive and negative shocks in both gold and oil volatilities have a different impact on the stock prices. Previous month's positive shock in gold volatility have a negative impact on stock prices while the previous month's positive shocks in crude oil volatility have a positive impact on stock prices of Chinese and South African stock markets. The previous month's negative shock in oil volatility has a negative impact on stock prices of India, South Africa, Malaysia, Thailand, Chile and Indonesian markets. Our findings regarding the impact of gold volatility on stock markets are in line with that of Aggarwal et al., (2014) and Mihaylov et al., (2015) suggesting that an increase in the volatility of gold market decreases stock prices in short-run. Overall, changes in gold prices (volatility) have a positive (negative) impact on the emerging stock markets. Change in crude oil prices positively impacts large BRICS stock markets and its volatility negatively impacts the India, Brazil and Thailand stock markets in the short-run.

The long-run dynamics are reported in the lower panel of Table 5. We applied the Wald test to verify the suitability of a nonlinear model and to examine the long-run asymmetries. The Wald

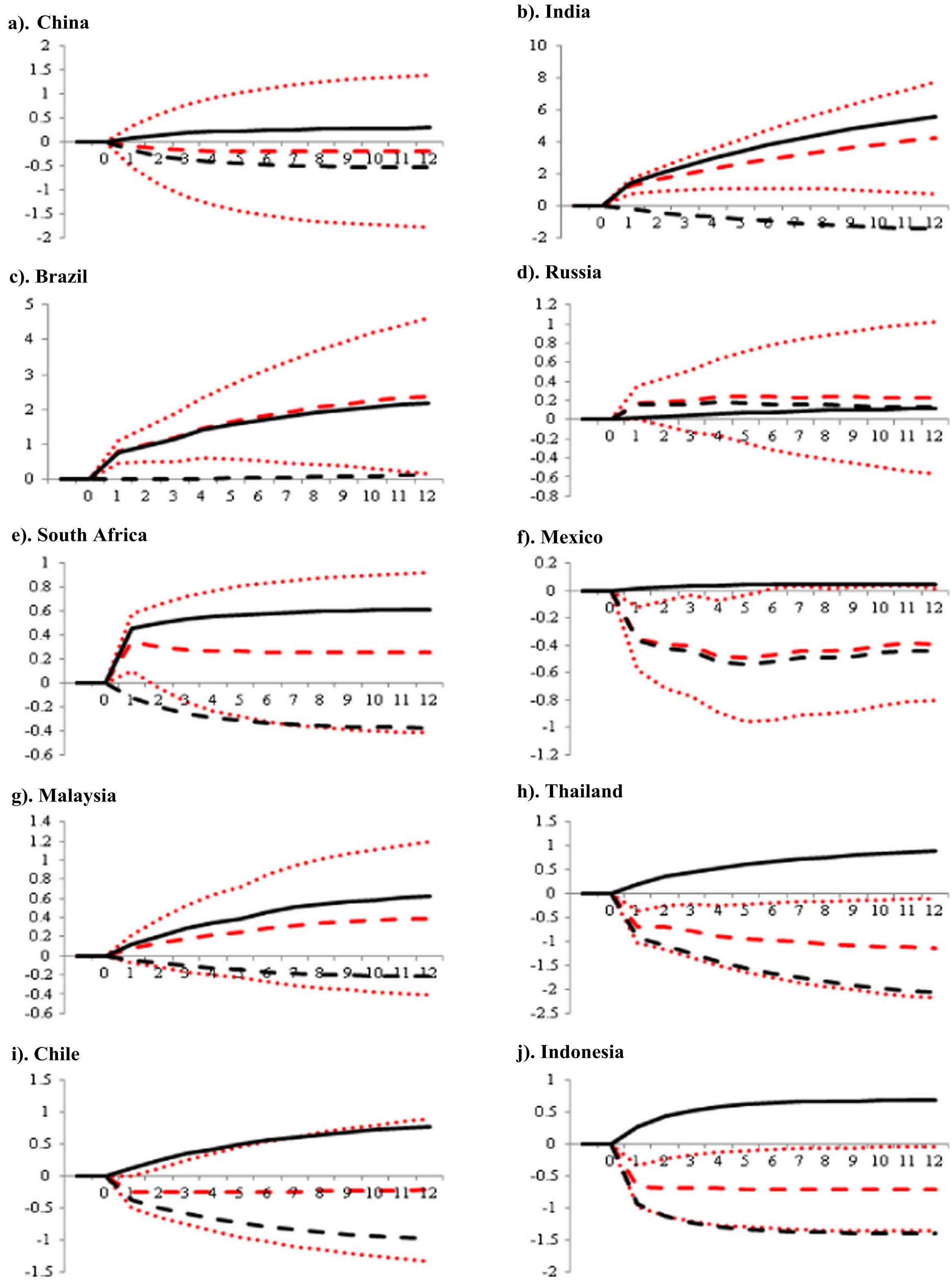

Fig. 1. Stock prices and Gold price LR and SR asymmetries. Note: Black (dotted) line show positive (negative) impact while red lines show asymmetry and confidence (upper and lower) bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

tests reject the null hypothesis of long-run symmetry of positive and negative components of all examined variables. Our finding shows that both positive and negative oil price shocks negatively impact emerging stock markets in the long-run. The increase in crude oil prices may result in an increase in the cost of production, which reduce the firms' profitability and finally decreases the stock prices in long-run. Sim and Zhou (2015) and Zhao et al. (2016) also find that oil shocks contribute towards the fluctuations in output and inflation, reduce real consumption and thereafter affect the profitability of firms.

Focusing on the estimated long-run coefficients of the asymmetric ARDL, we notice that gold price positive (LGP^{+}) and

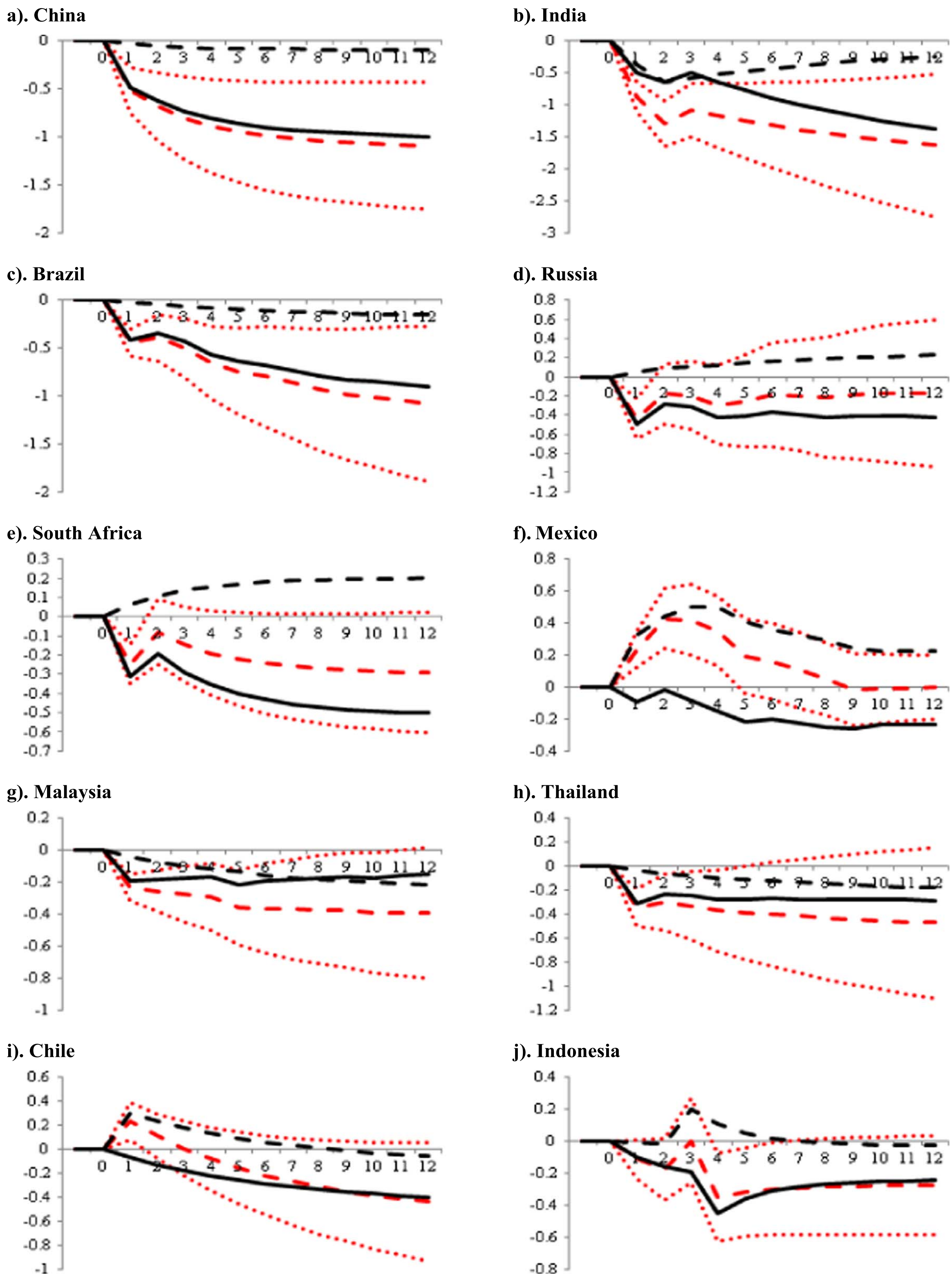

Fig. 2. Stock prices and Gold volatility LR and SR asymmetries. Note: Black (dotted) line show positive (negative) impact while red lines show asymmetry and confidence (upper and lower) bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

negative (GP^-) shocks significantly impact the emerging stock markets. Positive (negative) change in gold price increases (decreases) stock prices in the long-run. Bampinas and Panagiotidis (2015), Beckmann and Czudaj (2013), Bildirici and Turkmen (2015), Shahbaz et al. (2014) and Wang et al. (2011) among others argue that gold provides a hedge against inflation. Moreover, oil exporting countries invest their profits in gold market to maintain the commodity value which leads to significant increase in gold prices in parallel to stock prices.

The long-run coefficients of gold and oil volatilities are statistically significant (at conventional levels) and show that volatility in commodity markets decreases the stock prices in the long-run. These results, consistent with the findings of Ciner et al. (2013), Chen and Lin (2014) and Kumar (2014), indicate that commodities,

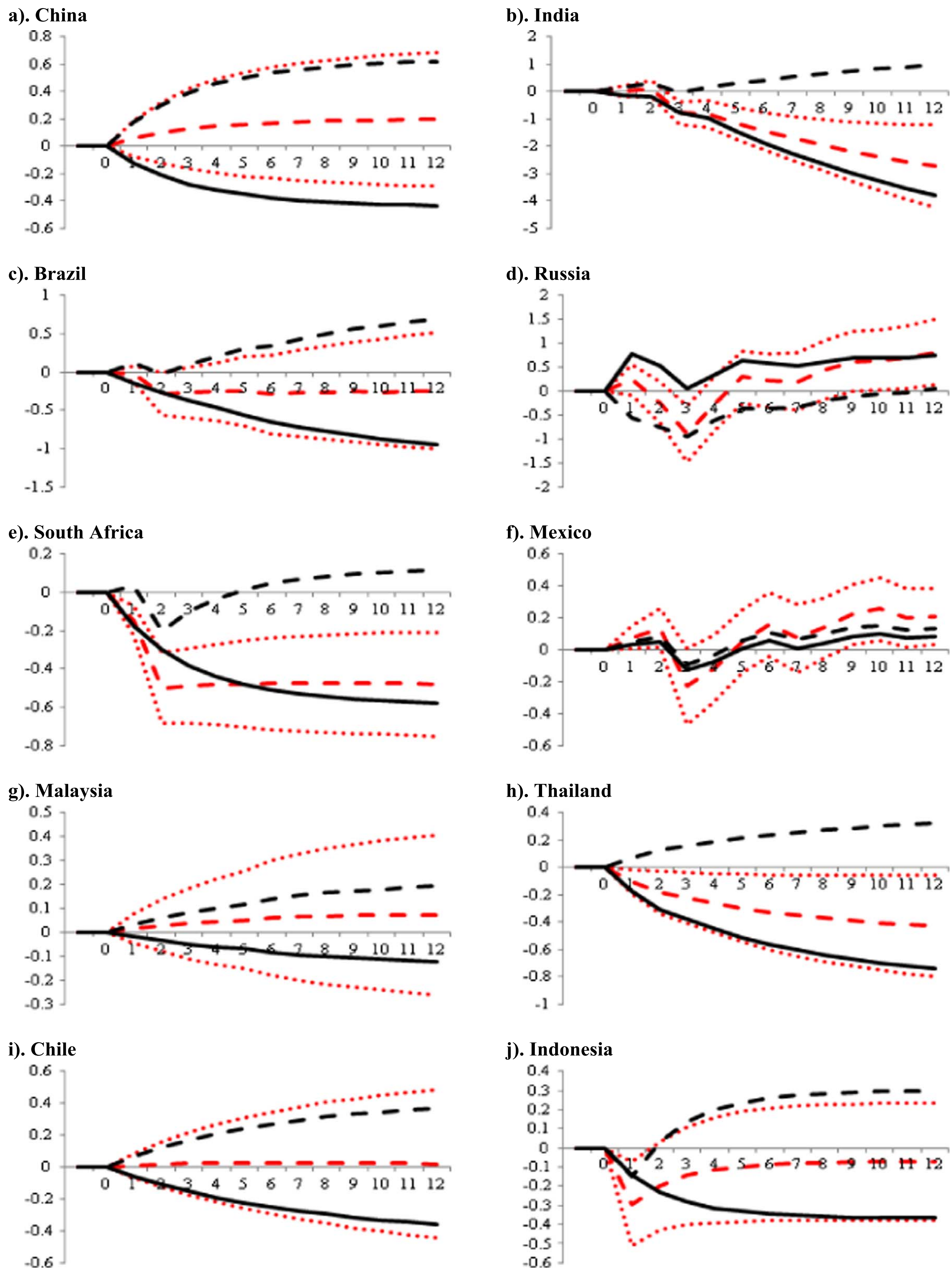

Fig. 3. Stock prices and oil price LR and SR asymmetries. Note: Black (dotted) line show positive (negative) impact while red lines show asymmetry and confidence (upper and lower) bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

especially the gold prices may reflect the future economic outlook. We argue that the gold and oil market volatilities are also of significant importance to predict/forecast the economic conditions in emerging markets. The hedging and stock market valuation decisions should incorporate the commodities volatility behavior.

Finally, the dynamic asymmetric relationship between given variables are further enriched by plotting the multipliers effects. These dynamic multipliers (see Figs. 1–4) show the adjustments of stock prices to a unit shock in gold prices, oil prices, and their associated volatilities from an initial level to their new equilibrium levels. The linear combinations of multipliers corresponding to the positive (black line) and negative (dashed black line) changes are presented through asymmetry curves. The overall asymmetry in the positive and negative shocks is presented through dashed red

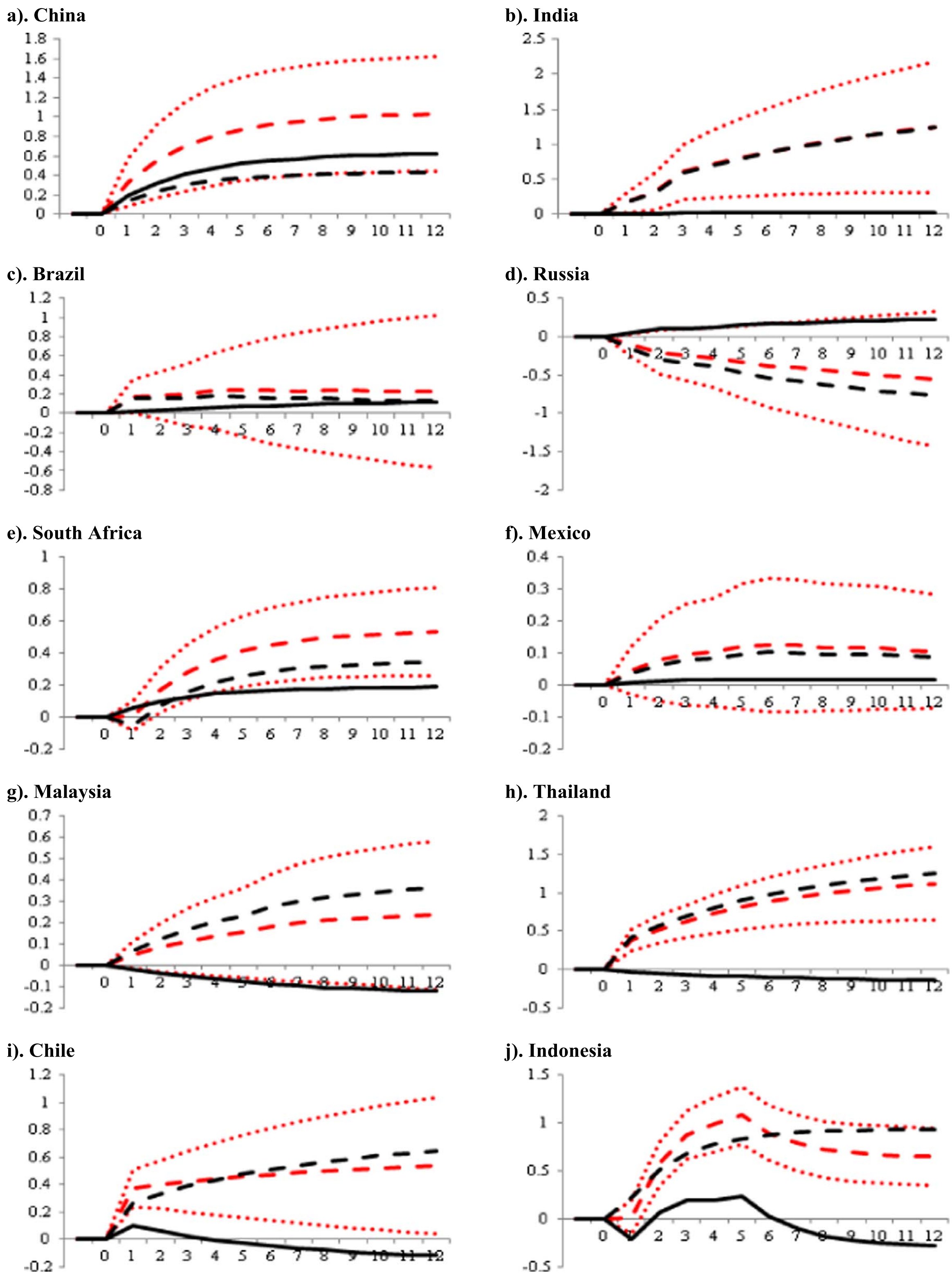

Fig. 4. Stock prices and oil volatility LR and SR asymmetries. Note: Black (dotted) line show positive (negative) impact while red lines show asymmetry and confidence (upper and lower) bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

lines and corresponding upper and lower bounds of asymmetry (at 95% confidence level) are plotted using dotted red lines.

The dynamic multipliers show that gold prices (Fig. 1) have a positive (negative) impact on large BRICS (Mexico, Malaysia, Thailand, Chile and Indonesian) stock markets. However, the gold volatility (Fig. 2) has a negative impact on all emerging stock markets except Mexico. The multiplier graphs show that the positive effects of gold volatility index are greater than the negative effect. Oil prices have a negative impact (Fig. 3) on most of the emerging stock markets except China, Mexico and Malaysia where the impact is positive. Notably, emerging stock markets respond quickly to the changes (both positive and negative) in oil prices. On the other hand, oil volatility (Fig. 4) positively impacts the emerging stock markets other than the Russian stock market. It is well clear from the multipliers figures that the impact of gold prices, oil prices and their associated volatilities are asymmetric.

As we noticed above that gold prices have a different direction of impact on returns in different countries, we will discuss now the possible explanation for it and how it can help the policy-makers of different countries when designing macroeconomic policies. It's a very well established that gold and stocks are negatively correlated. That is, if stocks go up, gold goes down and vice versa. However, one has to note that even if, both are negatively correlated at the aggregate level, this correlation may not be evident once we observe the pattern at the disaggregate level (i.e., breaking down them into individual stocks) because both react differently to changes in oil and gold prices. For example, a positive shock in oil prices may positively affect the energy stocks because of higher expected profits. Similarly, a positive shock in gold prices may positively affect Gold ETF's (Exchange Traded Fund) and banking stocks but other stocks might fall or remain stable. The evident different impact of positive and negative shocks of gold prices on returns in different countries is may be due to their currency market situations and level of economic growth, interest rate, and inflation. For example, an economy experiencing increasing inflation along with rising GDP may experience both rising gold and stocks, stocks rise on FDI infusion and gold rises because of inflation. In such an economy, a positive shock in gold prices, given that the interest rate is low, make it easy to choose gold as an alternative to bonds or stocks and other fixed-income investments, because they pay very little in income and have the risk of substantial decreases in value when rates rise and vice-versa. Further, in an economy where both interest rate and inflation are high positive (negative) shock is gold prices may negatively (positively) affect the stock market, whereas in an economy where both interest rate and inflation are low a positive (negative) shock in the gold prices may positively (negatively) affect the stock prices.

Our findings are in line with studies in existing literature such as Ewing and Malik (2013) and Tully and Lucey (2007) and expose that volatility in the gold market negatively impacts the stock prices. This finding highlights that the volatility behavior of gold markets is an essential factor and may be incorporated during investment and hedging decision making. The tradability of gold volatility index (GVX) at CBOE has significant importance for the investors to forecast the economic conditions. Our findings, consistent with Ebrahim et al. (2014), indicate that emerging stock markets are more vulnerable to bad news and events happening in the other markets such as commodities. Our findings regarding the impacts of gold prices, oil prices and their associated volatilities on stock prices of emerging markets corroborate with those of Arouri et al. (2011a, b), Chang et al. (2010), Hammoudeh and Yuan (2008), Lin et al. (2014) and Sadorsky (2014a, b) among others. However, the presence of both short- and long-run asymmetry in the relationship cast doubt on the relevance of linear and symmetric models.

5. Conclusion

In this paper, we examine the short- and long-run asymmetric impact of gold prices, oil prices and their associated volatilities on the stock prices of emerging markets. The volatility indices of gold and oil, readily tradable at the Chicago Board Option Exchange, are used to model their long-run impact on stock prices. The NARDL bounds testing approach developed by Shin et al. (2014) is utilized to determine the asymmetric cointegration among the variables.

The results indicate that the impact of gold prices, oil prices and their volatilities on stock prices are nonlinear during both short- and long-run. It is worth noting that the volatility indices of gold and oil are tradable securities differ from their prices and hence can be used to formulate different profitable strategies. The estimated results show that gold prices have a significant positive impact on stock prices while the gold volatility has a negative impact on emerging stock markets. The changes in crude oil prices show a positive impact on large BRICS stock markets. On the other hand, crude oil volatility with varying levels of coefficients negatively impacts the stock prices of India, Brazil and Thailand in the short-run. The long-run coefficients of gold and oil volatilities are also negative, indicating that higher volatility of commodity markets is a bad sign for the stock market investor and decreases the stock prices. These findings are important mainly because understanding the commodities volatility behavior can play a vital role during the valuation of derivatives and for hedging purposes. These volatility indices may also help in better forecasting of stock market trends, especially for the emerging stock markets.

Moreover, significant reactions of emerging stock markets to the changes in commodity prices and volatilities also make these markets more vulnerable to bad news/events that further contribute towards volatile and uncertain economic environment. Finally, the nonlinear cointegration analysis of gold and oil volatilities provides a better understanding of possible investment risks.

References

Aggarwal, R., Lucey, B.M., O'Connor, F.A., 2014. Rationality in precious metals forward markets: evidence of behavioural deviations in the gold markets. J. Multinatl. Financ. Manag. 25, 110–130.
An, H., Gao, X., Fang, W., Huang, X., Ding, Y., 2014. The role of fluctuating modes of autocorrelation in crude oil prices. Phys. A: Stat. Mech. Appl. 393, 382–390.
Anoruo, E., 2011. Testing for linear and nonlinear causality between crude oil price changes and stock market returns. Int. J. Econ. Sci. Appl. Res. 4 (3), 75–92.
Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2011a. Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. J. Int. Money Financ. 30 (7), 1387–1405.
Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2012. On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. Energy Econ. 34 (2), 611–617.
Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2011b. Return and volatility transmission between world oil prices and stock markets of the GCC countries. Econ. Model. 28 (4), 1815–1825.
Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2015. World gold prices and stock returns in China: insights for hedging and diversification strategies. Econ. Model. 44, 273–282.
Bampinas, G., Panagiotidis, T., 2015. Are gold and silver a hedge against inflation? A two century perspective. Int. Rev. Financ. Anal. 41, 267–276.
Basher, S.A., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: a comparison between DCC, ADCC and GO-GARCH. Energy Economics, Elsevier 54 (C), 235–247.
Banerjee, A., Dolado, J., Mestre, R., 1998. Error-correction mechanism tests for cointegration in single-equation framework. J. Time Series Anal. 19, 267–283.
Baur, D.G., 2012. Asymmetric volatility in the gold market. J. Altern. Investig. 14, 26–38.
Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? Anal. Stock. Bond. Gold Financ. Rev. 45 (2), 217–229.
Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Financ. 34 (8), 1886–1898.
Beckmann, J., Czudaj, R., 2013. Gold as an inflation hedge in a time-varying coefficient framework. N. Am. J. Econ. Financ. 24, 208–222.
Beckmann, J., Berger, T., Czudaj, R., 2015. Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. Econ. Model. 48, 16–24.
Bildirici, M.E., Turkmen, C., 2015. Nonlinear causality between oil and precious metals. Resour. Policy 46, 202–211.
Chan, K.F., Treepongkaruna, S., Brooks, R., Gray, S., 2011. Asset market linkages: evidence from financial, commodity and real estate assets. J. Bank. Financ. 35 (6), 1415–1426.
Chen, A.S., Lin, J.W., 2014. The relation between gold and stocks: an analysis of severe bear markets. Appl. Econ. Lett. 21 (3), 158–170.
Chen, W., Hamori, S., Kinkyo, T., 2014. Macroeconomic impacts of oil prices and underlying financial shocks. J. Int. Financ. Mark. Inst. Money 29, 1–12.
Chang, C.-L., McAleer, M., Tansuchat, R., 2010. Conditional correlations and volatility spillovers between crude oil and stock index returns, Discussion Paper, KIER Discussion Paper Series. Kyoto Institute of Economic Research, pp. 715–758.
Ciner, C., Gurdgiev, C., Lucey, B.M., 2013. Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates. Int. Rev. Financ. Anal. 29, 202–211.

Daskalaki, C., Skiadopoulos, G., 2011. Should investors include commodities in their portfolios after all? New evidence. J. Bank. Financ. 35 (10), 2606–2626.
Delatte, A.L., Lopez, C., 2013. Commodity and equity markets: some stylized facts from a copula approach. J. Bank. Financ. 37 (12), 5346–5356.
Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. American Statistical Association 74, 427–431.
Ebrahim, Z., Inderwildi, O.R., King, D.A., 2014. Macroeconomic impacts of oil price volatility: mitigation and resilience. Front. Energy 8 (1), 9–24.
Ewing, B.T., Malik, F., 2013. Volatility transmission between gold and oil futures under structural breaks. Int. Rev. Econ. Financ. 25, 113–121.
Fousekis, P., Katrakilidis, C., Trachanas, E., 2016. Vertical price transmission in the US beef sector: evidence from the nonlinear ARDL model. Econ. Model. 52, 499–506.
Gao, X., An, H., Fang, W., Li, H., Sun, X., 2014. The transmission of fluctuant patterns of the forex burden based on international crude oil prices. Energy 73, 380–386.
Gao, Z.K., Jin, N.D., 2012. A directed weighted complex network for characterizing chaotic dynamics from time series. Nonlinear Anal.: Real World Appl. 13 (2), 947–952.
Gao, Z.K., Yang, Y.X., Fang, P.C., Jin, N.D., Xia, C.Y., Hu, L.D., 2015. Multi-frequency complex network from time series for uncovering oil-water flow structure. Sci. Rep., 5.
Ghatak, S., Siddiki, J., 2001. The use of the ARDL approach in estimating virtual exchange rates in India. Journal of Applied Statistics, Taylor & Francis J. 28 (5), 573–583.
Goodman, B., 1956. The price of gold and international liquidity. J. Financ. 11 (1), 15–28.
Granger, C.W.J., Yoon, G., 2002. Hidden Cointegration, Royal Economic Society Annual Conference 2002 92, Royal Economic Society.
Hammoudeh, S., Yuan, Y., 2008. Metal volatility in presence of oil and interest rate shocks. Energy Econ. 30 (2), 606–620.
Huang, X., An, H., Gao, X., Hao, X., Liu, P., 2015. Multiresolution transmission of the correlation modes between bivariate time series based on complex network theory. Phys. A: Stat. Mech. Appl. 428, 493–506.
Jensen, G.R., Johnson, R.R., Mercer, J.M., 2000. Efficient use of commodity futures in diversified portfolios. J. Futur. Mark. 20 (5), 489–506.
Ji, Q., 2012. System analysis approach for the identification of factors driving crude oil prices. Comput. Ind. Eng. 63 (3), 615–625.
Kanjilal, K., Ghosh, S., 2014. Income and price elasticity of gold import demand in India: empirical evidence from threshold and ARDL bounds test cointegration. Resour. Policy 41, 135–142.
Kaufmann, T.D., Winters, R.A., 1989. The price of gold: a simple model. Resour. Policy 15 (4), 309–313.
Kumar, D., 2014. Return and volatility transmission between gold and stock sectors: application of portfolio management and hedging effectiveness. IIMB Manag. Rev. 26 (1), 5–16.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. J. Econometrics 54, 159–178.
Lee, W.C., Lin, H.N., 2012. Threshold effects in the relationships between USD and gold futures by panel smooth transition approach. Appl. Econ. Lett. 19 (11), 1065–1070.
Lin, B., Wesseh, P.K., Appiah, M.O., 2014. Oil price fluctuation, volatility spillover and the Ghanaian equity market: implication for portfolio management and hedging effectiveness. Energy Econ. 42, 172–182.
Ma, F., Wei, Y., Huang, D., Zhao, L., 2013. Cross-correlations between West Texas Intermediate crude oil and the stock markets of the BRIC. Phys. A: Stat. Mech. Appl. 392 (21), 5356–5368.
Manimaran, P., Panigrahi, P.K., Parikh, J.C., 2009. Multiresolution analysis of fluctuations in non-stationary time series through discrete wavelets. Phys. A: Stat. Mech. Appl. 388 (12), 2306–2314.
Mihaylov, G., Cheong, C.S., Zurbruegg, R., 2015. Can security analyst forecasts predict gold returns? Int. Rev. Financ. Anal. 41, 237–246.
Morana, C., 2013. Oil price dynamics, macro-finance interactions and the role of financial speculation. J. Bank. Financ. 37 (1), 206–226.
Naifar, N., Al Dohaiman, M.S., 2013. Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. Int. Rev. Econ. Financ. 27, 416–431.
Narayan, P.K., Narayan, S., 2007. Modelling oil price volatility. Energy Policy 35 (12), 6549–6553.
Narayan, P.K., Sharma, S.S., 2011. New evidence on oil price and firm returns. J. Bank. Financ. 35 (12), 3253–3262.
Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. J. Applied Econometrics 16, 289–326.
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.
Sadorsky, P., 2014a. Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. Energy Econ. 43, 72–81.
Sadorsky, P., 2014b. Modeling volatility and conditional correlations between socially responsible investments, gold and oil. Econ. Model. 38, 609–618.
Shahbaz, M., Tahir, M.I., Ali, I., Rehman, I.U., 2014. Is gold investment a hedge against inflation in Pakistan? A co-integration and causality analysis in the presence of structural breaks. N. Am. J. Econ. Financ. 28, 190–205.
Shin, Y., Yu, B., Greenwood-nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Sickles, R. C., Horrace, W.C (Eds.), Festschrift in Honor of Peter Schmidt Econometric Methods and Applications, pp. 281–314, http://dx.doi.org/10.1007/978-1-4899-8008-3.
Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. J. Bank. Financ. 55, 1–8.
Tiwari, A.K., Sahadudheen, I., 2015. Understanding the nexus between oil and gold. Resour. Policy 46, 85–91.
Tully, E., Lucey, B.M., 2007. A power GARCH examination of the gold market. Res. Int. Bus. Financ. 21 (2), 316–325.
Vacha, L., Barunik, J., 2012. Co-movement of energy commodities revisited: evidence from wavelet coherence analysis. Energy Econ. 34 (1), 241–247.
Wang, K.M., Lee, Y.M., Thi, T.B.N., 2011. Time and place where gold acts as an inflation hedge: an application of long-run and short-run threshold model. Econ. Model. 28 (3), 806–819.
Zhao, L., Zhang, X., Wang, S., Xu, S., 2016. The effects of oil price shocks on output and inflation in China. Energy Econ. 53, 101–110.