

Dynamic Causality Between Stock Return and Exchange Rate: Is Stock-Oriented Hypothesis More Relevant in Malaysia?

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Abstract In the aftermath of Lehman shock, the effect of quantitative easing policy swiftly permeated the emerging stock markets, causing substantial fluctuation in currency value of different countries. This study aims to determine whether short-term capital flow is more relevant than trade balance in affecting the exchange rate or vice versa by examining the dynamic relationship between stock return and change of Malaysian Ringgit to US Dollar (MYRUSD) as well as between stock return and change of Malaysian Ringgit to Chinese Yuan (MYRCNY). Based on daily data of July 2005–July 2015, our results show: First, in the pre-crisis period, stock returns are found to Granger cause MYRCNY and MYRUSD in mean and variance. Second, during the crisis, the causality from stock returns to MYRCNY and MYRUSD is only found in the mean. Third, in the post-crisis period, there is causality-in-mean from stock returns to MYRUSD, in addition to volatility spillover from stock returns to both MYRCNY and MYRUSD. Hence, it can be concluded that the stock-oriented hypothesis is more tenable in Malaysia, suggesting that MYRUSD is determined by the short-term capital flow. Furthermore, the forex market is informational inefficient during the post-crisis period when the stock return has predictive power over the exchange rate.

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1 Introduction

In the context of emerging market, is short-term portfolio flow more important than trade balance in determining the exchange rate? If the former prevails, the stock-oriented hypothesis dominates. If the latter prevails, the flow-oriented hypothesis is more relevant. In the aftermath of Lehman shock, the effect of quantitative easing policy swiftly permeated the emerging stock markets, causing substantial fluctuation in currency value of different countries (Koulakiotis et al. 2015). Given these tremendous changes in currency, domestic stock returns which are expressed in foreign currencies also responded asymmetrically to changes in the exchange rate (Walid et al. 2011). This asymmetric response has re-ignited the need to delve deep in how stock prices cause exchange rates and vice versa.

In 2015, Malaysia has 15.8% of its total trade with China. This percentage of share is recorded to be the highest, followed by 13% with Singapore, 8.8% with the United States (US) and 8.6% with Japan (Department of Statistics Malaysia 2016). Among the four major trading partners, Malaysia has established diplomatic relations with US and China in 1957 and 1974, respectively. Due to their significant economic and trade relations, the flow of trade, stock and exchange rate of Malaysia would be closely connected to US and China's economies. For example, several sectors particularly in manufacturing, construction and transportation are being transformed by huge and high-tech investments from China. Based on the China's Belt and Road initiative, Malaysia is able to gain opportunities from industry transformation and employment in enhancing the economic growth. Furthermore, China still buys Malaysian government bonds in line with market rules on a daily basis, giving a support to the Ringgit currency. Since the US is one of the largest foreign investors in Malaysia, the central bank of Malaysia has introduced several measures to realign the Ringgit-Dollar demand and supply levels. These measures consequently accommodate the trade between Malaysia and US in stabilizing the Ringgit performance.

Apart from the above reasons, our study only chooses two currency pairs, namely Malaysian Ringgit (MYR) to US Dollar (USD) exchange rate and MYR to Chinese Yuan (CNY) exchange rate. As shown in Fig. 1, Malaysian stock return (measured by the return of FTSE Bursa Malaysia Kuala Lumpur Composite Index, FBM KLCI) is found to exhibit several spikes in its volatility movement during the crisis period. In order to balance the demand and supply of domestic and foreign financial assets across a high volatile period, market participants amplify their portfolio hedging in order to engage in cross-border transactions and reduce the foreign exchange risk.

From the perspective of the asymmetric response to market shocks, this study addresses the following question: Does the dynamic causality between stock return and change of MYR to USD (MYRUSD) as well as between stock return and change

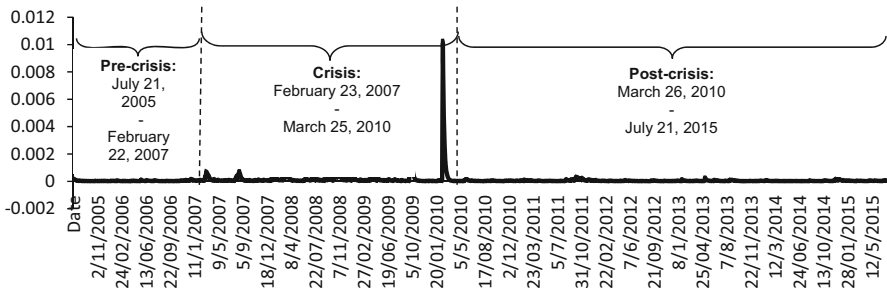


Fig. 1 Univariate conditional variance of FBM KLCI return, 2005–2015. *Source:* Authors' estimation based on MA(1)-GARCH(1,1) model of FBM KLCI return

of MYR to CNY (MYRCNY) sustain across the 2007/2009 financial crisis and tranquil periods? It would be interesting to examine whether or not stock prices and exchange rates behave differently during three sub-periods, namely the pre-crisis (July 21, 2005–February 22, 2007), crisis (February 23, 2007–March 25, 2010) and post-crisis (March 26, 2010–July 21, 2015) periods. Thus, this study concentrates on the mean (the first moment) and variance (the second moment) causalities in detecting significant relationships between stock return and change of MYRUSD as well as between stock return and change of MYRCNY.

This study is important for four reasons. First, the approach of cross-correlation function of standardized residuals and squared standardized residuals (Cheung and Ng 1996; Hong 2001) is used to obtain the response of exchange rates differentiate to shocks of stock returns. This approach can shed light on a non-linear causality between stock prices and exchange rates under low and high volatile sub-periods. The cross-correlation is modeled to detect more direct interdependence between stock prices and exchange rates along with volatility of both series.

Second, the understanding of the interdependence of both series is crucial because they play important role in the countries' economic performance (Nieh and Lee 2002; Tsai 2012). For example, an unexpected change in exchange rate will induce a change in the firms' present value through the value of the firms' expected future cash flow and cost of capital. As a result, the firms encounter difficulty in engaging cross-border transactions of financial markets. Such a performance reduces a country's international competitiveness and economic growth. In return, this economic exposure will stimulate the monetary authorities to undertake a crucial reform in the exchange rate regimes, thereby preventing the stock market from crashing and large current account deficits.

Third, it is helpful for fund managers to design their asset allocation and portfolio diversification in making decision of holding domestic or foreign equities. For example, in hedging and diversification strategies, they need to deal with the structural break in clarifying a supportive theoretical framework whether is based on the flow-oriented hypothesis or stock-oriented hypothesis. Ignoring such a structural break due to bad or good news can exaggerate the result of spillover effects (Salisu and Oloko 2015). Fourth, empirical studies on the linkages between stock return and exchange rate in emerging countries such as Malaysia are almost non-existent.

The rest of this study is organized as follows. Section two provides a review of the theoretical framework on the linkages between stock prices and exchange rates,

followed by the descriptions of data and methodology. The next section provides a discussion of the findings from empirical results. The last section concludes the study and provides inputs for policy implications.

2 Theoretical Framework: The Nexus between Stock Price and Exchange Rate

Economic theory provides various ways in explaining the interaction between stock price and exchange rate. To explain the causal direction of both series, it is worth mentioning that the empirical literature clearly offers two theoretical frameworks. The first framework is based on “flow-oriented hypothesis”. This theoretical framework hypothesizes that the exchange rate is essentially determined by a country’s current account balance or trade balance based on the following Hypothesis 1.

Hypothesis 1 There is causality from exchange rates to stock prices.

According to Hypothesis 1, the movement of exchange rates for a particular country triggers its chain of macroeconomic events through international competitiveness and trade balance mechanism, influencing its real output and hence stock market values (Dornbusch and Fischer 1980). For example, a local currency depreciation provides cheaper exports of domestic firms, leading to their greater competitiveness in the international transaction. These higher exports subsequently increase the domestic income. In turn, it appreciates the firms’ stock price since they are evaluated as the present value of the firms’ future cash flows. This hypothesis claims that the movement of exchange rates positively causes the movement of stock prices. The empirical evidence favors the flow-oriented hypothesis (see Pan et al. 2007; Chen et al. 2009; Walid et al. 2011; Boako et al. 2015; Fowowe 2015; Sui and Sun 2016). Furthermore, this hypothesis particularly holds in the export-dominated countries (Mozumder et al. 2015).

The second framework is based on “stock-oriented hypothesis” which supports the following Hypothesis 2. The hypothesis states that an increased stock price through the wealth effect tends to cause an increase in the demand for local currencies. Hence, there is an appreciation in the value of local currency.

Hypothesis 2 There is causality from stock prices to exchange rates.

The explanation to support Hypothesis 2 is the movement of stock prices in a country causes a change of domestic currencies to be in appreciation or depreciation through portfolio balance and capital mobility (Branson 1983; Frankel 1983). This hypothesis holds in the majority of developed countries (Kanas 2000; Yang and Doong 2004; Mozumder et al. 2015). However, the stock price is found to act as a lead variable in some emerging countries (Wu 2005; Mishra et al. 2007). For instance, among ASEAN-5 countries during 2000–2013, Liang et al. (2015) find evidence of portfolio balance in Malaysia, Philippines and Thailand in supporting such a hypothesis. Salisu and Oloko (2015) find the short-term volatility spillover from the stock market to foreign exchange market happens in Nigeria during 1999–2013. During the sample period of 2002–2012, Mozumder et al. (2015) find such a volatility spillover happens in the case of Ireland and Netherlands.

The influence of stock price movement on exchange rate movement is hypothesized through direct and indirect channels. The direct channel stipulates that the light of domestic stock market boom will encourage international investors to revise their portfolio selections, such that they begin to buy domestic assets and sell off foreign assets, thereby causing domestic currency values to rise (Lin 2012; Chkili and Nguyen 2014). For the indirect channel, high stock prices influence investors' decisions in demanding domestic assets to adjust their portfolio exposure. This consequently drives interest rates to be at higher levels, increasing foreign demand for domestic currency in buying new domestic assets. As a result, domestic currency tends to appreciate in values (Walid et al. 2011: 274).

However, past findings have not reached a clear consensus in demonstrating whether stock prices affect exchange rates or stock prices are affected by exchange rates. The reason is these findings remain as weak in explaining the driving forces behind such a relation especially for the periods of financial crises. The occurrence of the unexpected event causes market participants interpret the same information differently, thereby leading to the asymmetric information. Such asymmetry will break down in the tail of information flow between the two series, where one of the series becomes noisier. Subsequently, it induces the international trade flow or capital flow, reflecting a degree of maturity in financial markets. As a conclusion, a linkage between stock and foreign exchange markets depends on the maturity of financial markets (Moore and Wang 2014).

The issue of financial crises motives several researchers to dwell on dynamic causality between stock price and exchange rate. However, the directional of causality between stock return and change of exchange rate that corresponds to financial crises remains an unsettled issue as mixed findings are reported in the literature reviewed earlier. For instance, Azman-Saini et al. (2003) use the Granger causality test prescribed by Toda and Yamamoto (1995). Their evidence from Thailand indicates that the Asian financial crisis leads to causality running from exchange rates to stock prices.

By using a bivariate exponential generalized autoregressive conditional heteroscedasticity (EGARCH) and EGARCH-X, Wu (2005) compares the volatility transmission between stock and foreign exchange markets during and after the Asian financial crisis. The author finds that the spillover effect increases during the recovery period, indicating that the strength of the transmission mechanism has increased after the Asian financial crisis. This finding suggests that the impact of Asian financial crisis on the interaction of the stock and foreign exchange markets is greater for Indonesia, Japan, Philippines and Thailand. In addition, Pan et al. (2007) use a vector autoregressive (VAR) model to analyze the relationship between stock price and exchange rate in seven East Asia countries. They find mixed results for the period of pre-Asian financial crisis. During such a crisis, they further find that exchange rates significantly impact stock prices.

Based on an autoregressive distributed lag (ARDL) model, Lin (2012) takes some economic and policy events such as the market liberalization (1992–1997), 1997 Asian crisis, recovery (1999–2008) and 2008 global crisis periods into account. The finding suggests that the comovement of stock price and exchange rate for several Asian emerging markets is stronger during the crisis periods than during tranquil ones. Furthermore, Rutledge et al. (2014) find that Chinese Renminbi exchange rates and Chinese stock

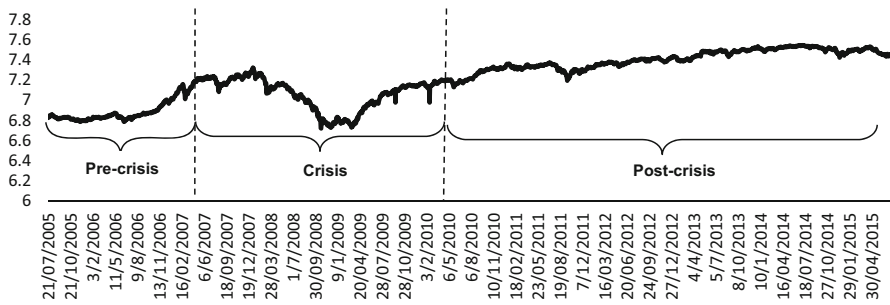


Fig. 2 Movement of ln FBM KLCI index, 2005–2015. *Source:* Bloomberg

exchange indices are cointegrated during the period of post-managed floating exchange rates. Then, they find both series exhibit a bidirectional causal effect before the global financial crisis. In the period of such a crisis, no evidence of existing the relationship and causal effect between both series is found.

Moore and Wang (2014) find that a degree of capital mobility increases in Singapore and Thailand during the period of post-financial crisis. As the result, trade balance becomes the main determinant of dynamic correlation between real exchange rate and stock price for some Asian markets. In the case of Brazil, Russia, Indian and China except for South Africa, Chkili and Nguyen (2014) use Markow switching VAR models and find that stock prices significantly affect foreign exchange rates during a high volatile period. Fowowe (2015) uses multivariate causality tests with structural breaks for the sample period of 2003–2013. The author finds that causality from exchange rates to stock prices happens in Nigeria through the “flow” channel.

Mozumder et al. (2015) find that volatility spillover effect of stock prices on exchange rates is asymmetry during the period of 2008/2009 global financial crisis. This effect indicates that good news about stock prices have a greater impact on foreign investors’ demand for local currencies as compared to bad news. They find that the direction of volatility spillover from stock prices to exchange rates happens in the developed countries, namely Ireland, the Netherlands and Spain. They further find the direction of volatility spillover is mixed in the case of Brazil, Turkey and South Africa. Among Brazil, Russia, Indian, China and South Africa (BRICS), Sui and Sun (2016) find that magnitude of the spillover effect from exchange rates to stock returns increases significantly during the period of 2007/2009 financial crisis.

3 Data

The daily data on the series of Malaysian stock price and exchange rate are sourced from the Bloomberg covering the period of July 21, 2005–July 21, 2015. The exchange rates are denominated in terms of MYR to USD and MYR to CNY. The movement of each series during the sample period is shown in Figs. 2, 3 and 4.

Based on a quick observation from Figs. 2, 3 and 4, these series exhibit a similar movement during the periods around 2008/09 global financial crisis. From April 2009 onwards when KLCI returns started to have an upward swing, the MYRUSD and

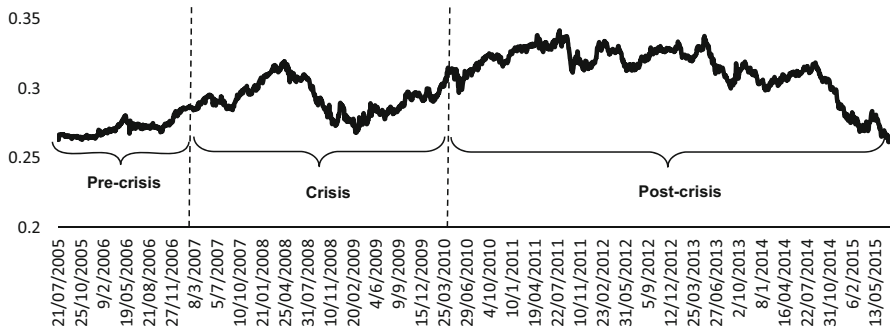


Fig. 3 Movement of currency of Malaysian Ringgit relative to US Dollar, 2005–2015. *Source:* Bloomberg

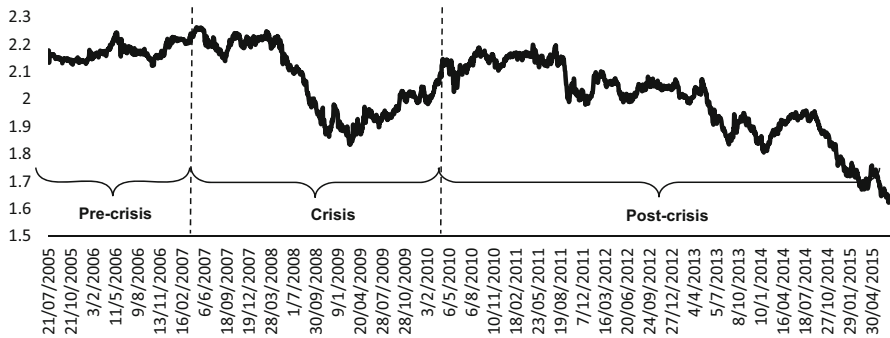


Fig. 4 Movement of currency of Malaysian Ringgit relative to Chinese Yuan Renminbi, 2005–2015. *Source:* Bloomberg

MYRCNY started to have the upward trend as well. This concurs with our reported findings in Sect. 5 that in line with the stock-oriented hypothesis, foreign players demanded domestic currency of MYR in order to invest in the stock market. Hence, this has resulted in the higher exchange rate for Malaysian Ringgit with respect to US Dollar or Renminbi. This trend was observed until 2014 when Federal Reserve was expected to end the Quantitative Easing Policy by normalizing the US interest rate. This resulted in a stronger USD relative to other currencies including MYR after 2014.

These series are transformed to be the first difference of stock price (a daily stock return, SR) and first difference of exchange rate (a daily change of exchange rate, EX) in the logarithmic form. After the first difference, the results of augmented Dickey-Fuller (Dickey and Fuller 1979) unit root test in Table 1 indicate that all series are stationary at the 1% significance level.

Before the analysis, some descriptive statistical methods are used to check the distributional characteristic of a stationary series in each sub-period. Table 2 presents the corresponding results and shows that all series are not normally distributed. As observed, the stock return is negatively skewed during the crisis period. After the crisis, a change of MYR to CNY exchange rate is positively skewed, while a change of MYR to USD exchange rate is found to be negatively skewed during the crisis period. This suggests that a change of MYR against USD is sensitive towards the global financial

Table 1 Results of ADF unit root test for daily stock return and change of exchange rate

Pre-crisis			Crisis			Post-crisis		
FBM	MYR	MYR	FBM	MYR	MYR	FBM	MYR	MYR
KLCI	CNY	USD	KLCI	CNY	USD	KLCI	CNY	USD
<i>Model with a constant</i>								
-16.83***	-22.8***	-20.63***	-32.57***	-35.89***	-34.9***	-32.43***	-23.84***	-23.1***
(0)	(1)	(1)	(0)	(0)	(0)	(0)	(2)	(2)
<i>Model with a constant and trend</i>								
-17.59***	-22.8***	-20.64***	-32.58***	-35.9***	-34.8***	-32.45***	-23.9***	-23.2***
(0)	(1)	(1)	(0)	(0)	(0)	(0)	(2)	(2)

SR denotes FBMKLCI, while EX denotes MYRCNY and MYRUSD. ADF stands for augmented Dickey-Fuller. Critical values are based on Mackinnon (1991)

***Shows the null hypothesis of "there exists a unit root" is rejected at the 1% level of significance. The optimal lag length of ADF test is reported in () as to ensure the residuals are white noise

crisis. A high excess kurtosis value indicates that all series have highly leptokurtic distribution relative to the normal distribution, which means that the volatility of both series can be modeled by GARCH-type models.

4 The Cross-Correlation Function of Standardized Residuals and Squared Standardized Residuals (CCF)

To investigate the causal relationship between stock prices and exchange rates in Malaysia, this study uses the CCF approach which is developed by Cheung and Ng (1996) and further improved by Hong (2001). There are four reasons for using such an approach. First, this approach can detect non-linear causal relationship in mean (first moment) and variance (second moment) of both stationary series (Henry et al. 2007: 123). Second, it has the ability to specify correctly the first moment dynamic (mean) and second-moment dynamic (variance). Third, it can detect significant causality of both series for a large number of observations at longer lags. Fourth, it can reveal useful information on the causality pattern (Cheung and Ng 1996: 36).

When a cross-correlation decays as the lag order increases, the test based on Cheung and Ng (1996) allocates equal weighting to each lag can be subject to severe size distortions in the presence of causality-in-mean. Furthermore, the pattern of causality-in-variance in the non-linear form cannot be detected with zero cross-correlation between innovations. To overcome this limitation, Hong (2001) develops the non-uniform weighting cross-correlations in a simulation study by providing flexible weighting scheme for cross-correlation at each lag. For example, larger weights are permitted for cross-correlations at lower order lags and otherwise. This non-uniform weighting is expected to give better power against the alternative whose cross-correlations decay to zero as the lag order increases (Hong 2001: 185). Overall, the advantage of this approach is the flexibility to specify the innovation process and provide robustness to asymmetric and leptokurtosis errors.

Table 2 Descriptive statistics for daily stock return and change of exchange rate

	Pre-crisis			Crisis			Post-crisis		
	FBM KLCI	MYR CNY	MYR USD	FBM KLCI	MYR CNY	MYR USD	FBM KLCI	MYR CNY	MYR USD
Mean	0.0008	4.76×10^{-5}	0.0002	3.78×10^{-5}	-0.0001	7.01×10^{-5}	0.0002	-0.0002	-0.0001
SD	0.0053	0.004	0.0041	0.0155	0.0054	0.005	0.0057	0.0051	0.0049
Maximum	0.0191	0.0236	0.0285	0.1602	0.0246	0.025	0.0332	0.0272	0.0272
Minimum	-0.020	-0.022	-0.0267	-0.1557	-0.03	-0.029	-0.025	-0.026	-0.026
Skewness	0.0180	-0.1986	0.1451	-0.5232	-0.2	-0.208	-0.195	0.1949	0.1894
Kurtosis	4.7069	10.0231	13.202	46.345	6.7013	6.4393	6.1334	5.5697	5.8872
Jarque-Bera	46.879	795.839	1675.96	57.650	425.02	368.06	540.86	366.48	460
<i>P</i> value***	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observation	386	386	386	736	736	736	1302	1302	1302

SR denotes FBMKLCI, while EX denotes MYRCNY and MYRUSD. *P* value is the probability value of the Jarque-Bera test statistic
 ***Shows that the null hypothesis of a normal distribution is rejected at the 1% level

We specify univariate equations for daily stock return and change of exchange rate by assuming both series are expressed as Eqs. (1) and (2).

$$SR_t = \mu_{SR,t} + \sqrt{h_{SR,t}}\varepsilon_t \tag{1}$$

$$EX_t = \mu_{EX,t} + \sqrt{h_{EX,t}}\xi_t \tag{2}$$

where SR_t and EX_t are the daily stock return and change of exchange rate at the time t , respectively; $\mu_{SR,t}$ and $\mu_{EX,t}$ are the conditional mean of SR_t and EX_t , respectively; $h_{SR,t}$ and $h_{EX,t}$ are the conditional variance of SR_t and EX_t , respectively; ε_t and ξ_t are two independent white noise processes with zero mean and unit variance.

Based on both SR_t and EX_t series, the following sets of information are defined as Eqs. (3), (4) and (5).

$$I_{SR,t} = (SR_{t-j}; j \geq 0) \tag{3}$$

$$I_{EX,t} = (EX_{t-j}; j \geq 0) \tag{4}$$

$$I_{SR,EX,t} = (SR_{t-j}, EX_{t-j}; j \geq 0) \tag{5}$$

Equation (6) indicates that a daily change of exchange rate causes a daily stock return in mean with respect to $I_{SR,EX,t-1}$. Similarly, Eq. (7) indicates that a daily stock return causes a daily change of exchange rate in mean with respect to $I_{SR,EX,t-1}$.

$$E [SR_t | I_{SR,t-1}] \neq E [SR_t | I_{SR,EX,t-1}] \tag{6}$$

$$E [EX_t | I_{EX,t-1}] \neq E [EX_t | I_{SR,EX,t-1}] \tag{7}$$

The standardized innovations for both series [obtained from Eqs. (1) and (2)] are written as follows:

$$\varepsilon_t = \frac{SR_t - \mu_{SR,t}}{\sqrt{h_{SR,t}}} \tag{8}$$

$$\xi_t = \frac{EX_t - \mu_{EX,t}}{\sqrt{h_{EX,t}}} \tag{9}$$

ε_t and ξ_t are unobservable. To test the null hypothesis of no causality-in-mean, the estimated ε_t and ξ_t are used to compute the sample cross-correlation coefficients at a lag k , $\hat{r}_{\varepsilon\xi}(k)$ by using Eq. (10).

$$\hat{r}_{\varepsilon\xi}(k) = \frac{C_{\varepsilon\xi}(k)}{\sqrt{C_{\varepsilon\varepsilon}(0) C_{\xi\xi}(0)}} \tag{10}$$

where $C_{\varepsilon\xi}(k)$ is the k th lag sample cross-covariance given by

$$C_{\varepsilon\xi}(k) = \begin{cases} T^{-1} \sum_{t=k+1}^T \hat{\varepsilon}_t \hat{\xi}_{t-k}, & k \geq 0 \\ T^{-1} \sum_{t=-k+1}^T \hat{\varepsilon}_{t+k} \hat{\xi}_t, & k < 0 \end{cases}$$

$C_{\varepsilon\varepsilon}(0)$ is the sample variance of standardized residuals for a daily stock return; and $C_{\xi\xi}(0)$ is the sample variance of standardized residuals for a daily change of exchange rate.

Based on Eq. (10), the test statistic value is computed by using Eq. (11) under the regularity condition. The null hypothesis of no causality-in-mean is rejected if the test statistic value greater than the critical value of χ^2 distribution.

$$S_1 = T \left[\sum_{i=1}^k (\hat{r}_{\varepsilon\xi}(k))^2 \right] \xrightarrow{L} \chi^2(k) \tag{11}$$

where \xrightarrow{L} denotes convergence in the distribution.

When the degree of freedom k is large, this test statistic is transformed into a standard normal distribution by subtracting the mean of k and dividing by standard deviation of $(2k)^{1/2}$ (Hong 2001: 192). As a consequence, the standardized version S_1 is written as Eq. (12).

$$M_1 = \frac{S_1 - k}{\sqrt{2k}} \xrightarrow{L} N(0, 1) \tag{12}$$

The test statistic based on Eq. (12) is compared to the upper tailed critical value of standard normal distribution. If the test statistic is greater than the critical value, then we reject the null hypothesis of no causality-in-mean.

Equation (13) indicates that a daily change of exchange rate causes a daily stock return in variance with respect to $I_{SR,EX,t-1}$, while Eq. (14) indicates that a daily stock return causes a daily change of exchange rate in variance with respect to $I_{SR,EX,t-1}$.

$$E \left[(SR_t - \mu_{SR,t})^2 | I_{SR,t-1} \right] \neq E \left[(SR_t - \mu_{SR,t})^2 | I_{SR,EX,t-1} \right] \tag{13}$$

$$E \left[(EX_t - \mu_{EX,t})^2 | I_{EX,t-1} \right] \neq E \left[(EX_t - \mu_{EX,t})^2 | I_{SR,EX,t-1} \right] \tag{14}$$

where $\mu_{SR,t}$ is the mean of daily stock return conditioned on $I_{SR,t-1}$; and $\mu_{EX,t}$ is the mean of daily change of exchange rate conditioned on $I_{EX,t-1}$.

The square of the standardized innovations for respective series [obtained from Eqs. (1) and (2)] are written as follows:

$$u_t = \frac{(SR_t - \mu_{SR,t})^2}{h_{SR,t}} \tag{15}$$

$$v_t = \frac{(EX_t - \mu_{EX,t})^2}{h_{EX,t}} \tag{16}$$

u_t and v_t are unobservable. To test the null hypothesis of no causality-in-variance, the estimated u_t and v_t are used to compute the sample cross-correlation coefficients at lag k , $\hat{r}_{uv}(k)$ by using Eq. (17).

$$\hat{r}_{uv}(k) = \frac{C_{uv}(k)}{\sqrt{C_{uv}(0)C_{uv}(0)}} \tag{17}$$

where $C_{uv}(k)$ is the k th lag sample cross-covariance given by

$$C_{uv}(k) = \begin{cases} T^{-1} \sum_{t=k+1}^T \hat{u}_t \hat{u}_{t-k}, & k \geq 0 \\ T^{-1} \sum_{t=-k+1}^T \hat{u}_{t+k} \hat{u}_t, & k < 0 \end{cases},$$

$C_{uu}(0)$ is the sample variance of squared standardized residuals for a daily stock return; and $C_{vv}(0)$ is the sample variance of squared standardized residuals for a daily change of exchange rate.

Under the regularity condition, the null hypothesis of no causality-in-variance is rejected if the test statistic value based on Eq. (18) greater than the critical value of χ^2 distribution.

$$S_2 = T \left[\sum_{i=1}^k (\hat{u}_{uv}(k))^2 \right] \xrightarrow{L} \chi^2(k) \quad (18)$$

As stated above, when the degree of freedom of k is large, Eq. (18) is transformed into a standard normal distribution by subtracting the mean of k and dividing by standard deviation of $(2k)^{1/2}$ (Hong 2001: 192). The standardized version of S_2 is written as Eq. (19).

$$M_2 = \frac{S_2 - k}{\sqrt{2k}} \xrightarrow{L} N(0, 1) \quad (19)$$

If the test statistic based on Eq. (19) is greater than the critical value of normal distribution, then we reject the null hypothesis of no causality-in-variance.

5 Empirical Results

To control for any serial dependence in both series, the lagged term of its own value and lagged term of forecasted error are included. In explaining the conditional mean of a series, the appropriate orders for autoregressive (AR) that maximize the log likelihood function are determined by using correlogram of the partial autocorrelation function (PACF). Meanwhile, the orders for moving average (MA) are determined based on correlogram of the autocorrelation function (ACF). Based on the conditional mean equation, the existence of the generalized autoregressive conditional heteroscedasticity (GARCH) effect is examined further based on the ACF and PACF correlograms on squared residuals. Furthermore, the selected model specification for each series is based on correlograms with Schwarz's information criterion (SIC).

Table 3 summarizes the parameter estimates for each selected model specification with a generalized error distribution. It is noted that majority of coefficients for ARCH and GARCH terms at a higher order are statistically significant at the 1% level. This observation provides strong evidence of volatility spillover for the series. The sum of coefficients for both terms is found to be lesser than unity, indicating that the volatility in daily stock returns and changes in the exchange rate are persistent. This implies

Table 3 Results of estimation

Conditional mean equation: $SR_t = a_0 + a_1 SR_{t-1} + b_1 \varepsilon_{SR,t-1} + \varepsilon_{SR,t}$, $\varepsilon_{SR,t} \sim GED(0, \sigma_{SR,t}^2)$
 $EX_t = a_0 + a_1 EX_{t-1} + b_1 \varepsilon_{EX,t-1} + \varepsilon_{EX,t}$, $\varepsilon_{EX,t} \sim GED(0, \sigma_{EX,t}^2)$
 Conditional variance equation: $\sigma_{SR,t}^2 = w + \alpha_1 \varepsilon_{SR,t-1}^2 + \beta_1 \sigma_{SR,t-1}^2$
 $\sigma_{EX,t}^2 = w + \alpha_1 \varepsilon_{EX,t-1}^2 + \beta_1 \sigma_{EX,t-1}^2$

Coefficients	Pre-crisis						Crisis						Post-crisis					
	FBMKLCI AR(1) -GARCH(1,1)	MYRCNY MA(1) -GARCH(1,1)	MYRUSD MA(1) -GARCH(1,1)	FBMKLCI MA(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	FBMKLCI MA(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	FBMKLCI AR(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	FBMKLCI AR(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)			
Constant (a_0)	0.0004** (0.0002)	6.42×10^{-5} (5.96×10^{-5})	0.0002** (6.84×10^{-5})	0.0003 (0.0003)	1.74×10^{-5} (0.0001)	0.0002 (0.0001)	0.0003 (0.0003)	1.74×10^{-5} (0.0001)	0.0002 (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)	-0.0001 (0.0001)	-2.89 $\times 10^{-5}$ (0.0001)			
AR(1) (a_1)	0.1440*** (0.048)	-	-	-	-0.2069*** (0.035)	-0.1772*** (0.035)	-	-0.2069*** (0.035)	-0.1772*** (0.035)	0.0716*** (0.0275)	0.0716*** (0.0275)	0.0716*** (0.0275)	-0.1212*** (0.0256)	-0.1212*** (0.0256)	-0.0604** (0.0268)			
MA(1) (b_1)	-	-0.4640*** (0.0403)	-0.4319*** (0.0405)	0.0759*** (0.0277)	-	-	0.0759*** (0.0277)	-	-	-	-	-	-	-	-			
Constant (w)	7.09×10^{-7} (6.4×10^{-7})	1.61×10^{-6} ** (7.64×10^{-7})	8.4×10^{-7} * (4.80×10^{-7})	5.01×10^{-5} *** (1.4×10^{-5})	7.9×10^{-7} ** (3.3×10^{-7})	1.1×10^{-6} ** (4.7×10^{-7})	5.01×10^{-5} *** (1.4×10^{-5})	7.9×10^{-7} ** (3.3×10^{-7})	1.1×10^{-6} ** (4.7×10^{-7})	1.7×10^{-5} *** (5.5×10^{-7})	1.7×10^{-5} *** (5.5×10^{-7})	1.7×10^{-5} *** (5.5×10^{-7})	5.8×10^{-7} ** (2.6×10^{-7})	5.8×10^{-7} ** (2.6×10^{-7})	7.43×10^{-7} ** (3.13×10^{-7})			
ARCH (α_1)	0.0791** (0.0351)	0.2377** (0.0999)	0.1560** (0.076)	0.2288** (0.0916)	0.0865*** (0.0247)	0.0992*** (0.0290)	0.2288** (0.0916)	0.0865*** (0.0247)	0.0992*** (0.0290)	0.1084*** (0.0223)	0.1084*** (0.0223)	0.1084*** (0.0223)	0.0655*** (0.0166)	0.0655*** (0.0166)	0.0709*** (0.0173)			
GARCH (β_1)	0.8975 *** (0.0505)	0.6496*** (0.1138)	0.7916*** (0.0788)	0.4647*** (0.1268)	0.8867*** (0.0271)	0.864*** (0.0344)	0.4647*** (0.1268)	0.8867*** (0.0271)	0.864*** (0.0344)	0.8387*** (0.0325)	0.8387*** (0.0325)	0.8387*** (0.0325)	0.9131*** (0.0226)	0.9131*** (0.0226)	0.8981*** (0.0257)			
Volatility persistence	0.9767	0.8873	0.9476	0.6935	0.9732	0.9633	0.6935	0.9732	0.9633	0.9471	0.9471	0.9471	0.9787	0.9787	0.969			

Table 3 continued

Conditional mean equation: $SR_t = a_0 + a_1 SR_{t-1} + b_1 \varepsilon_{SR,t-1} + \varepsilon_{SR,t}$, $\varepsilon_{SR,t} \sim GED(0, \sigma_{SR,t}^2)$
 $EX_t = a_0 + a_1 EX_{t-1} + b_1 \varepsilon_{EX,t-1} + \varepsilon_{EX,t}$, $\varepsilon_{EX,t} \sim GED(0, \sigma_{EX,t}^2)$
 Conditional variance equation: $\sigma_{SR,t}^2 = w + \alpha_1 \varepsilon_{SR,t-1}^2 + \beta_1 \sigma_{SR,t-1}^2$
 $\sigma_{EX,t}^2 = w + \alpha_1 \varepsilon_{EX,t-1}^2 + \beta_1 \sigma_{EX,t-1}^2$

Coefficients	Pre-crisis				Crisis				Post-crisis			
	FBMKLCI AR(1) -GARCH(1,1)	MYRCNY MA(1) -GARCH(1,1)	MYRUSD MA(1) -GARCH(1,1)	MYRUSD MA(1) -GARCH(1,1)	FBMKLCI MA(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	FBMKLCI AR(1) -GARCH(1,1)	MYRCNY AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)	MYRUSD AR(1) -GARCH(1,1)
Log-likelihood	1510.114	1685.059	1667.339	1667.339	2306.874	2898.929	2886.564	2886.564	5016.114	5128.276	5128.276	5171.265
SIC	-7.7520	-8.6383	-8.5465	-8.5465	-6.2149	-7.8344	-7.8007	-7.8007	-7.6781	-7.8505	-7.8505	-7.9166
$Q(20)$	28.376 [0.101]	31.264 [0.038]	31.264 [0.038]	31.264 [0.038]	6.6113 [0.996]	15.427 [0.751]	17.912 [0.593]	17.912 [0.593]	12.511 [0.897]	31.453 [0.049]	31.453 [0.049]	32.452 [0.039]
$Q^2(20)$	16.660 [0.675]	7.9742 [0.987]	7.9742 [0.987]	7.9742 [0.987]	0.8133 [1.000]	12.532 [0.897]	14.608 [0.798]	14.608 [0.798]	14.911 [0.781]	15.047 [0.774]	15.047 [0.774]	16.445 [0.689]
ARCH-LM	0.1923 [0.661]	0.1321 [0.7162]	0.1321 [0.7162]	0.1321 [0.7162]	0.0969 [0.7556]	1.4943 [0.2215]	0.664 [0.4152]	0.664 [0.4152]	1.3833 [0.2395]	0.4197 [0.5171]	0.4197 [0.5171]	0.3244 [0.569]

SR denotes FBMKLCI, while EX denotes MYRCNY and MYRUSD
 ***, **, *Indicate statistical significance at 1%, 5% and 10% level respectively. All standard errors for the estimates are reported in (). $Q(20)$ and $Q^2(20)$ denote the Ljung-Box test statistics for autocorrelation of standardized residuals and squared standardized residuals of up to 20 lags respectively. ARCH-LM stands for the Lagrange multiplier test for autoregressive conditional heteroscedasticity. All P values are reported in []

that volatility persistence for all series is stable and died out slowly. The past shocks are major drivers of volatility for both series.

For diagnostic testing, the Ljung–Box statistics for $Q(20)$ and $Q^2(20)$ are used to test the null hypothesis of no serial correlation up to order 20 for standardized residuals and squared standardized residuals, respectively. The ARCH-Lagrange Multiplier (LM) statistics are used to test the null hypothesis of no heteroskedasticity. Both test statistics for $Q^2(20)$ and ARCH-LM are well above the 5% significance level for all cases. These statistics indicate that there is no residual dependence whether in the linear or non-linear form. This supports that the selected model specifications adequately fit these data.

The next step is to obtain the standardized innovations and square of standardized innovations based on the estimated results in Table 3. Here, the CCF approach developed by Hong (2001) is conducted to test the causality-in-mean and causality-in-variance between stock return and change of exchange rate.

5.1 Causality-in-Mean Between Stock Return and Change of Exchange Rate: Pre-, during and Post-crisis

The results on causality-in-mean testing between both series are summarized in Table 4. As observed, causality-in-mean from daily stock returns to daily changes of exchange rate happens in the full sample period. This direction of causality for most of the sub-periods is found to be similar to the causality in the full sample.

During the pre-crisis period, the causality from FBMKLCI to MYRCNY is found to happen at lag equals to 5, 10, 15, 30, 35 and 40 days. During the crisis period, it happens in all lags, except for the lag of 35 days. During the post-crisis period, no evidence of causality between FBMKLCI and MYRCNY is found. The finding of no mean spillover between both series suggests that Malaysia and China are more involved in the trade related activities, hence trade flow is more prominent than capital flow.

On the contrary, the causality-in-mean from FBMKLCI to MYRUSD happens in all sub-periods at lower-and higher-order lags. During the post-crisis period, the results clearly show that the causal effect from FBMKLCI to MYRUSD for most of the lags, while the opposite direction of mean causality is only found at lag equals to 20, 25, 30, 35 and 40 days. This supports the notion that the US is still the largest foreign investor for Malaysia which provides sources of foreign direct investment to the country.

For all sub-periods, the finding of Granger causality-in-mean from daily stock returns to daily changes of exchange rate supports the “stock-oriented hypothesis”. This can be attributed to the causal effect between stock prices and exchange rates which is driven by international investment capital flows rather than trade flows. This finding is consistent with Moore and Wang (2014) and Liang et al. (2015), suggesting that financial markets in developing countries are still not mature.

Table 4 Test of causality-in-mean based on Hong's (2001) approach

		<i>k</i>	5	10	15	20	25	30	35	40
<i>Full sample period</i>										
FBMKLCI → MYRCNY	M_1	24.3010***	17.0449***	13.8235***	11.5152***	9.7008***	9.2353***	-0.6503	8.5343***	
MYRCNY → FBMKLCI	M_1	-0.2988	-0.9346	-1.3863	-0.6318	-0.4707	-0.9189	-1.3807	-0.3384	
FBMKLCI → MYRUSD	M_1	29.5005***	20.5731***	16.5052***	13.8921***	11.8440***	10.7796***	-1.3453	9.8097***	
MYRUSD → FBMKLCI	M_1	-0.3550	-0.4377	-1.1016	-0.6222	-0.3026	-0.6409	-0.8732	-0.1045	
<i>Pre-crisis</i>										
FBMKLCI → MYRCNY	M_1	2.3205**	3.0216***	2.1218**	1.2304	1.1503	1.4360*	2.6257***	3.1416***	
MYRCNY → FBMKLCI	M_1	0.2862	0.1499	0.1184	0.3499	0.2543	0.3553	-0.7588	0.0529	
FBMKLCI → MYRUSD	M_1	3.4205***	4.1857***	3.0320***	2.0238**	1.8849**	2.0588**	2.2486**	2.6169***	
MYRUSD → FBMKLCI	M_1	0.3008	-0.2221	-0.3018	-0.2190	-0.4434	-0.3804	-1.4163	-0.3811	
<i>Crisis</i>										
FBMKLCI → MYRCNY	M_1	10.73***	7.1188***	5.3536***	4.1947***	3.3537***	3.0875***	-1.5011	2.5791***	
MYRCNY → FBMKLCI	M_1	-0.4601	-0.9947	-0.8976	-1.2484	-0.9450	-1.1237	-1.4397	-1.3335	
FBMKLCI → MYRUSD	M_1	10.7204***	7.4335***	5.5774***	4.4026***	3.4298***	3.2352***	-1.4344	2.8015***	
MYRUSD → FBMKLCI	M_1	-0.9219	-1.5518	-1.9330	-2.2497	-2.3499	-2.5886	-2.8843	-3.0349	
<i>Post-crisis</i>										
FBMKLCI → MYRCNY	M_1	0.1998	-0.4104	-0.9731	-1.2074	-1.4737	-1.4932	-2.0872	-1.9996	
MYRCNY → FBMKLCI	M_1	-0.9388	-0.8663	-0.7974	-1.2074	-0.7529	0.2142	-0.2663	-0.2229	
FBMKLCI → MYRUSD	M_1	29.11670***	20.6298***	17.9734***	15.4261***	13.1280***	11.6610***	-0.0826	9.8807***	
MYRUSD → FBMKLCI	M_1	-0.5731	-0.0365	-0.1450	1.4099*	1.3338*	1.3994*	1.7701**	2.5791***	

This table shows the causality test statistic, M_1 calculated from Eq. (12). SR denotes FBMKLCI, while EX denotes MYRCNY and MYRUSD. "SR → EX" stands for FBMKLCI return Granger causes a change of exchange rate in mean with respect to $I_{SR, EX, t-k}$. "EX → SR" stands for a change of exchange rate Granger causes FBMKLCI return in mean with respect to $I_{SR, EX, t-k}$. k indicates a truncated lag number. The null hypothesis of no causality-in-mean is rejected if the test statistic greater than the upper-tailed critical value of standard normal distribution

***, **, *Indicate statistical significance at the 1%, 5% and 10% level respectively

5.2 Causality-in-Variance Between Stock Return and Change of Exchange Rate: Pre-Crisis, Crisis and Post-Crisis

This study further focuses on volatility spillover effect (the second moment) between daily stock return and change of exchange rate. This effect cannot be neglected from the analysis because it provides particularly useful insights into how information is transmitted from the stock market to the foreign exchange market and vice versa. According to Ross (1989), causality-in-variance is tested to reveal information flow or volatility spillover across different financial markets.

The results of the causality-in-variance test in Table 5 show that there is no volatility spillover between daily stock return and change of exchange rate in the full sample period. During the pre- and post-crisis periods, volatility of daily stock returns is found to cause fluctuation of daily exchange rates. This finding is in conformity with the finding of causality-in-mean test which supports the “stock-oriented hypothesis”. During the pre-crisis period, such causality from FBMKLCI to MYRCNY happens when lag equals to 10, 15, 20, 25, 30, 35 and 40 days. There is a similar finding for the causality from FBMKLCI to MYRUSD. The opposite causality from MYRCNY to FBMKLCI is found to happen at the lower-order lag of 10 days only, while causality from MYRUSD to FBMKLCI happens at lower-order lags for 10 and 15 days. This implies that a less significant relation from exchange rates to stock prices which mildly supports the “flow-oriented hypothesis”.

During the crisis period, there is no significant causality-in-variance between FBMKLCI and MYRCNY as well as between FBMKLCI and MYRUSD. One of the reasons could be there was prolonged period of crisis as bad news of the US Sub-prime Mortgage started to flow in the market in late 2007, followed by one and another event, and finally culminated in the collapse of Lehman Brothers. Hence, investors were used to the new normal and formed an expectation for the worst outcome as more and worse news unfolded themselves. Despite the effort by the US Government to bail out some of the financial institutions, the Dow Jones recorded 40% decline from January 11, 2008 to October 29, 2008.

In the aftermath of a crisis, a significant causality-in-variance from daily stock returns to daily changes of exchange rate happens in the most of lag orders. This indicates that the forex market is informational inefficient during the post-crisis period, where the volatility of stock returns has predictive power on the volatility of exchange rates. The volatility spillover from the stock market to the foreign exchange market which is found in pre-crisis period remains the same in the post-crisis period. In this regard, volatility spillover effect between stock return and change in the exchange rate is robust with the respect to the time period considered for the financial crisis as the sample period is divided into low and high volatile periods.

6 Conclusion

In this paper, the approach of cross-correlation function is used to examine the relationship between daily FBM KLCI returns and daily changes of MYRUSD as well as between daily FBM KLCI returns and daily changes of MYRCNY. For the sample

Table 5 Test of causality-in-variance based on Hong's (2001) approach

<i>k</i>	5	10	15	20	25	30	35	40
<i>Full sample period</i>								
FBMKLCI → MYRCNY	<i>M</i> ₂ - 0.0546	-1.0804	-1.1591	-1.6942	-2.1082	-1.8734	0.3091	0.3025
MYRCNY → FBMKLCI	<i>M</i> ₂ - 1.3955	-1.9422	-2.1959	-2.5392	-2.3235	-2.0881	-2.4404	-2.6138
FBMKLCI → MYRUSD	<i>M</i> ₂ - 0.1582	-1.1517	-1.2778	-1.8118	-2.2025	-2.0077	0.7805	0.7103
MYRUSD → FBMKLCI	<i>M</i> ₂ - 1.3975	-1.9604	-2.1875	-2.5174	-2.0936	-1.9573	-2.2943	-2.4525
<i>Pre-crisis</i>								
FBMKLCI → MYRCNY	<i>M</i> ₂ - 1.3138	8.3433***	6.7597***	5.2458***	4.3339***	3.5219***	4.1924***	4.5489***
MYRCNY → FBMKLCI	<i>M</i> ₂ 0.5110	1.8050**	1.0693	1.0144	0.7536	0.9957	0.6853	0.5781
FBMKLCI → MYRUSD	<i>M</i> ₂ - 1.4217	11.0015***	9.3220***	7.5434***	6.3567***	5.3689***	5.7517***	6.3012***
MYRUSD → FBMKLCI	<i>M</i> ₂ 1.0454	2.5318***	1.5062*	0.9825	0.2870	1.2087	0.6507	0.4539
<i>Crisis</i>								
FBMKLCI → MYRCNY	<i>M</i> ₂ - 0.2638	-1.0924	-1.1029	-1.5873	-2.0416	-2.4665	-3.2708	-2.9523
MYRCNY → FBMKLCI	<i>M</i> ₂ - 1.3262	-1.9249	-2.0222	-2.1741	-1.9594	-1.7803	-2.1760	-2.4049
FBMKLCI → MYRUSD	<i>M</i> ₂ - 0.4102	-1.2172	-1.4401	-1.8725	-2.2621	-2.6780	-3.4139	-3.1248
MYRUSD → FBMKLCI	<i>M</i> ₂ - 1.2916	-1.8957	-2.0301	-2.1561	-1.9948	-1.9504	-2.3202	-2.5291
<i>Post-crisis</i>								
FBMKLCI → MYRCNY	<i>M</i> ₂ 61.197***	42.3331***	33.7232***	28.5931***	25.2524***	22.7685***	-2.6058	19.4371
MYRCNY → FBMKLCI	<i>M</i> ₂ - 1.0642	-1.6468	-1.7241	-1.3525	-1.5699	0.3022	-0.2320	-0.4994
FBMKLCI → MYRUSD	<i>M</i> ₂ 17.3285***	11.6717***	8.9030***	7.4190***	6.2099***	5.2094***	-1.6438	4.1916***
MYRUSD → FBMKLCI	<i>M</i> ₂ - 0.9060	-1.6360	-1.6488	-1.0478	-0.6152	-0.8685	-1.3090	-1.6332

This table shows the causality test statistic, *M*₂ calculated from Eq. (19). SR denotes FBMKLCI, while EX denotes MYRCNY and MYRUSD. “SR → EX” stands for FBMKLCI return Granger causes a change of exchange rates in variance with respect to *I*_{SR, EX, *t*-*j*}; “EX → SR” stands for a change of exchange rate Granger causes FBMKLCI return in variance with respect to *I*_{SR, EX, *t*-*j*}. *k* indicates a truncated lag number. The null hypothesis of no causality-in-variance is rejected if the test statistic greater than the upper-tailed critical value of standard normal distribution

***, **, *Indicate statistical significance at the 1%, 5% and 10% level, respectively

period of July 2005–July 2015, such an examination is performed for the pre-crisis, crisis and post-crisis periods.

Based on our empirical results on causality-in-mean and causality-in-variance tests, there are three findings: First, in the pre-crisis period, stock returns are found to Granger cause MYRCNY and MYRUSD in mean and variance. Second, during the crisis, the causality from stock returns to MYRCNY and MYRUSD is only found in the mean. Third, in the post-crisis period, there is causality-in-mean from stock returns to MYRUSD. However, causality-in-variance or volatility spillover is found from stock returns to both MYRCNY and MYRUSD.

A general observation is that the impact of stock returns on MYRUSD appears to be significant throughout all the sub-periods. In addition, most of the spillovers in mean during the sample period can be attributable to the channel running from daily stock returns to daily changes in exchange rates. This means that the stock-oriented hypothesis is tenable in Malaysia. Towards this end, improved portfolio balances can help to stimulate the performance of the foreign exchange markets. Apart from that, this study suggests that stability of MYR especially against USD of being determined by a short-term flow of portfolio balance into the stock market across the crisis rather than trade balance.

Our findings have several important implications with respect to policy making and portfolio hedging. First, policy makers are suggested to keep the value of Malaysian currency based on the economic fundamentals rather than stock market performance. The reason is low interest rates will lead to a tremendous outflow of short-term funds to markets which offer higher interest rates. The outflow of a lot of funds (hot money) tend to affect the local currencies and the balance of payments. Second, institutional investors in the equity market are suggested to utilize information from the stock market as effective hedging instruments in making a sound decision in their currency trading, especially for Malaysian Ringgit to US Dollar exchange rate.

Our study provides small theoretical advances based on the use of CCF approach, further work can be done to obtain more insights on the dynamic causality between stock return and exchange rate. The first is to examine the sensitivity of stock returns to the appreciation or depreciation of Malaysian currency. The second is to examine the sensitivity of Malaysian currency to bad or good news in the stock market.

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