Emerging Markets Review 12 (2011) 272–292

Contents lists available at ScienceDirect

Emerging Markets Review

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

Stock market volatility and exchange rates in emerging countries: A Markov-state switching approach

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ARTICLE INFO

Article history:
Received 4 May 2010
Received in revised form 6 April 2011
Accepted 7 April 2011
Available online 19 April 2011

JEL classification:
C22
C58
F31
F47
G01
O11

Keywords:
Markov regime switching
Stock market volatility
Exchange rate changes
Time varying transition probabilities

ABSTRACT

In this paper we employ a Markov-Switching EGARCH model to investigate the dynamic linkage between stock price volatility and exchange rate changes for four emerging countries over the period 1994–2009. Results distinguish between two different regimes in both the conditional mean and the conditional variance of stock returns. The first corresponds to a high mean-low variance regime and the second regime is characterized by a low mean and a high variance. Moreover, we provide strong evidence that the relationship between stock and foreign exchange markets is regime dependent and stock-price volatility responds asymmetrically to events in the foreign exchange market. Our results demonstrate that foreign exchange rate changes have a significant impact on the probability of transition across regimes.

1. Introduction

During the last two decades, emerging countries have experienced several crises, namely the stock market crash in 1987, the Asian currency crises in July 1997, the Mexican currency crisis in 1994 and the subprime crisis of 2007–2008. These "turbulent" episodes have been characterized by large negative asset returns and high volatility and their effects have swiftly proliferated to other emerging economies. These features have greatly increased foreign exchange (FX) rates volatility and, therefore, the risk associated with international

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doi:10.1016/j.ememar.2011.04.003

portfolios: foreign stock returns expressed in domestic currency are systematically affected by FX rate movements and investment in foreign stock markets thus involves exposure to FX rate risks.

The empirical literature provides conflicting findings regarding the dynamic linkage between FX and stock markets. Early studies including Jorion (1990, 1991) suggest that FX rate changes offer little or no predictive power for stock returns volatility, whilst others (see e.g. Dumas and Solnik, 1995; Roll, 1992) claim the existence of a strong linkage between FX rate changes and stock market volatility. Mixed empirical evidence is accompanied by the lack of a theoretical consensus on the relationship between stock and FX markets. Although sophisticated econometric approaches have been implemented to research this topic, the evidence is somewhat mixed as to whether FX market volatility affects (or is affected by) stock market behavior. While empirical methodologies vary widely, these studies are generally founded on first moments in the specification of the dynamic relationship between stock prices and exchange rates and have not allowed for similar switching behavior in stock market volatility. Moreover, empirical investigations of the dynamic linkage between FX rate changes and stock markets volatility have tended to focus upon the major developed markets and only a very limited body of research is devoted to emerging stock markets. Furthermore, there is very little empirical research that investigates volatility spillovers between FX and stock markets when stock market volatility may itself switch between two or more regimes. Our study examines volatility spillovers between FX markets and equity markets in selected emerging countries using a Markov-state switching approach. More precisely, our main research questions are: 1) Is there any regime switching behavior in volatility on emerging stock markets? 2) Are there any volatility spillovers between FX and stock markets? 3) Is the impact of FX markets volatility on the stock market regime dependent?

Such empirical research may have several practical implications for traders, portfolio managers and policymakers. It can be helpful for traders in explaining the flow of information between stock and FX markets. Results may also be useful for assessing the informational efficiency of emerging stock markets. More importantly, results may provide insight into the way that FX rate volatility shocks are transmitted to stock markets and assess the degree and persistence of these innovations over time. For portfolio hedgers, it is crucial to spell out how markets are linked over time to develop an effective hedging strategy. From a financial stability perspective, the volatility transmission across the two markets is also an important consideration for policymakers.

We distinguish our study from previous studies in several ways. First of all, while previous empirical investigations of the link between FX markets and stock prices are mainly devoted to developed markets, and sometimes to Pacific Basin countries, our interest is focused on four emerging countries, namely Hong Kong, Singapore, Malaysia and Mexico that were affected by several crises. Secondly, unlike most studies in the literature that only estimate the relationship between FX rate changes and stock market return volatility for a whole period, we attempt to estimate during “good” and “bad” periods. This is made possible by using a two regime MS-EGARCH model. To the best of our knowledge, ours is the first study of emerging nations stock and FX markets to employ this model. The use of the MS-EGARCH model is motivated by at least three points: 1) This model allows the variance of stock returns to switch across different regimes. 2) The model is able to detect regime dependence in the impact, persistence and asymmetric response to shocks since the conditional variance depends on past shocks and the present and past states of the economy. 3) This model is founded on the assumption that stock returns may shift across different volatility regimes, which is linked to the diverse perceptions and reactions of FX traders and stock market participants to volatility spillovers between FX and equity markets (see e.g. Aloui and Jammazi, 2008; and Wang and Theobald, 2008).

This paper is structured as follows. Section 2 presents a brief review of theory related to the volatility spillovers between exchange rates and stock markets. Section 3 discusses previous empirical studies. Section 4 presents a preliminary analysis of the data. Section 5 details the econometric methodology used. The empirical results are reported in Section 6. Section 7 summarizes the main conclusions.

2. The linkage between FX and stock markets: background theory

Economic theory states that there are various ways in which stock and FX markets can interact. This makes empirical analysis of the interdependence of these markets so interesting. In particular, theoretical approaches have failed to reach a consensus on the existence of a link between stock prices and exchange rates or on the direction of causality. Theoretical approaches take one of two major forms: 1) the "flow-oriented" approach (e.g. Dornbush and Fisher, 1980) and 2) the "stock-oriented" approach (e.g. Branson, 1983; Frankel, 1983). In the flow-oriented approach, the exchange rate is essentially determined by a country's current account balance or trade balance. These models assume that FX rate changes affect international competitiveness and trade balance. Consequently, they affect real income and inputs. Flow-oriented models claim a positive linkage between the FX rate and stock prices. Local currency depreciation leads to a greater competitiveness of domestic firms given that their exports will be cheaper in international trade. Higher exports will increase the domestic income and hence the firms' stock prices will appreciate since they are evaluated as the present value of the firms' future cash-flows.

Under the stock-oriented approach the FX rate is determined by the demand and supply of financial assets such as equities and bonds. Broadly speaking, we can identify two types of stock-oriented models: the portfolio balance and monetary models. The portfolio balance model (see e.g. Branson and Henderson, 1985; Frankel, 1983), claims the existence of a negative linkage between stock prices and FX rates. More precisely, these models consider an internationally diversified portfolio and the function of FX rate movements in balancing the demand and supply of domestic and foreign financial assets. In this way, an increase in domestic stock price returns will produce an appreciation of the domestic currency. Two main channels (i.e. direct and indirect) are frequently referred to in the literature. The direct channel stipulates that a domestic stock price increase will encourage the international investors to revise their portfolio selection. Specifically, they will jointly buy more domestic assets and sell foreign ones in order to have domestic currency available for buying new domestic assets and, consequently, domestic currency will depreciate. The main idea of the indirect channel is that an increase in domestic stock assets will increase wealth. Demand increases amongst domestic investors leading to higher interest rates. Consequently, higher interest increases foreign demand for domestic currency, in order to buy new domestic assets, which, in turn, leads to domestic currency appreciation. Under the monetary approach, the FX rate is assimilated into financial asset prices. Seen as a value of a financial asset which is determined by the present value of anticipated cash-flows, the FX rate dynamics are determined by all the relevant macroeconomic factors affecting the anticipated value. As a result, if there are common factors affecting the two variables, stock price innovations may have an impact, or be influenced, by the FX rate's behavior.

3. FX rates and stock markets volatility: the empirical literature

3.1. Regime-switching models

Markov-switching autoregressive specifications (MS-AR) have been heavily employed in stock and FX markets studies to capture regime-switching behavior. Turner et al. (1989) and Chu et al. (1996) are the first to employ the MS-AR process. Their study was extended by Schaller and Van Norden (1997). These authors provide strong evidence of regime switching behavior in stock market returns. Hishiyima (1998) finds evidence for regime-switching behavior in volatility in the aggregate stock market returns for five developed economies. Maheu and McCurdy (2000) study US markets and also find that switching occurs between two regimes (high return-stable state and low return-volatile state). Guidolin and Timmermann (2006) use a multivariate MS-AR model to investigate volatility spillovers and regime shifts in the dynamic linkage between US equity and bond markets. Ismail and Isa (2008) use a two regime MS-AR model to capture regime-switching behavior in both the mean and the variance of the Malaysian equity market. They conclude that the MS-AR model is able to capture the timing of regime shifts occurring during the period 1974–2003 and generated by the 1974 oil shock, 1987 stock market crash and the Asian financial crisis of 1997.

Several other studies have also, applied the Markov switching autoregressive models (MS-AR) to capture sudden shifts in financial time series. Wang and Theobald (2008) implement an MS-AR model to investigate the regime switching behavior of six Asian emerging stock markets over the period 1970–2004. They conclude that there are two or three volatility states for the selected stock markets. Moreover, they find that switching between regimes is associated with international, as well as country specific, events that lead to fluctuating levels of confidence within these markets. Using a similar approach, Moore and Wang (2007) study stock returns for new EU member states. Evidence is found of regime-switching behavior in stock market volatility, with the Asian and Russian financial crises closely associated with high-volatility regimes.

Cai (1994) propose a switching AR-Markov ARCH model to describe the monthly excess returns of the three month T-bill using the period 1964–1991. Edwards and Susmel (2003) study interest-rate volatility in emerging markets. These authors employ a variant of the Hamilton and Susmel (1994) switching ARCH (SWARCH) model and find strong evidence of regime switching in the behavior of interest rate volatility in emerging markets. The same model was employed by Brunetti et al. (2008) for the Southeast Asian FX market. They distinguish between two different regimes: a "calm" regime characterized by low exchange rate changes and low volatility, and a "turbulent" regime characterized by high exchange rate devaluation and high volatility. Using a SWARCH-L model for four Latin American stock markets, Diamandis (2008) reveals the existence of more than one volatility regime, with volatility increasing significantly during crisis periods.

Other authors propose the use of more advanced econometric techniques including multivariate Markov switching models. They were concerned with two issues: 1) identifying regime shifts in stock markets and 2) assessing the relationship between financial and economic variables. Typically authors investigate the impact of crude oil volatility shocks and exchange rate movements on economic activity and business cycles. Kanas (2005) employs a Markov Switching Vector Autoregression (MS-VAR) specification to explore the linkage in volatility regimes between the Mexican currency market and six emerging equity markets. He finds evidence of interdependence between the volatility regime of the Mexican currency and the volatility regime of the equity markets and that the regime of the Mexican currency market causes the regime of some equity markets. Kanas and Kouretas (2007) examine the short-run and long-run relationship between the parallel and official markets for US dollars in Greece using a bivariate Markov Switching Vector Error Correction Model (MS-VECM).

In a more recent study, Henry (2009) employs a regime switching MS-EGARCH model in order to investigate the relationship between short term interest rates and the UK equity market. In the first regime (low mean-high volatility), the conditional variance of equity returns responds persistently but symmetrically to equity return innovations. In the second regime (high return-low volatility), equity volatility responds asymmetrically and without persistence to shocks to equity returns. A similar approach is employed by Aloui and Jammazi (2008) to investigate the effects of crude oil volatility shocks on the behavior of three developed stock markets: France, UK and Japan. Their results suggest that real stock market returns switch between two regimes. Moreover, the authors find a significant effect of crude oil shocks on stock markets and that the effect is positive during recession states of stock markets and negative during expansion states.

Mandilaras and Bird (2010) propose a Markov regime switching methodology to model movements and contagion in the foreign exchange markets of the European Monetary System. They find that most FX market correlations increase during the crisis period. Gruo et al. (2010) use a multivariate vector autoregressive model with Markov regime switching to study contagion effects among the stock market, real estate market, credit default market, and energy market during the recent financial crisis. Their model distinguishes between two regimes: a stable regime with low variance and a high-risk regime with high variance which occurs during the subprime crisis. In a similar fashion, their results demonstrate that contagion effects between markets are more pronounced during the financial crisis.

3.2. The interplay between FX markets and stock markets

The effect of FX market shocks on stock market volatility is the subject of a vast literature.[1] Phylaktis and Ravazzolo (2005) study the long-run and short-run dynamics between stock prices and exchange rates by using cointegration and multivariate Granger causality tests for some pacific basin countries. Their results indicate that stock prices and FX markets are positively linked. Aloui (2007) explores the nature of mean, volatility and causality transmission mechanisms between stock and FX markets for the United States and some major European markets for the period pre- and post-euro. Using a multivariate EGARCH model Aloui (2007) finds that movements of stock prices affect exchange rate dynamics for the two periods pre- and post-euro. However, stock markets are less influenced by exchange rates movements for the two periods.

[1] In our empirical review, we focused on a number of more recent studies. For earlier research, see Aggarwal (1981), Bahmani-Oskooe and Sohrabian (1992), Abdalla and Murinde (1997), Chiang et al. (2000), Granger et al. (2000), Nieh and Lee (2001), Hatemi-J and Roca (2005), and Pan et al. (2007).

Mun (2007) investigates the extent to which volatility and correlations in equity markets are influenced by exchange rate fluctuations during the period 1990–2003. It is found that higher FX rate variability mostly increases local stock market volatility but decreases volatility for US stock markets. Furthermore, higher exchange rate fluctuations reduce the correlation between US and local stock markets. Yang and Doong (2004) employ a multivariate EGARCH model to capture asymmetries in the volatility transmission mechanism between stock prices and exchange rates for the G7 countries over the period 1979–1999. Results obtained show that exchange rate changes have a direct impact on future changes of stock prices.

In a more recent paper, Zhao (2010) analyzes the dynamic relationship between the real effective exchange rate and the Chinese stock price, using a VAR with a multivariate GARCH model. The results show that there is no stable long run equilibrium relationship between the two financial markets. Furthermore, the paper reveals that bidirectional causality exists between volatility on the two markets. Using a copula-based approach, Ning (2010) investigates the dependence structure between the equity market and the foreign exchange market for the period pre- and post euro using the financial markets of the G5 countries (US, UK, Germany, Japan, France). Significant and positive tail dependence is found between the foreign exchange market movements and the stock market in each country for the two sub-periods. Diamandis and Drakos (2011) examine dynamic linkages between exchange rates and stock prices for Latin America countries. Their empirical results show that there is a significant long run relationship between the local stock market and the foreign exchange market but that the stability of the relationship is affected by financial and currency crises such as the Mexican currency crisis of 1994 and the 2007–2009 subprime crisis. Kutty (2010) applies a VAR model to investigate the relationship between stock and FX markets in Mexico between January 1989 and December 2006. He concludes that stock prices Granger cause exchange rates in the short run but that there is no significant relationship between these two markets in the long run. Aydemir and Demirhan (2009) find a bidirectional causal relationship between exchange rate and stock market indices in Turkey. Yau and Nieh (2009) find evidence of long term-equilibrium and asymmetric causal relationships between the exchange rate and stock prices in Taiwan and Japan.

Despite the sizeable literature that examines the relationship between stock and FX markets, studies that estimate these links using MS-GARCH and/or MS-AR models are extremely limited. Flavin et al. (2008) employ a Markov Switching approach to markets in the East Asian region and found that shocks that originate in either equity or FX markets over-spill and influence the other market during “turbulent” market conditions.

As mentioned above, our research is distinguishable from a number of previous studies. More specifically, the dynamic relationship between exchange rates and stock prices is investigated for four emerging countries: Hong Kong, Singapore, Malaysia and Mexico. From a methodological perspective, we employ a MS-EGARCH model proposed by Henry (2009).

4. Data description and preliminary analysis

The data consists of weekly closing stock market indexes denominated in local currency and exchange rates for four emerging countries, namely Hong Kong, Singapore, Malaysia and Mexico. Our choice of sample is motivated by several factors. Firstly, these countries are from two different regions, namely East-Asia and Latin America. This allows us to examine the relationship between stock and FX markets in Asia and assess the evidence for contagion between Asia and Latin America. Spillover effects from regional and global stock markets to local emerging markets, including those in Asia and Latin America, are discussed in Beirne et al. (2010). Evidence for contagion across Asian markets is found in Brana and Lahet (2010) and in Bodart and Candelon (2009). Contagion across Latin American countries, caused by the financial crises of the 1990s, is found in Ara jo (2009). Secondly, these four emerging countries have not adopted a full floating exchange rate system and have imposed some capital controls (see Diamandis and Drakos, 2011; Pan et al., 2007). Thus, examining these markets allows us gage the effect the exchange rate arrangement has upon the relationship between stock and FX markets. Thirdly, the study is intended to add to the literature on the integration between stock and FX markets in emerging countries. Fourthly, as discussed below, our sample covers various periods of crises. As reported in Fayyad and Daly (2011) such external shocks can affect the stock markets of emerging and developed countries differently.

To study the relationship between exchange rate movements and stock market volatility during bad and good times we choose data from December 1994 to March 2009. There have been frequent currency and financial crises during this period; the Mexico currency crisis in 1994, the Asian financial crisis in 1997, the Russian financial crisis in 1998 and the subprime crisis in 2007–2008. We use weekly data to avoid the problem of non-synchronous trading and short-term correlations due to noise with higher frequencies such as daily data. Low-frequency data also allow us to isolate cyclical variations and to better analyze regime shifts across time. Hamilton and Susmel (1994) suggest that Markov-switching heteroskedasticity is more appropriate for low frequency data such as weekly or monthly data. Moreover, according to Aloui and Jammazi (2008) regime switching can be detected more clearly across time using low frequency data.

The stock index series are from the ECONSTATS database. Exchange rates are extracted from the PACIFIC exchange rate database and are expressed in US dollar per local currency (direct quotation system).The stock market asset returns ($r_{i,t}$) and the rate of changes in exchange rate ($e_{i,t}$) are computed as follows:

$$r_{i,t} = 100 \times ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{1a}$$

and

$$e_{i,t} = 100 \times ln\left(\frac{f_{i,t}}{f_{i,t-1}}\right) \tag{1b}$$

where $P_{i,t}$ is the stock price index for the stock market (i) at time (t). $r_{i,t}$ is the stock market return. $f_{i,t}$ is the exchange rates of currency (i) at time (t) and $e_{i,t}$ is the rate of the exchange rate changes (nominal appreciation or depreciation).

Table 1 (Panels A and B) reports descriptive statistics for the stock index and FX rate changes time series. From these summary statistics, several traits can be identified. Firstly, Mexico has the highest mean among the four emerging stock markets, followed by Hong Kong, and Singapore. Additionally, it can be seen that the selected emerging stock markets are characterized by higher levels of volatility given that the standard deviations are significantly higher than the mean. Skewness normality tests indicate that return distributions are negatively and significantly skewed for all time series except for Malaysia. In addition, high excess kurtosis values suggest that all the stock return distributions are highly leptokurtic relative to the normal distribution. This result is confirmed by the Jarque–Berra test statistics which reject the hypothesis of normality of the stock index returns at the 1% significance level. Thirdly, the Ljung–Box statistics for testing serial correlation in the returns [$Q(36)$] and squared returns [$Q^2(36)$] series reject the null hypothesis and suggest the existence of autoregressive conditional heteroskedasticity. Fig. 2(a)–(d)

Table 1
Sample statistics for the weekly market returns and FX rate changes.

	Hong Kong	Singapore	Malaysia	Mexico
Panel A: stock returns				
Mean	0.0573	−0.0473	−0.019	0.2838
Std. dev.	3.652	3.275	3.298	3.396
Skewness	−0.508	−0.597	0.166	−0.267
Kurtosis	6.233	11.86	11.41	6.046
J-B	354.7	2468.9	2185.9	295.9
Q(36)	51.09	51.05	113.72	57.79
$Q^2(36)$	202.68	154.02	549.8	166.5
Panel B: FX rates				
Mean	0.0002	0.007	0.0497	−0.146
Std. dev.	0.075	0.651	1.036	1.592
Skewness	−1.429	0.542	2.256	2.222
Kurtosis	21.09	8.525	59.86	21.842
J-B	10356.4	978.8	100466	11571.5
Q(36)	104.64	104.3	188.16	80.37
$Q^2(36)$	250.6	601.9	415.9	146.25

Note: $\mathbf{Q}(36)$ and $\mathbf{Q}^2(36)$ are the Ljung–Box $\mathbf{Q}$-statistic for the 36th orders in the levels and squares of the returns, respectively. J–B statistic is the Jarque–Bera test for normality.

indicate volatility clustering in the series of stock returns: large (small) changes in the stock price tend to be followed by large (small) changes. These characteristics motivate the use of GARCH models to adequately describe stock return volatility dynamics. From the statistics reported in Panel B, we can see that, except for the Mexico peso, all the currencies exhibit a positive mean return or a nominal depreciation against the U.S. dollar. Malaysia suffers from the highest currency depreciation while Mexico appears to suffer the most volatile currency fluctuations during the sample period. Finally, Jarque–Berra tests indicate that we can reject the null hypothesis of normality of the FX rate changes for all countries.

Table 2 reports conventional unit root and stationarity test results for the stock and FX market time series. Three alternative tests are employed namely the Augmented Dicky and Fuller (1979) (ADF), the Phillips and Perron (1988) (PP) and Kwiatkowski et al. (1992) (KPSS) tests. From the results of the ADF and PP tests, at the 1% significance level, both stock indexes and FX rates are non-stationary but their first order differences are stationary (i.e. stock index returns and FX rate changes). Thus both sets of series are I(1). Finally, the KPSS test for the null hypothesis of level or trend stationary against the alternative of non-stationary is also applied to provide robust results. Using this test we reject the null hypothesis of stationarity in the levels of all series. However, when the first differences of each stock price index and FX rates series is taken, the KPSS test again indicates that these series are I(1).

5. Empirical framework and methodology

5.1. The univariate EGARCH specification

There are several studies including Koutmos and Booth (1995), Aloui (2007), Narayan et al. (2007) and Mun (2007) use the EGARCH model to describe the volatility of stock returns, in particular, the asymmetry

Table 2
Unit root and stationarity tests.

Country	ADF t-tests		PP t-tests		KPSS t-tests	
	t_μ	t_τ	t_μ	t_τ	η_μ	η_τ
Hong Kong						
P_{it}	−1.8509	−1.708	−2.012	−2.005	1.495	0.278
r_{it}	−26.835**	−26.856**	−26.901**	−26.915**	0.110**	0.0734**
f_{it}	−2.568	−2.833	−2.635	−3.033	1.632	0.461
e_{it}	−31.441**	−31.428**	−32.368**	−32.517**	0.1048**	0.0402**
Singapore						
P_{it}	−1.3484	−1.3301	−1.597	−1.631	0.9884	0.4055
r_{it}	−25.863**	−25.848**	−26.146**	−26.917**	0.1027**	0.1071**
f_{it}	−1.5403	−1.4277	−1.4857	−1.3718	0.7926	0.7638
e_{it}	−20.975**	−21.009**	−21.065**	−21.087**	0.2429**	0.0729**
Malaysia						
P_{it}	−1.5028	−1.708	−1.838	−1.922	0.693	0.481
r_{it}	−26.295**	−26.278**	−26.932**	−26.917**	0.069**	0.0603**
f_{it}	−2.028	−1.546	−1.916	−1.657	1.213	0.6137
e_{it}	−8.797**	−12.684**	−23.134**	−23.113**	0.219**	0.0738**
Mexico						
P_{it}	−0.7179	−1.543	−0.702	−1.5303	2.587	0.574
r_{it}	−26.289**	−26.282**	−26.311**	−26.281**	0.077**	0.070**
f_{it}	−1.0713	−2.898	−1.322	−3.0048	2.784	0.2615
e_{it}	−16.176**	−16.178**	−27.94**	−27.936**	0.2231**	0.1424**

Notes: (*) and (**) indicate significance at the 5% and 1% respectively, t_μ and t_τ are the standard augmented Dickey–Fuller (ADF) test statistics and Phillips–Perron (PP) test statistics when the relevant auxiliary regression contains a constant and a constant and trend, respectively. η_μ and η_τ are the KPSS test statistics when the relevant auxiliary regression contains a constant and a constant and trend, respectively (Kwiatkowski et al., 1992). The critical values for KPSS test at the 1% and 5% significance levels are: 0.739, 0.463 (with constant) and 0.216, 0.146 (with constant and trend).

in stock market volatility and the transmission of volatility between stock and FX markets. The EGARCH (1,1) specification proposed by Nelson (1991) can be written as follows:

$$\Phi(L)r_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, h_t) \tag{2a}$$

$$log(h_t) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{2b}$$

where ω, α, β, and δ are constant parameters. The EGARCH model presents several advantages: first of all, unlike the GARCH model which imposes the nonnegative constraints on the parameters, the EGARCH model does not impose such restrictions. Secondly, the EGARCH model can successfully capture the asymmetric volatility[2] in the stock market through the parameter δ, since this coefficient is typically negative; a negative shock (ε_t<0) generates more volatility than a positive shock (ε_t>0) of equal magnitude. In their paper, Engle and Ng (1993) examine the relation between news measured by ε_{t-1} and conditional variance h_t as the news impact curve which relates past returns shocks (i.e. news) to current volatility. With reference to Engle and Ng (1993), the news impact curve for the EGARCH model when the lagged conditional variance is evaluated at its unconditional level, can be written as:

$$h_t = \begin{cases} A.exp\left[\dfrac{\delta+\alpha}{\sigma}\varepsilon_{t-1}\right] & for\ \varepsilon_{t-1}>0 \\ A.exp\left[\dfrac{\delta-\alpha}{\sigma}\varepsilon_{t-1}\right] & for\ \varepsilon_{t-1}<0 \end{cases} \tag{3}$$

where $A = \sigma^{2\beta}exp\left[\omega-\alpha\sqrt{2/\pi}\right]$, σ is the unconditional return standard deviation. According to Eq. (3), "good news" and "bad news" have a different impact on volatility.

5.2. The MS-EGARCH specification

In this sub-section, we extend our analysis in order to investigate the dynamic linkage between stock prices and FX rates. Our main aim is to check whether FX market volatility has an impact on the stock market volatility behavior. Therefore, the Markov-Switching EGARCH framework introduced by Henry (2009) enables one not only to understand the volatility transmission between stock and FX markets but also to investigate this relationship for any state of the market. The MS-EGARCH specification can be written as:

$$\Phi(L)r_t = \mu_{i,t} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, h_{i,t}\right) \tag{4a}$$

$$log\left(h_{i,t}\right) = \omega_i + \alpha_i\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta_i log(h_{t-1}) + \delta_i\frac{\varepsilon_{i,t-1}}{\sqrt{h_{t-1}}} \tag{4b}$$

The mean and the conditional variance depend on the regime at time (t), indexed by S_t, which takes the value of 0 or 1 depending to the state of the market. S_t is assumed to be a two state Markov process with transition probability matrix $\mathbf{P}=\langle P_{ij}\rangle$, $i, j=0, 1$ where

$$p^{ij} = P\left[S_t = \frac{j}{S_{t-1}} = i\right]\ with\ \sum_{j=0}^{1} p^{ij} = 1\ for\ all\ i,j\in\{0,1\}. \tag{5}$$

[2] Engle and Ng (1993) suggest that EGARCH model differs from the standard GARCH model in two main respects. First, the EGARCH model allows good news and bad news to have a different impact on volatility, while the standard GARCH model does not. Secondly, the EGARCH model allows "big news" to have a greater impact on volatility than the standard GARCH model.

Hamilton and Susmel (1994), Cai (1994) and Henry (2009) argue that transition probabilities are initially assumed to be constant and equal to

$$P^{00} = \frac{exp\{\theta_0\}}{1 + exp\{\theta_0\}} \tag{6a}$$

and

$$p^{11} = \frac{exp\{\gamma_0\}}{1 + exp\{\gamma_0\}} \tag{6b}$$

Later, the assumption of fixed transition probability will be relaxed to examine how exchange rate changes may affect these probabilities.

5.3. The augmented MS-EGARCH specification

In order to assess the impact of FX rate changes on the mean and the variance of the stock market return, we propose an augmented MS-EGARCH framework. Formally, the augmented MS-EGARCH specification can be written as follows:

$$\Phi(L)r_t = \mu_{i,t} +_i e_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N\left(0, h_{i,t}\right) \tag{7a}$$

$$log\left(h_{i,t}\right) = \omega_i + \alpha_i\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta_i log(h_{t-1}) + \delta_i \frac{\varepsilon_{i,t-1}}{\sqrt{h_{t-1}}} + \phi_i e_{t-1} \tag{7b}$$

Brunetti et al. (2008) claim that constant transition probabilities seem over restrictive and the transition probabilities may depend on economic variables. Here, we allow the transition probabilities to depend on the FX rate changes measured by e_t. Therefore, the time transition probabilities matrix $P(t)$ can be written as follows:

$$P^{ij}(t) = P\left(s_t = \frac{j}{s_{t-1}} = i, e_{t-1}\right) = \begin{bmatrix} P_t^{00}(e_{t-1}) & 1-P_t^{11}(e_{t-1}) \\ 1-P_t^{00}(e_{t-1}) & P_t^{11}(e_{t-1}) \end{bmatrix} \tag{8}$$

Henry (2009) asserts that fluctuations in economic variables will mean that the regime-switching probabilities will vary over time. Consequently, it is possible to investigate whether FX rate changes influence the movements of the stock market and further to allow the regime-switching probabilities to change across volatility regimes. According to Filardo (1994), the transition probabilities are given by:

$$P_t^{00} = \frac{exp(\theta_0 + \theta_1 e_{t-1})}{1 + exp(\theta_0 + \theta_1 e_{t-1})} \text{ and } P_t^{11} = \frac{exp(\gamma_0 + \gamma_1 e_{t-1})}{1 + exp(\gamma_0 + \gamma_1 e_{t-1})} \tag{9}$$

It follows that

$$\frac{\partial P_t^{00}}{\partial e_{t-1}} = \theta_1 P_t^{00}\left(1-P_t^{00}\right) \text{ and } \frac{\partial P_t^{11}}{\partial e_{t-1}} = \gamma_1 P_t^{11}\left(1-P_t^{11}\right). \tag{10}$$

Following Filardo (1994), the transition probabilities are non negative and vary between zero and one, implying that signs of $\frac{\partial P_t^{00}}{\partial e_{t-1}}$ and $\frac{\partial P_t^{11}}{\partial e_{t-1}}$ are governed by the signs of θ_1 and γ_1. However, the transition probabilities are functions of θ_1, γ_1 and exchange rate changes. For $\theta_1 > 0$ a positive shock in the exchange market implies that the equity returns are more likely to stay in Regime 0 (in our case high return-low volatility). Equally, $\theta_1 < 0$ implies that the probability of switching to Regime 1 (low mean-high volatility) is more likely following a positive shock in the FX market. We note that the FX rate changes appear in each of

Eqs. (7a) and (7b), thus allowing for the possibility that, in each regime, exchange rate volatility may affect *both* the mean and the volatility of stock market returns.

6. Empirical results

6.1. The univariate EGARCH model

Before estimating the EGARCH model we specify the mean equation as an autoregressive AR(p) model. We employ the Akaike (1974) and Hannan and Quinn (1979) information criteria to determine the order of the model. Both criteria state that the appropriate autoregressive order is equal to zero for all the selected stock markets. The estimation results for the EGARCH model (Eqs. (2a) and (2b)) are displayed in Table 3.

From the results in Table 3 we see that using the Ljung–Box test we retain the null hypothesis of no serial correlation in the residuals [Q(10)] and squared residuals [$Q^2(10)$] series. Therefore, as noted above, the EGARCH model appears to successfully capture volatility clustering in the stock return series.

The estimated parameters of the variance equation are all significantly different from zero for all the selected stock markets and the model is stationary given that $|\beta|<1$. Moreover, the level of persistence in volatility is extremely high — the magnitude of the coefficient β is around 0.97. Using these results, it is possible to estimate the degree of persistence based on the half-life of a shock in the stock market, defined as

Table 3
Estimation results of univariate EGARCH(1,1) and a two regimes MS-EGARCH(1,1).

	Hong Kong		Singapore		Malaysia		Mexico	
	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH
Likelihood	−1920.6	−1919.52	−1800.7	−1755.32	−1756.2	−1734.78	−1959.9	−1938.7
LR		2.16		90.76		42.84		42.4
μ_0	0.111	0.295^{**}	−0.011	0.113	0.044	0.213^{*}	0.388^{***}	0.586^{***}
	(1.075)	(2.46)	(0.121)	(1.038)	(0.577)	(1.996)	(3.275)	(3.62)
μ_1		-0.496^{*}		-0.38^{*}		−0.506		-0.712^{*}
		(−1.76)		(−1.44)		(−1.403)		(−1.507)
ω_0	-0.083^{***}	1.356^{***}	-0.072^{***}	0.603	-0.131^{***}	0.763^{**}	-0.046^{*}	0.987^{**}
	(−2.655)	(7.15)	(−4.549)	(0.31)	(−6.398)	(2.67)	(−1.568)	(2.34)
ω_1		1.710^{***}		1.620^{***}		1.798^{***}		1.708^{***}
		(9.77)		(3.509)		(3.23)		(8.98)
α_0	0.184^{***}	−0.142	0.189^{***}	0.083^{***}	0.208^{***}	0.069^{***}	0.184^{***}	−0.101
	(5.607)	(0.18)	(7.85)	(6.328)	(7.741)	(4.10)	(5.82)	(−0.16)
α_1		0.20^{**}		0.162		0.074^{*}		0.278^{*}
		(2.64)		(1.007)		(1.94)		(2.008)
β_0	0.974^{***}	0.209	0.967^{***}	0.986^{***}	0.986^{***}	0.990^{***}	0.960^{***}	0.27^{***}
	(123.7)	(0.796)	(139.7)	(27.17)	(210.8)	(29.3)	(88.9)	(4.44)
β_1		-0.77^{***}		0.433		−0.350		0.715^{*}
		(−4.46)		(−0.15)		(−1.36)		(1.53)
δ_0	-0.087^{***}	0.897	-0.099^{***}	-0.048^{**}	-0.030^{***}	-0.029^{*}	-0.082^{***}	−0.458
	(−4.184)	(0.69)	(−7.85)	(−2.51)	(−2.669)	(−1.93)	(−4.75)	(−0.334)
δ_1		−0.88		-0.548^{***}		-0.511^{***}		0.698
		(−0.63)		(−2.694)		(−3.19)		(0.465)
θ_0		5.065^{***}		3.487^{***}		3.351^{***}		3.682^{***}
γ_0		-5.222^{***}		-3.240^{***}		-1.507^{**}		-3.477^{***}
p^{00}		0.99		0.97		0.96		0.98
p^{11}		0.98		0.96		0.82		0.97
Q(10)	10.258	8.744	16.266	16.474	20.041	26.65	12.48	10.077
	[0.593]	[0.725]	[0.179]	[0.17]	[0.066]	[0.009]	[0.408]	[0.609]
$Q^2(10)$	8.339	19.24	19.24	7.245	5.155	10.89	5.874	8.903
	[0.758]	[0.083]	[0.083]	[0.841]	[0.953]	[0.538]	[0.922]	[0.711]

Notes: Student-t statistics of parameters are reported in parentheses, (*), (**) and (***) denote significance at 10, 5 and 1% respectively. The likelihood ratio (LR) test is calculated as follows: $2\times|\mathbf{lnL}_{\mathbf{MS-EGARCH}}-\mathbf{lnL}_{\mathbf{EGARCH}}|$. The fixed transition probabilities are specified as $\mathbf{P}^{00}=\frac{\exp(\theta_0)}{1}+\exp(\theta_0)$ and $\mathbf{P}^{11}=\frac{\exp(\gamma_0)}{1}+\exp(\gamma_0)$. $\mathbf{Q}(10)$ and $\mathbf{Q}^2(10)$ is the Ljung–Box test, the null hypothesis is no serial correlations in the residuals and squared residuals at lag 10. P-value are displayed in brackets [.].

(ln(0.5)/lnβ). The volatility shocks in the stock markets for Hong Kong, Singapore, Malaysia and Mexico last on average 26, 21, 49 and 17 weeks, respectively. Moreover, the coefficient δ is significant and negative providing evidence for asymmetric behavior in the volatility. As shown by news impact curves in Fig. 1(a)–(d) a negative shock in the stock market has more impact than a positive shock of equal magnitude. Finally, the EGARCH model predicts a highest weekly return of 0.388% for Mexico, corresponding to an annual return of 20.2%, followed by Hong Kong and Malaysia, whilst the Singapore stock market exhibits the lowest return.

6.2. Identifying volatility regimes in the emerging stock markets behavior

A number of previous studies (see e.g. Aloui and Jammazi, 2008; Chen, 2007; Maheu and McCurdy, 2000; Moore and Wang, 2007; Wang and Theobald, 2008) find evidence for regime switching in stock market returns. This conclusion is supported by our empirical results. Results from the two state MS-EGARCH model are reported in Table 3. Several observations merit further discussion.

- We use a likelihood-ratio statistic to test the null hypothesis of no regime switching, represented by single EGARCH(1,1) process, against the alternative of a two-regime MS-EGARCH specification. We note that critical values for this test, two means and two variances model, are tabulated by Garcia and Perron (1996) and Garcia (1998) based on results in Davies (1987). On all markets the likelihood ratio test leads us to reject the null hypothesis of no switching at the 5% significance level.
- Results from the MS-EGARCH model identify two types of regime shifts: Regime 0 with higher mean and lower variance "bull-market" and Regime 1 with lower mean and higher variance "bear-market" (see e.g. Maheu and McCurdy, 2000, p. 103). The average returns are higher in Regime 0 and estimates of the intercept term in the conditional variance term are higher in Regime 1.
- Thirdly, the probability that a week of low volatility will be followed by a week of low volatility — the transition probability from Regime 0 to Regime 0 (p^{00}) is 0.99 for Hong Kong, 0.97 for Singapore, 0.96 for Malaysia and 0.98 for Mexico. The probability that a week of high volatility will be followed by another

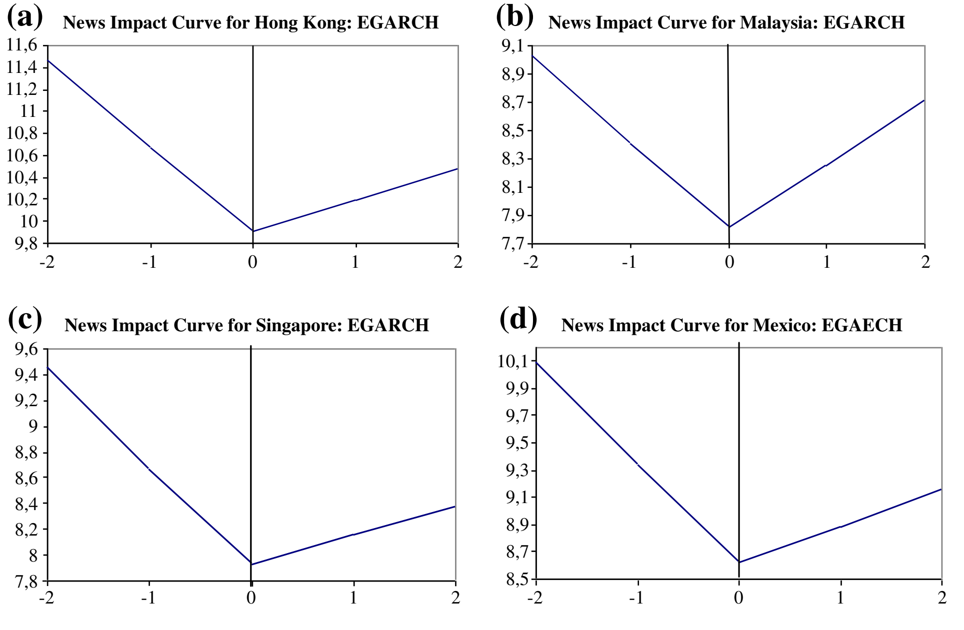

Fig. 1. (a) The news impact curve for a single regime EGARCH (Hong Kong). (b). The news impact curve for a single regime EGARCH (Malaysia). (c) The news impact curve for a single regime EGARCH (Singapore). (d) The news impact curve for a single regime EGARCH (Mexico).

week of high volatility (p^{11}) is 0.98 for Hong Kong, 0.96 for Singapore, 0.82 for Malaysia and 0.97 for Mexico. The average duration,[3] in weeks, of Regime 0 is 76.9 (Hong Kong), 33.3 (Singapore), 25 (Malaysia), and 45.4 (Mexico). Regime 1 is less persistent than Regime 0 on all the selected stock markets and the average duration ranges from 40 weeks for Hong Kong to 5.5 weeks for Malaysia. Inter alia, these figures mean that there is an unconditional probability of 0.65 that a low volatility regime occurs in Hong Kong and an unconditional probability of 0.8 that a low volatility regime occurs in Malaysia.

- As shown in Table 3, $|\alpha_1|>|\alpha_0|$ implying that any shocks arriving in Regime 1 lead to more volatility in the stock market as compared to Regime 0. Therefore, the estimated parameter β_0 is positive and significantly different from zero for all the stock markets except for Hong Kong, indicating that these shocks are persistent over time. The parameter δ_1 is negative and significantly different from zero for Singapore and Malaysia, thus showing the asymmetric reaction of markets to external shocks. Thus, in Regime 1 the market will react more sharply to "bad news" than "good news" of equal size and, given that $|\alpha_1|<|\delta_1|$, "good news" leads to a reduction in stock market volatility.

Fig. 2(a)–(d) (see left vertical panel) plot the weekly stock returns (upper series) and the conditional variance obtained from estimation of MS-EGARCH model (lower series). These weekly stock return plots indicate the presence of volatility clustering: large (small) changes in the stock prices index tend to be followed by large (small) changes by either sign. These plots also highlight the way in which the conditional variance switches between high and low states. The right vertical panel provides the smoothed probabilities of Regime 0 "bull market" generated from the two-state MS-EGARCH(1,1) model.

Low values of this variable thus indicate periods of crisis. Several weeks of the sample are characterized by high volatility and this "can be attributed to several economic and political events that took place in the emerging markets during the period under investigation" (Kanas and Kouretas, 2007, p.442). We follow the literature standard (see e.g. Aloui and Jammazi, 2008; Diamandis, 2008; Hamilton, 1989, 1996; Kanas and Kouretas, 2007) in classifying the regime switches. The market is assessed as being in Regime i if the smoothed probability $P_i(s_t=i)$ is higher than 0.5. Table 4 lists the observed regime switches.

Fig. 2(a)–(d) (right Panel) and Table 4 show that there are common regime-switching patterns in the selected markets. Results show that periods of high volatility generally coincide for all three Asian countries. More specifically, the stock returns of Hong Kong exhibit a first period of high volatility with a fall in returns during the Mexican currency crisis that took place in late 1994. This result is in line with Kanas (2005) who found evidence of regime dependence between the Mexican currency market and the volatility of some Asian emerging markets. MS-EGARCH estimates show that all three markets entered the high volatility regime and recession phase in the last week of 1994 and stayed in this regime for on average 16 weeks. Stock returns of the Asian countries then moved again to the high volatility regime in October 1997 corresponding to the Asian currency crisis. These results corroborate with the conclusions of Tai (2007), namely a significant impact of the Asian crisis upon the conditional variance for Asian emerging markets and some financial contagion occurring across emerging countries. In addition, Fig. 2(a)–(c) indicate that Hong Kong, Singapore and Malaysia remained in a high-volatility regime after October 1997, a period which encapsulates the Russian crisis in the summer of 1998 and the Brazilian crisis of 1999. There is also a significant increase in stock market volatility in late 2001 as a result of the 9/11 terrorist attack. This event affects all the Asian stock markets and a spell of high volatility remains for around 23 weeks in Hong Kong and Singapore and 12 weeks in Malaysia. Ismail and Isa (2008) claim that the 2001 falls in the Malaysian stock market are as a result of the economic downturn in the US because the US was Malaysia main trade partner. Finally, we observe that the Asian markets switch to a regime of high volatility in mid 2007, an event which may be attributed to the subprime crisis in the US.

Results for Mexico (see Fig. 2(d)) highlight a high volatility state that extends from late 1994 through much of 1995. This period corresponds to domestic event when the Mexican peso crisis took place. The Mexican stock market next shifts to a high volatility regime between October and December 1997. This period is associated with the Asian financial crisis and suggests that financial instability has been rapidly transmitted through emerging economies. In addition, Fig. 2(d) suggests that Mexico also shifts to a high-volatility regime during the Russian crisis and following the terrorist attack of September, 11 2001. A

[3] The average duration of regime (j) is computed as follows: $D=\frac{1}{1-P^{jj}}$, $j=0,1$.

further high-volatility regime on the Mexican stock market occurs in 2002 and appears linked to the Argentinean crisis of 2002. In contrast, however, it seems more difficult to attribute the high volatility state detected mid 2006 and early 2007 to external events. Overall, these results indicate that the Mexican stock market moved to a high-volatility regime not only during internal crises such as the Mexican currency crisis but also during other major international crises such as the US subprime crisis.

6.3. FX volatility spillover effects

In light of the previous analysis showing the existence of a two-state volatility regime in emerging stock markets, it is of interest to determine the impact of FX market volatility upon the regime-switching transition probabilities. We employ an extended MS-EGARCH specification to investigate. Maximum likelihood estimates of the extended MS-EGARCH model are shown in Table 5. In the mean equation he estimated coefficient of the FX rate changes has a negative sign and is statistically significant at the 1% level for all markets. Thus, FX market volatility reduces stock market returns. There are a number of reasons for this negative effect. The most important reason is that any change in the FX rate may reduce the firm's profitability and hence its equity market value. It is well documented that FX rate volatility has a negative impact on international trade, country's competitiveness and trade balance. In this way, it may have a negative impact on real income and economic growth. Consequently, it may have a negative impact on the current and future cash-flows of the domestic firms and in turn their stock prices. Our result is in line with a number of previous studies including Aloui (2007) and Yang and Doong (2004). In Yang and Doong (2004), FX rate currency depreciation may have, in the short-run, a negative effect on the stock market. Explicitly, it is well known that the domestic counterpart of currency depreciation is inflation which in turn may wield a dampening effect on the stock market. Purchasing power parity theory dictates that higher domestic inflation leads to local currency depreciation, thus encouraging foreign investors to reduce their portfolios of domestic assets and leading to falls in the stock market (Yang and Doong, 2004, p. 147).

Results for the variance equation, see Table 5, indicate that all the EGARCH coefficients are statistically significant. In particular, we find evidence for the asymmetric volatility of stock market returns. The parameter δ is negative for all the selected markets indicating that a negative shock generates more volatility then a positive shock of the same magnitude. Moreover, the parameter $\varnothing$ measuring the volatility spillover from the FX market to the stock market is positively and statistically significant for all the emerging countries, with the exception of Hong Kong. Thus, we have evidence for volatility spillovers between the two markets with an increase in FX market volatility leading to an increase in stock market volatility. This finding is in line with previous research — see e.g. Mishara et al. (2007) who studied the Indian stock market.

The likelihood ratio test indicates that the augmented MS-EGARCH model offers a significant improvement over a simple EGARCH model incorporating the exchange rate changes. We reject the null hypothesis of no regime switching in the relationship between FX rate changes and stock returns volatility at the 5% level. Results of the extended MS-EGARCH are similar to earlier results in that we can identify two regimes: Regime 0 (high mean-low variance) and Regime 1 (low mean high-variance). From these results, we see that the estimated coefficient of the FX rate changes in the mean equation is significantly different from zero for all countries in Regime 0, whilst we retain the same hypothesis in Regime 1 for all countries except for Singapore. This result implies that events in the FX market have a statistically significant impact upon the conditional mean of r_t during periods of low volatility.

In the conditional variance equation all the estimated coefficients of the FX rate changes are statistically significantly different from zero for all countries. We note that this impact is negative in Regime 0 and positive in Regime 1. Moreover, parameter estimates indicate that the relationship between the conditional volatility of r_t and changes in the FX market is state contingent: $|\varnothing_1|>|\varnothing_0|$ for all countries except for Singapore, implying that in a regime of high volatility the positive effect of FX rate changes on stock returns volatility is much stronger than its negative effect in a calm regime. This result tallies with some previous research, see e.g. Aloui (2007), Yang and Doong (2004) and Kanas (2000), reporting an

Fig. 2. (a)–(d) Left vertical axis: weekly stock return (upper panel) and the MS-EGARCH conditional variance (lower panel). Right vertical axis: the smooth probabilities from the MS-EGARCH specification.

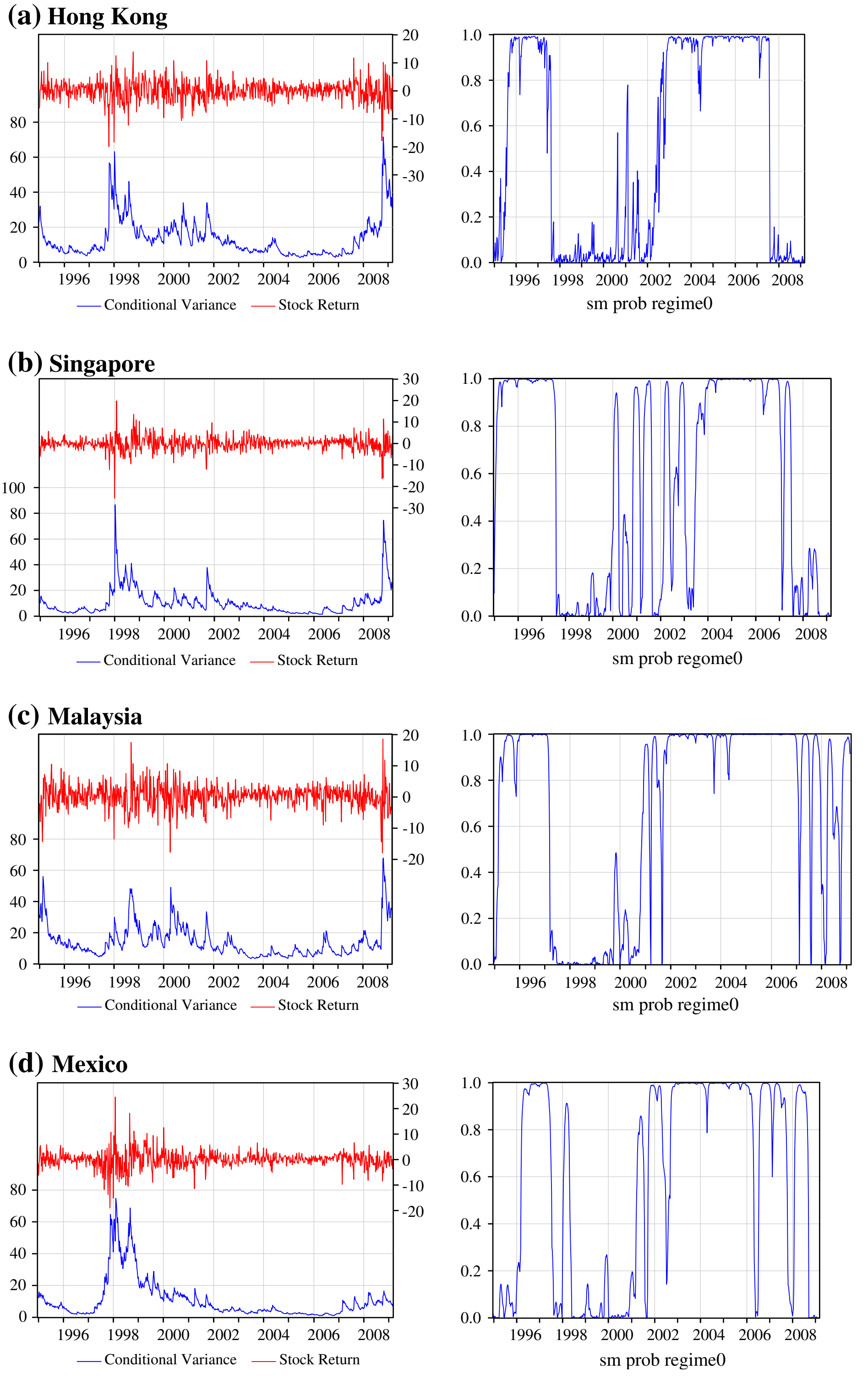
(a) Hong Kong
Conditional Variance
Stock Return
sm prob regime0
(b) Singapore
Conditional Variance
Stock Return
sm prob regome0
(c) Malaysia
Conditional Variance
Stock Return
sm prob regime0
(d) Mexico
Conditional Variance
Stock Return
sm prob regime0

Table 4
Duration of regime 0 and 1.

Country	Regime 0 (high mean-low variance)	Regime 1 (low mean-high variance)
Hong Kong	1995:20–1997:19	1994:52–1995:19
	1997:25–1997:39	1997:20–1997:24
	2000:21–2000:35	1997:40–2000:20
	2001:04–2001:07	2000:36–2001:03
	2001:20–2001:21	2001:08–2001:19
	2001:30–2001:35	2001:22–2001:29
	2002:33–2002:36	2001:36–2002:32
	2002:47–2007:30	2002:37–2002:46
		2007:31–2009:11
Singapore	1995:15–1997:35	1994:52–1995:14
	1999:49–2000:14	1997:36–1999:48
	2000:25–2000:32	2000:15–2000:24
	2000:45–2001:07	2000:33–2000:44
	2001:18–2001:35	2001:08–2001:17
	2002:11–2002:21	2001:36–2002:10
	2002:42–2003:03	2002:22–2002:41
	2003:39–2006:52	2003:04–2003:38
	2007:16–2007:30	2007:01–2007:15
		2007:31–2009:11
Malaysia	1995:17–1997:25	1994:52–1995:16
	1999:43–2000:01	1997:26–1999:42
	2000:50–2001:08	2000:02–2000:49
	2001:17–2001:35	2001:09–2001:16
	2001:41–2007:01	2001:36–2001:40
	2007:13–2007:29	2007:02–2007:12
	2007:36–2007:51	2007:30–2007:35
	2008:13–2008:28	2007:52–2008:14
	2008:46–2009:11	2008:29–2008:45
Mexico	1996:11–1997:31	1994:52–1996:10
	1998:05–1998:17	1997:32–1998:04
	1999:04–2000:03	1998:18–1999:03
	2001:12–2001:35	2000:04–2001:11
	2001:41–2002:20	2001:36–2001:40
	2002:45–2006:14	2002:21–2002:44
	2006:32–2007:05	2006:15–2006:31
	2007:12–2007:37	2007:06–2007:11
	2008:10–2008:35	2007:38–2008:09
		2008:36–2009:11

Notes: Regime chronology according to MS-EGARCH for emerging stock markets. Stock market classified as being in Regime 0 if the smoothed probability $\mathbf{P}^{00} > 0.5$ and being in Regime 1 if the smoothed probability $\mathbf{P}^{11} > 0.5$.

asymmetric response in the stock market to exchange rate shocks. The results thus show that events in the FX market significantly increase stock market volatility during “turbulent” periods. Similar findings are presented in Kanas (2000) and Flavin et al. (2008). The dynamic linkage between FX rate changes and stock market prices and volatility, according to the state of the market is shown in Fig. 3(a) and (b).

The relationship between stock market behavior and FX rate changes is depicted in Fig. 4(a)–(d). The figures jointly display the smoothed probability of Regime 1 (low mean-high volatility) for stock returns and FX rate movements. The FX rate changes clearly exhibit volatility clustering. Further, these graphs also show that clusters of extreme values in the FX rates changes can be clearly identified with a high probability of being in a “turbulent” stock market regime.

Also, we can observe that the time-varying transition probability is function of innovations in the exchange market. As shown in Table 5, θ_1 is negative and γ_1 is positive and statistically significant. Positive values of γ_1 imply that a positive shock in the FX market increases the probability ($P_t^{11}(e_{t-1})$) of staying in Regime 1 (low mean-high volatility). Similarly, since $\theta_1 < 0$ a negative shock increases the probability of switching to a calmer stock market regime. Fig. 5(a)–(d) plot the values of P^{00} and P^{11} implied by changes

Table 5
Relationship between exchange rate changes and stock markets volatility from fitted EGARCH and augmented MS-EGARCH models.

	Hong Kong		Singapore		Malaysia		Mexico	
	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH	EGARCH	MS-EGARCH
Likelihood	−1912.05	−1892.17	−1752.64	−1746.1	−1712.5	−1705.35	−1905.48	−1893.56
LR		39.76		13.08		14.3		23.84
μ_0	0.122	0.321***	0.074	0.138*	0.093*	0.287***	0.346***	0.623***
	(1.165)	(2.837)	(0.94)	(1.56)	(1.302)	(5.705)	(3.207)	(2.846)
μ_1		−0.387		−0.255		−0.406**		−0.753**
		(−1.428)		(−0.848)		(−2.289)		(−2.02)
η_0	−6.83***	−4.406***	−0.736***	−0.575***	−0.965***	−1.099***	−0.972***	−0.786***
	(−4.75)	(−8.11)	(−5.13)	(−3.03)	(−7.01)	(−25.7)	(−10.07)	(−3.86)
η_1		−1.066		−1.156***		0.083		−0.371
		(−0.391)		(−2.299)		(0.387)		(−1.018)
ω_0	−0.091**	1.08***	−0.096***	0.894**	−0.10***	0.101	−0.034	0.913***
	(−2.51)	(2.334)	(−3.25)	(2.11)	(−3.45)	(0.449)	(−1.14)	(2.17)
ω_1		3.771*		2.237***		0.623		1.784***
		(1.522)		(3.74)		(0.997)		(3.197)
α_0	0.192***	0.078***	0.181***	0.214***	0.153***	0.108**	0.143***	0.179***
	(−5.19)	(2.926)	(4.33)	(2.927)	(4.15)	(2.22)	(3.93)	(2.83)
α_1		−0.044		0.158		0.091***		0.150
		(−1.14)		(0.828)		(3.134)		(1.17)
β_0	0.974***	0.974***	0.978***	0.99***	0.989***	0.919***	0.966***	0.626*
	(12.35)	(5.43)	(11.07)	(2.91)	(16.3)	(6.51)	(9.11)	(1.601)
β_1		−0.061		−0.307***		0.106*		0.306
		(−1.24)		(−2.29)		(1.849)		(0.774)
δ_0	−0.093***	−0.067	−0.0783***	−0.654	−0.017	−0.111	−0.036*	−0.737
	(−4.01)	(−0.134)	(−4.47)	(−1.493)	(−0.84)	(−0.651)	(−1.69)	(0.201)
δ_1		−0.434		−1.793		−0.234		0.325
		(1.24)		(−1.49)		(−0.77)		(−0.937)
$\varnothing_0$	−0.292	−0.369	0.051*	−0.765***	0.039**	−0.579***	0.046***	−0.031***
	(−0.86)	(−1.11)	(1.85)	(−4.625)	(2.201)	(−2.656)	(3.63)	(−2.378)
$\varnothing_1$		1.592**		0.648***		0.851***		0.068*
		(2.05)		(5.345)		(3.774)		(1.731)
θ_0		1.67***		2.329***		2.937***		4.0233***
θ_1		−2.547***		−1.165**		−0.233*		−1.571**
γ_0		2.571***		1.596**		0.9448**		3.753***
γ_1		0.568*		0.484*		0.4032**		0.3938*
Q(10)	11.42	14.199	9.262	11.767	7.842	9.369	13.06	10.28
	[0.293]	[0.288]	[0.507]	[0.301]	[0.644]	[0.671]	[0.220]	[0.416]
$Q^2(10)$	6.288	9.967	11.99	5.756	2.128	11.653	7.832	11.552
	[0.737]	[0.619]	[0.286]	[0.835]	[0.995]	[0.474]	[0.645]	[0.316]

Notes: Student-t statistics of parameters are reported in parentheses, *, ** and *** denote significance at 10, 5 and 1% respectively. The likelihood ratio (LR) test is calculated as follows: $2 \times |lnL_{MS-EGARCH} - lnL_{EGARCH}|$. Q(10) and $Q^2(10)$ is the Ljung Box test, the null hypothesis is no serial correlations in the residuals and squared residuals at lag 10. The EGARCH model is presented as: $log(h_t) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \varnothing e_{t-1}$ and the extended MS-EGARCH model is presented as: $log(h_{i,t}) = \omega_i + \alpha_i\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta_i log(h_{t-1}) + \delta_i\frac{\varepsilon_{i,t-1}}{\sqrt{h_{t-1}}} + \phi_i e_{t-1}$.

in the FX rate, thus highlighting the regime dependence in the relationship between stock markets and FX markets.

Fig. 5(a) and (b) show that for Hong Kong and Singapore and in the absence of change in the FX rate (with $e_{t-1} = 0$) the probability of remaining in the calm regime having started there is approximately 0.8 for Hong Kong and 0.9 for Singapore. As the FX rate changes increase the probability of remaining in the calm regime decreases. Similarly, when $e_{t-1} = 0$ the probability of remaining in the turbulent regime having started there is around 0.9 for Hong Kong and 0.8 for Singapore. As FX rate changes increase the probability of remaining in the turbulent regime increases.

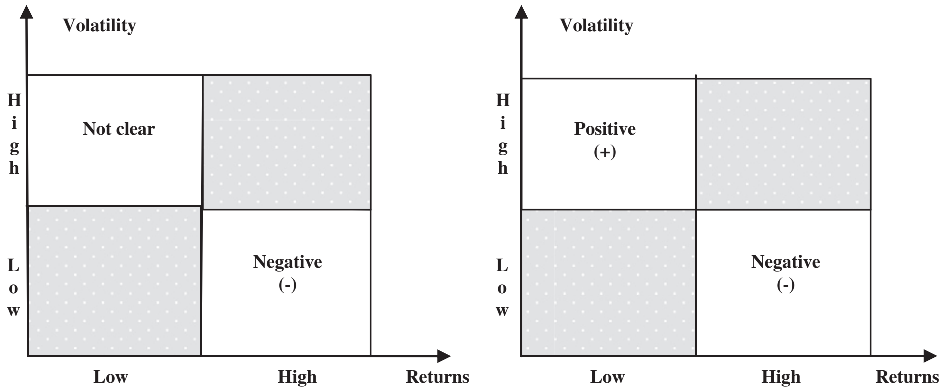

Fig. 3. (a) The effect of FX rate changes on stock market returns according to the state of the market. (b) The effect of FX rate changes on stock market volatility according to the state of the market.

Fig. 5(c)–(d) suggest that when $e_{t-1} = 0$ the probability P^{00} of staying in Regime 0 is almost unity for Malaysia and Mexico. As the FX rate changes increases the probability of remaining in a calm regime decreases. Thus, a positive shock in the FX market makes a return to a turbulent regime more likely. The

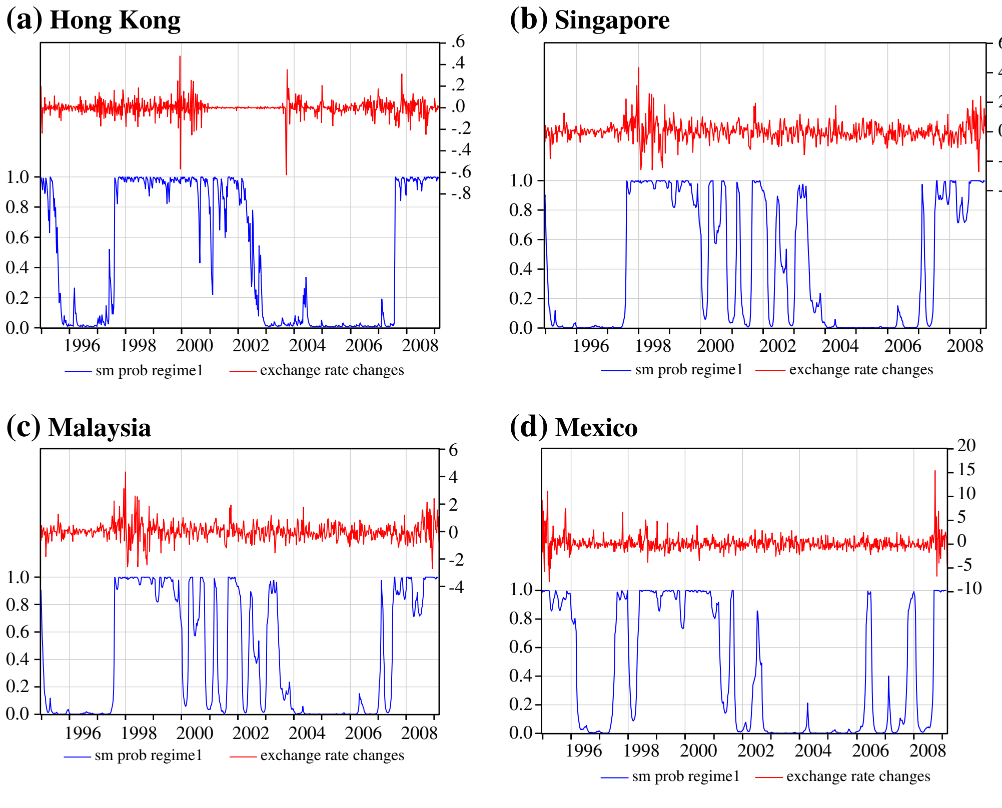

Fig. 4. (a)–(d): Relationship between probability of bear market and FX rate changes.

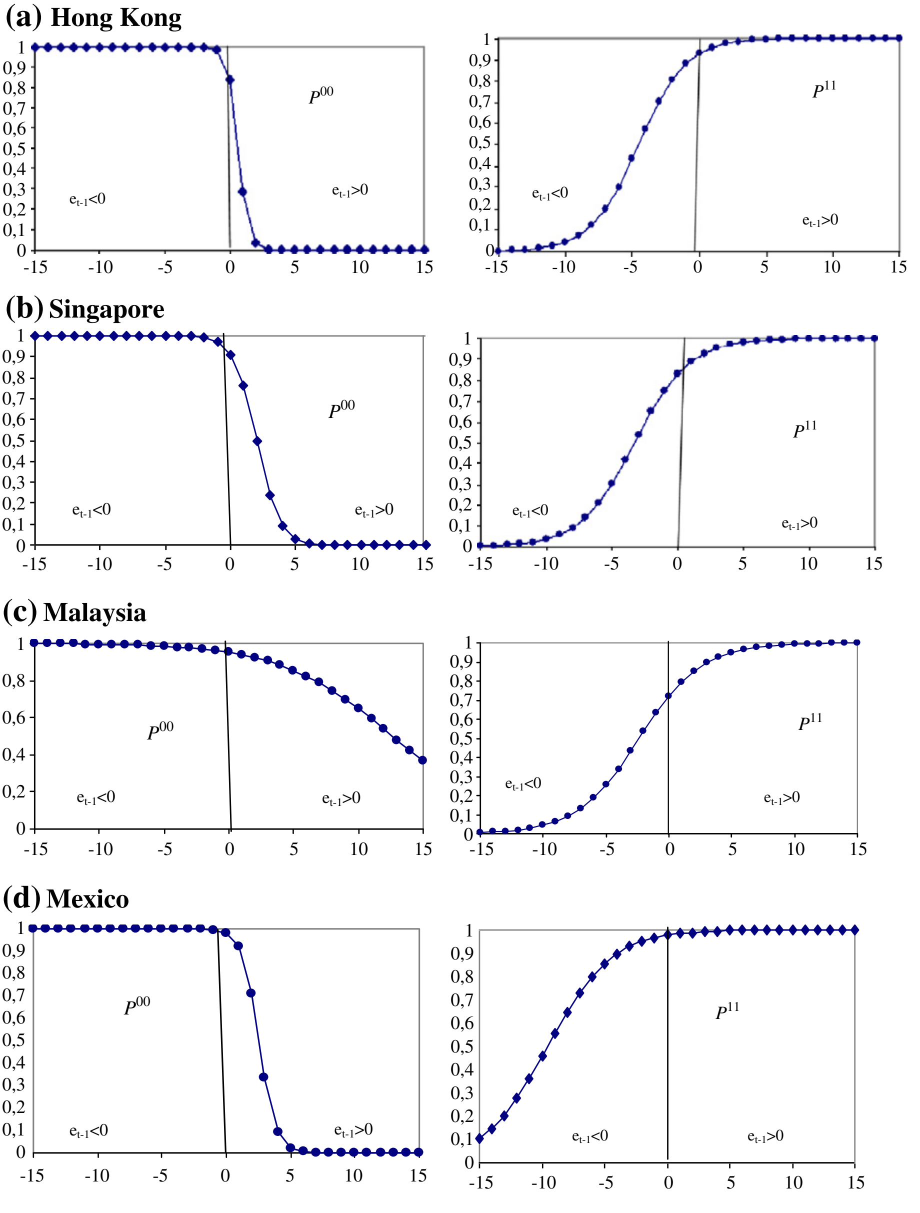

Fig. 5. (a)–(d) — Regime-switching probabilities and changes in exchange rate.

effect is particularly rapid for Mexico but rather less so for Malaysia. In the absence of changes in the FX rate the probability of remaining in a turbulent regime having started there is around 0.7 for Malaysia and 0.9 for Mexico. Once again, we see that as the FX rate changes increase the probability of staying in the turbulent regime increases.

Finally, results in Table 5 show that, within each regime, the Ljung Box test rejects the null hypothesis of no serial correlations in the residuals and squared residuals at lag 10. Thus, this indicates that volatility clustering in stock returns is adequately described by our extended MS-EGARCH model.

7. Summary and concluding remarks

This paper has investigated the impact of FX rate changes on stock market volatility, using weekly data for four emerging markets (Hong Kong, Singapore, Malaysia and Mexico). Our methodology is based on a two regime Markov switching-EGARCH model that allows separate estimation of the relationship between stock and FX markets in "calm" and "turbulent" periods. Results provide strong evidence of regime-switching behavior in volatility on emerging stock markets and reveal the presence of two volatility regimes. The first regime corresponds to high mean-low variance regime. This regime tends to be dominant for all countries and its persistence ranges from 77 weeks in Hong Kong to 25 weeks in Malaysia. The second regime is a low mean-high variance regime and appears less dominant. Periods of high volatility in all four stock markets coincide with several economic and political events such as Mexican currency crisis, Asian financial crisis, the terrorist attacks of 2001 and the US subprime crisis of 2008. Extending the MS-EGARCH model, to allow for a dynamic linkage between FX rate changes and stock market behavior, provides evidence that the relationship between stock and FX markets is regime dependent and stock price volatility reacts asymmetrically to events in the FX market. Furthermore, FX rate changes play a significant role in determining the switch between calmer and more turbulent periods in emerging stock markets.

Our findings have several economic and financial management implications. Firstly, portfolio managers and hedgers may be better able to understand the dynamic linkage between FX markets and equity markets. Specifically, they may be better able to adopt appropriate hedging strategies to better guard against currency risk during future crises that may occur in emerging countries. Secondly, such results may be helpful for policy makers from a financial stability perspective, providing governments and central banks with insights into volatility spillovers and risk transmission between FX markets and stock markets. Finally, results may also allow one to assess the level of emerging stock market informational efficiency.

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