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International portfolio flows and exchange rate volatility in emerging Asian markets ☆

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ABSTRACT

This paper investigates the effects of equity and bond portfolio inflows on exchange rate volatility using monthly bilateral data for the US *vis-a-vis* seven Asian developing and emerging countries (India, Indonesia, Pakistan, the Philippines, South Korea, Taiwan and Thailand) over the period 1993:01–2015:11. GARCH models and Markov switching specifications with time-varying transition probabilities are estimated in addition to a benchmark linear model. The evidence suggests that high (low) exchange rate volatility is associated with equity (bond) inflows from the Asian countries toward the US in all cases, with the exception of the Philippines. Therefore, capital controls could be an effective tool to stabilise the foreign exchange market in countries where flows affect exchange rate volatility.

1. Introduction

The deregulation of financial markets and the increase in cross-border capital flows are widely believed to be an important factor behind the recently observed excess volatility of some of the main currencies. A case in point is the US dollar, which was relatively stable in the 1970s but became highly volatile since the early 1980s. Gross cross-border portfolio (equity and bond) flows amounted to only 4% of GDP in 1975, but this percentage surged to 100% in the early 1990s and had reached 245% by 2000 (Hau and Rey, 2006). By comparison, global capital flows increased from about 2% of world GDP in 1975 to over 20% in 2007. However, they declined sharply at the time of the collapse of Lehman Brothers in September 2008, before starting to rise again in 2009 (see Milesi-Ferretti and Tille, 2011).

Cross-border capital flows could also be behind multiple equilibria. For example, Jeanne and Rose (2002) showed that exchange rate volatility may differ between countries with a floating regime, even if their macroeconomic fundamentals are similar, as a result of ‘noise trading’ in the foreign exchange markets.[1] Chen (2006) found that higher interest rates move

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[1] Self-fulfilling currency crises can also generate multiple equilibria for exchange rates and their volatility (see, e.g., Jeanne and Masson, 2000).

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exchange rates to the high volatility regime using data from Indonesia, South Korea, the Philippines, Thailand, Mexico and Turkey. More recently, Lovcha and Perez-Laborda (2013) argued that investors react differently in different states of the market. There is now extensive evidence that equity and bond portfolio flows change with the degree of uncertainty in the foreign exchange market. For example, Fidora et al. (2007) found that exchange rate volatility is a key factor leading to bilateral portfolio home bias in a number of industrialised and emerging economies. Bayoumi (1990) concluded that net capital flows as a percentage of GDP were much larger during the gold standard (1880–1913) than during the floating exchange rate period (1965–1986). Bacchetta and van Wincoop (2000) showed, in the context of a two-period general equilibrium model, that exchange rate uncertainty dampens net international capital flows; extensive empirical evidence is provided in a recent study by Caporale et al. (2015) for various countries.[2] Baek (2006) documented that portfolio investment flows to Asia are driven by investors' appetite for risk; capital inflows turned into outflows following the Mexican peso crisis of 1994 and the Asian financial crisis of 1997–1998.[3]

Most previous empirical papers on the linkages between exchange rates and flows focus on developed economies (e.g., Brooks et al., 2004; Siourounis, 2004; Hau and Rey, 2006; Chaban, 2009; Menla Ali et al., 2014, Menla Ali et al., 2016). The few exceptions considering instead developing and emerging countries include Ibarra (2011), Kodongo and Ojah (2012), and Combes et al. (2012), who examine respectively Mexico vis-à-vis the US, four African countries (Egypt, Morocco, Nigeria, and South Africa) vis-à-vis the US, and a panel of 42 emerging and developing economies. Moreover, state-dependent effects of flows on exchange rate volatility have not been adequately investigated, especially in the case of emerging and developing countries, even though the existence of multiple equilibria for exchange rates and their volatility in these economies has been well documented (see, e.g., Chen, 2006; Lovcha and Perez-Laborda, 2013; among others). The present study aims to fill these gaps by examining the relationship between equity and bond flows and exchange rate changes and their volatility in a set of emerging markets in both linear and nonlinear frameworks, with the dataset including monthly bilateral data for the US vis-à-vis seven Asian developing and emerging market countries, namely India, Indonesia, Pakistan, the Philippines, South Korea, Taiwan and Thailand over the period 1993:01–2015:11. Net portfolio flows to emerging Asia have exhibited considerable volatility in the most recent years, the Asian financial crisis and the recent global financial crisis being their main driving forces. As documented by IMF (2011), 31 "surge" episodes in net private capital flows to Asia, calculated following the methodology outlined in IMF (2007), have occurred during the last 20 years.[4] When capital flows are extremely volatile, domestic policy responses might be necessary. For instance, many central banks in this region intervened extensively in their currency markets to mitigate the impact of inflows and outflows. However, a thorough analysis of the impact of capital flows on exchange rate volatility is still missing, and, to the best of our knowledge, our study is the first empirical investigation of the possibly nonlinear impact of international equity and bond portfolio flows on exchange rate dynamics for the chosen group of countries.

Our econometric approach is the following. First, we use the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (see Engle, 1982; Bollerslev, 1986) to examine the direct impact of flows on exchange rate volatility. Then, we estimate a time-varying transition probability Markov-switching specification, which separates periods of high and low exchange rate volatility, to examine whether flows affect the transition probabilities of switching between volatility states. Specifically, we model the probabilistic structure of the transition from one regime to the other as a function of cross-border net equity and bond portfolio flows. Therefore the model examines the impact of equity and bond portfolio flows for different states of a currency's volatility. Robustness checks are also carried out by including control variables in the empirical specifications.

Understanding the possibly nonlinear impact of flows on currency volatility is crucial for designing appropriate policies aimed at achieving economic and financial stability in different states of the economy. For instance, if higher inflows move the exchange rate to a high volatility regime, standard monetary policy measures might not be sufficient and capital controls might be necessary to reduce inflows and stabilise the foreign exchange market. Distinguishing between different types of portfolio flows is also very important, since these could have different effects on exchange rate volatility. This is particularly relevant in the case of emerging markets, where certain markets are less liquid and shallower. Gadanecz et al. (2014), for instance, pointed out that foreign investors tend to hedge their holdings of bonds denominated in local currency in emerging countries using foreign exchange instruments (e.g., foreign exchange options) that protect them against high market risk because such bonds are less liquid. Moreover, Ananchotikul and Zhang (2014) provided evidence of the existence of differences in the dynamics of high-frequency equity and bond flows, especially in their response to extreme market events. They found, for example, that equity flows to emerging economies declined sharply prior to the Bear Sterns event in mid-March 2008, while bond flows appeared not to be affected. By contrast, after the Lehman collapse, equity flows remained relatively stable, while bond flows reversed sharply. Nonetheless, investors retrenched from emerging bond and equity markets to similar degrees during the May 2013 quantitative easing event. All in all, understanding the response of exchange rate volatility to each type of flows is of paramount importance, and we provide some empirical evidence on this issue.

[2] Both Batten and Vo (2010) and Daly and Vo (2013) reported instead that exchange rate volatility reduces equity home bias in Australia.

[3] Eichengreen and Mody (1998) also found that emerging bond markets are primarily driven by shifts in market sentiment rather than changes in economic fundamentals.

[4] An episode of large net private capital flows for a particular country is defined as a period of two or more quarters during which these flows (as a share of GDP) are significantly larger (one standard deviation) than their historical trend, or above the 75th percentile of their distribution over the whole sample (see IMF, 2007).

The remainder of the paper is organised as follows. Section 2 describes the data. Section 3 outlines the econometric models and the hypotheses tested. Section 4 discusses the empirical results. Finally Section 5 offers some concluding remarks.

2. Data description

We examine the impact of net equity and net bond portfolio flows on exchange rate dynamics for the US *vis-à-vis* seven Asian developing and emerging market countries, namely India, Indonesia, Pakistan, the Philippines, South Korea, Taiwan and Thailand. China, Hong Kong, and Malaysia were excluded because their currencies were fixed *vis-a-vis* the US dollar.[5] The US is treated as the domestic economy throughout. We use monthly data on equity and bond portfolio flows and end-of-period exchange rates defined as US dollars per unit of foreign currency for the period 1993:01 to 2015:11, except for Pakistan for which flow data are only available till 2014:11. The data source for exchange rates is the IMF's International Financial Statistics (IFS), whilst portfolio flows were obtained from the US Treasury International Capital (TIC) System.[6] As pointed out by Edison and Warnock (2008), the US TIC data have three main limitations. First, they only cover transactions involving US residents, i.e., they represent bilateral US portfolio inflows and outflows and do not include other cross-border portfolio flows. Second, transactions taking place via third countries lead to a financial centre bias in the bilateral flows data as they are recorded against the foreign intermediary rather than where the issuer of the foreign security resides. Third, financing of cross-border mergers through stock swaps makes the analysis of equity flows rather difficult. Despite these limitations, the TIC data have been widely used in the empirical literature as still being informative about bilateral portfolio investments between the US and the rest of the world. Moreover, the second and third issue mentioned above are likely to be trivial in the context of emerging and developing countries.

Log changes of exchange rates are calculated as $r_t = 100 \times (E_t/E_{t-1})$, where E_t is the log of the exchange rate at time *t*. Net portfolio flows are constructed as the difference between portfolio inflows and outflows. While inflows are measured as net purchases and sales of domestic assets (equities and bonds) by foreign residents, outflows are defined as net purchases and sales of foreign assets (equities and bonds) by domestic residents. Therefore, positive numbers indicate net equity and net bond portfolio inflows toward the US or outflows from the Asian countries. Following Brennan and Cao (1997), Hau and Rey (2006), and Chaban (2009) among others, the flows are normalised using their past 12-month average.

A wide range of descriptive statistics is presented in Table 1. The mean monthly changes of exchange rates are negative, suggesting a US dollar appreciation against all Asian currencies over the sample period. The biggest one occurred *vis-a-vis* the Indonesian currency (-0.694), followed by the Pakistani one (-0.514), whilst the smallest occurred *vis-a-vis* the Taiwanese dollar (-0.094), and the Thai baht (-0.124). Net bond flows are positive for all countries but Pakistan and the Philippines, the latter two experiencing bond inflows *vis-a-vis* the US. On the contrary, net equity flows are all negative, hence the US, on average, experiences equity outflows toward the Asian countries.

Exchange rate volatility, on the other hand, ranges from 1.55 and 1.61 respectively for Taiwan and Pakistan to 7.59 for Indonesia. The volatility of net bond flows ranges instead from 9.70 (highest) for Pakistan to 1.42 (lowest) for Taiwan, with the corresponding volatility for net equity flows ranging from 2.39, 2.05, and 2.01 (highest) respectively for Pakistan, the Philippines, and India to 1.40 (lowest) for Thailand. Equity flows exhibit higher volatility compared with bond flows in all cases, except India, Pakistan, and Thailand. Further, exchange rate volatility is higher than for both types of flows in Indonesia, South Korea and the Philippines, lower than for equity flows in Taiwan and for bond flows in Thailand, and lower than for both types of flows in India and Pakistan. All series exhibit strong skewness and excess kurtosis. Finally, the Jarque-Bera (JB) test statistics reject the null hypothesis of normality in all cases.

3. The econometric models

We investigate the linkages between net equity and net bond portfolio flows and exchange rates using different models. The linear model, commonly used in the literature (e.g., Brooks et al., 2004; Hau and Rey, 2006; among others) and to be taken only as the benchmark specification, has the following form[7]:

$$r_t = \mu + \sum_{n=1}^{12} \phi_n r_{t-n} + \sum_{k=1}^{4} \beta_1^k nbf_{t-k} + \sum_{k=1}^{4} \beta_2^k nef_{t-k} + \sigma\varepsilon_t, \tag{1}$$

where r_t = (log changes of exchange rates), and $\{\varepsilon_t\}$ are i.i.d. errors with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t^2) = 1$. nbf_{t-k} and nef_{t-k} refer to net bond and net equity inflows respectively. Autoregressive terms $\sum_{n=1}^{12} \phi_n$, up to twelve lags, are also included to capture exchange rate dynamics.

[5] Hong Kong adopted a currency board system in October 1983; China's exchange rate was fixed to the US dollar until 2005, and Malaysia pegged its currency to the US dollar in the period following the Asian financial crisis till the middle of 2005.

[6] These data were retrieved from the US Treasury Department website: http://www.treasury.gov/resource-center/data-chart-center/tic/Pages/country-longterm.aspx.

[7] This model is estimated only for sake of completeness. Since it assumes a constant variance it cannot be directly compared to the other specifications adopted below.

Table 1
Descriptive statistics.

		Mean	St. dev	Skewness	Ex.kurtosis	JB
India	r_t	−0.305	1.977	−0.514	6.006	115.3[a]
	nbf_t	0.094	2.062	1.871	19.86	3406.8[a]
	nef_t	−0.897	2.018	−2.138	14.12	1621.0[a]
Indonesia	r_t	−0.694	7.597	−5.482	68.41	5022.2[a]
	nbf_t	0.026	1.700	−0.088	6.253	121.2[a]
	nef_t	−0.403	1.979	−1.047	11.03	787.4[a]
South Korea	r_t	−0.139	4.171	−2.557	26.56	6639.6[a]
	nbf_t	0.431	1.636	−1.481	11.62	948.6[a]
	nef_t	−0.697	1.753	−3.521	32.39	1042.8[a]
Pakistan	r_t	−0.514	1.611	−2.010	13.25	1324.7[a]
	nbf_t	−0.728	9.706	−6.030	51.06	2681.1[a]
	nef_t	−0.392	2.391	−2.769	25.38	5802.9[a]
Philippines	r_t	−0.234	2.459	−1.509	10.52	717.4[a]
	nbf_t	−0.028	1.737	−1.592	8.320	419.7[a]
	nef_t	−0.347	2.058	4.917	65.02	4305.8[a]
Taiwan	r_t	−0.094	1.554	−0.249	6.592	143.5[a]
	nbf_t	0.468	1.428	−1.901	10.76	816.8[a]
	nef_t	−0.469	1.739	0.107	8.403	319.2[a]
Thailand	r_t	−0.124	3.174	−1.554	25.51	5639.9[a]
	nbf_t	0.335	4.782	12.26	184.7	3600.1[a]
	nef_t	−0.286	1.409	0.059	3.610	422.7[a]

Notes: r_t, nbf_t, and nef_t indicate the changes of the individual Asian currencies in units of US dollars multiplied by 100, net bond inflows and net equity inflows, respectively; JB is the Jarque-Bera test for normality.
[a] Statistical significance at the 1% level.

As the focus of the paper is on the linkages between equity and bond inflows and exchange rate volatility, we investigate the dynamics linking the three variables of interest using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model (see Engle, 1982; Bollerslev, 1986)[8]:

$$\begin{aligned} r_t &= \mu + \sum_{n=1}^{12} \phi_n r_{t-n} + \varepsilon_t, \quad \varepsilon_t|\Omega_{t-1} \sim N(0, \sigma_t^2) \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{k=1}^{4} \psi_1^k nbf_{t-k} + \sum_{k=1}^{4} \psi_2^k nef_{t-k}, \end{aligned} \tag{2}$$

where $\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t^2)$ is the innovation which is conditionally normal with zero mean and variance σ_t^2. Further, ψ_1^k and ψ_2^k are the main parameters of interest measuring respectively the kth lag impact of net bond and net equity flows on the conditional variance of exchange rate changes σ_t^2. A rich dynamic structure analysis is allowed for by including up to four lags for both types of flows (i.e., $k = 1, \ldots, 4$). Finally, the following standard regularity conditions apply for this model: $\alpha, \beta > 0$ and $\alpha + \beta < 1$.

The GARCH model provides evidence on the direct impact of flows on exchange rate volatility. We also estimate a regime-switching model allowing for volatility shifts (i.e., for periods of both high and low exchange rate volatility) to examine whether flows affect the transition probabilities associated with switching between volatility states.[9] The specification is the following:

$$\begin{aligned} r_t &= \mu(s_t) + \sum_{n=1}^{12} \phi_n r_{t-n} + \sigma(s_t)\varepsilon_t, \quad \varepsilon_t \sim N(0,1) \\ \mu(s_t) &= \sum_{i=1}^{2} \mu^{(i)} \mathbf{1}\{s_t = i\}, \sigma(s_t) = \sum_{i=1}^{2} \sigma^{(i)} \mathbf{1}\{s_t = i\}, (t \in \mathbb{T}) \end{aligned} \tag{3}$$

where $\{\varepsilon_t\}$ are i.i.d. errors with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t^2) = 1$, and $\{s_t\}$ are random variables in $S = \{1, 2\}$ that indicate the unobserved state of the system at date t. Throughout, the regime indicators $\{s_t\}$ are assumed to form a Markov chain on S with a transition probability matrix $P' = [p_{ij}]_{2\times2}$, where $p_{ij} = \Pr(s_t = j|s_{t-1} = i)$, with $i, j \in \mathbb{S}$, and $p_{i1} = 1 - p_{i2}$ $(i \in \mathbb{S})$, with each column adding up to unity and all elements being non-negative. We also allow for a time-varying conditional mean $(\mu(s_t))$.

[8] Several GARCH specifications were estimated and the results showed that the standard GARCH specification is superior to other specifications. We also allowed for asymmetric as well as in-mean effects; however, such effects were not found to be significant.
[9] Note that the GARCH models consider the direct impact of flows on exchange rate volatility, whereas the Markov regime-switching specifications examine whether flows affect the transition probabilities of switching between volatility states, and therefore whether they have an indirect effect on volatility. The two models can be seen as complementary in investigating the linkages between flows and volatility.

Therefore, the parameter vector for the mean, Eq. (3), is defined by the autoregressive terms $\sum_{n=1}^{12}\phi_n$, up to twelve lags, and both $\mu^{(i)}$ $(i = 1, 2)$ and $\sigma^{(i)}$ $(i = 1, 2)$, which are real constants (where 1 stays for low and 2 for high). Net equity and net bond portfolio flows enter the model through the time-varying transition probabilities as in the specification by Filardo (1994). In particular, rather than examining the impact of flows on exchange rate volatility directly, as in Eq. (2), the model allows the probabilities to depend on flows instead. That is, each conditional volatility (where $\sigma^{(1)}$ stands for low volatility and $\sigma^{(2)}$ for high volatility) follows a regime-shift process and the transition mechanism governing $\{s_t\}$ is specified as:

$$p_t^l = \frac{\exp\{\eta_0 + \sum_{k=1}^{4}\eta_1^k nbf_{t-k} + \sum_{k=1}^{4}\eta_2^k nef_{t-k}\}}{1 + \exp\{\eta_0 + \sum_{k=1}^{4}\eta_1^k nbf_{t-k} + \sum_{k=1}^{4}\eta_2^k nef_{t-k}\}}; \qquad (4)$$

$$p_t^h = \frac{\exp\{\gamma_0 + \sum_{k=1}^{4}\gamma_1^k nbf_{t-k} + \sum_{k=1}^{4}\gamma_2^k nef_{t-k}\}}{1 + \exp\{\gamma_0 + \sum_{k=1}^{4}\gamma_1^k nbf_{t-k} + \sum_{k=1}^{4}\gamma_2^k nef_{t-k}\}}.$$

As in the previous case, up to four lags of both types of flows are included. Note that, since p_t^h/nbf_{t-k} (p_t^h/nef_{t-k}) has the same sign as γ_1^k (γ_2^k), $\gamma_1^k > 0$ $(\gamma_2^k > 0)$ implies that an increase in nbf_{t-k} (nef_{t-k}) increases the probability of remaining in the state characterised by high exchange rate volatility. Similarly, $\eta_1^k > 0$ $(\eta_2^k > 0)$ implies that an increase in nbf_{t-k} (nef_{t-k}) increases the probability of remaining in the state characterised by low exchange rate volatility. The maximum likelihood estimation is performed using the EM algorithm described by Hamilton (1989, 1990).

4. Empirical results

4.1. OLS and GARCH results

First we report the estimates of the linear model, Eq. (1), where net (equity and bond) flows are regressors in a standard OLS setting. The results, displayed in Table 2, indicate that neither type of flows has a statistically significant effect on exchange rate changes. The only exceptions are net bond flows in the cases of India, Indonesia, Pakistan, the Philippines and South Korea. This general pattern suggests that the simple linear model fails to capture the relationship between flows

Table 2
Estimated linear models.

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
μ	−0.236[c] (0.137)	−0.758 (0.470)	−0.363[a] (0.113)	−0.145 (0.152)	−0.563[b] (0.276)	−0.089 (0.101)	−0.126 (0.197)
β_1^1				0.158[c] (0.086)	0.684[a] (0.162)	0.054 (0.066)	−0.007 (0.039)
β_1^2	0.105[c] (0.057)						
β_1^3		0.580[b] (0.268)	0.019[c] (0.010)				
β_1^4							
β_2^1	−0.005 (0.066)	−0.242 (0.231)	−0.031 (0.041)	0.045 (0.072)	−0.182 (0.142)	0.027 (0.054)	−0.040 (0.139)
β_2^2							
β_2^3							
β_2^4							
ϕ_1	0.154[b] (0.061)	0.076 (0.060)	0.167[a] (0.062)	0.073 (0.061)	−0.053 (0.060)		0.199[a] (0.061)
ϕ_2	−0.096 (0.061)		0.029 (0.063)	0.048 (0.060)	−0.013 (0.059)		−0.104[c] (0.062)
ϕ_3	0.129[b] (0.061)		0.084 (0.062)	0.108[c] (0.060)	0.001 (0.060)		0.106[c] (0.062)
ϕ_4	−0.167[a] (0.061)				−0.090 (0.059)		−0.109[c] (0.061)
ϕ_5	0.112[c] (0.061)						
σ	1.977	7.638	1.650	2.470	4.210	1.557	3.203
LogLik	−554.73	−934.73	−490.98	−623.77	−759.86	−504.65	−689.41
$Q(6)$	6.565 [0.363]	5.212 [0.516]	2.748 [0.840]	2.641 [0.852]	1.129 [0.980]	7.557 [0.272]	0.434 [0.999]
$Q(12)$	11.55 [0.482]	11.02 [0.527]	13.75 [0.317]	14.49 [0.270]	12.64 [0.395]	14.97 [0.243]	4.686 [0.968]
$Q^2(6)$	44.29 [0.000]	16.75 [0.010]	3.043 [0.803]	116.7 [0.000]	49.14 [0.000]	34.63 [0.000]	54.80 [0.000]
$Q^2(12)$	64.69 [0.000]	22.62 [0.000]	18.96 [0.089]	135.7 [0.000]	51.69 [0.000]	52.34 [0.000]	101.8 [0.000]

Autocorrelation and heteroscedasticity-consistent standard errors are reported in parentheses (.). β_1^k and β_2^k measure the kth lag effects of net bond and net equity inflows respectively on exchange rate changes, as in Eq. (1). The lag length of the model is selected using the Akaike information criterion (AIC), subject to correction for serial correlation by the inclusion of further lags. $Q(p)$ and $Q^2_{(p)}$ are respectively the Ljung and Box (1978) tests for the pth order autocorrelations in the standardised and squared standardised residuals; p-values are reported in square brackets [.].

[a] Statistical significance at the 1% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 10% level.

Table 3
Estimated GARCH models.

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
Conditional mean equation							
μ	−0.157 (0.115)	−0.093 (0.270)	−0.146 (0.106)	0.046 (0.109)	0.080 (0.379)	−0.067 (0.090)	0.194 (0.211)
ϕ_1	0.147[c] (0.083)	0.102 (0.093)	0.218[a] (0.067)	0.087 (0.082)	−0.086 (0.131)	0.152[a] (0.060)	0.317[a] (0.104)
ϕ_2	−0.075 (0.062)		0.060 (0.108)	−0.001 (0.060)	−0.076 (0.121)	0.0001 (0.073)	
ϕ_3	0.175[a] (0.055)		0.149[b] (0.067)	0.074 (0.079)	0.018 (0.114)	0.023 (0.060)	
ϕ_4	−0.136[a] (0.038)			−0.145[a] (0.053)	−0.016 (0.074)	−0.140[b] (0.061)	
ϕ_5				0.030 (0.066)			
ϕ_6				0.146[b] (0.058)			
Conditional variance equation							
ω	1.129[a] (0.261)	5.676[a] (0.911)	0.175[a] (0.008)	1.159[a] (0.211)	13.43[a] (2.031)	0.259[a] (0.099)	2.458[a] (0.725)
α	0.364[a] (0.100)	0.550[a] (0.041)	0.072[a] (0.011)	0.424[a] (0.115)	0.148[b] (0.059)	0.047[c] (0.028)	0.358[a] (0.028)
β	0.401[a] (0.094)	0.433[a] (0.025)	0.860[a] (0.004)	0.450[a] (0.088)	0.497[a] (0.045)	0.856[a] (0.057)	0.432[a] (0.128)
ψ_1^1		−1.333[a] (0.287)	−0.036[a] (0.002)	−0.477[a] (0.115)	−4.433[a] (0.596)	0.061[b] (0.031)	
ψ_1^2							
ψ_1^3	−0.093[a] (0.023)						−0.046[a] (0.007)
ψ_1^4							
ψ_2^1	0.108[c] (0.060)	0.535[a] (0.099)			1.782[a] (0.291)	0.160[a] (0.035)	1.075[a] (0.304)
ψ_2^2				0.200[c] (0.114)			
ψ_2^3							
ψ_2^4			0.109[a] (0.009)				
LogLik	−525.45	−744.83	−469.55	575.14	−712.22	−479.51	−620.00
$Q_{(6)}$	8.279 [0.218]	7.435 [0.282]	2.481 [0.871]	8.049 [0.234]	5.267 [0.510]	1.659 [0.948]	6.900 [0.330]
$Q_{(12)}$	12.83 [0.382]	12.79 [0.384]	14.99 [0.242]	14.51 [0.269]	16.47 [0.170]	10.15 [0.602]	11.16 [0.515]
$Q^2_{(6)}$	10.32 [0.112]	6.541 [0.365]	3.665 [0.722]	6.123 [0.409]	6.777 [0.342]	1.659 [0.948]	2.437 [0.875]
$Q^2_{(12)}$	6.231 [0.903]	10.34 [0.586]	8.112 [0.776]	6.591 [0.883]	7.267 [0.839]	10.15 [0.602]	4.117 [0.981]

Notes: The conditional mean and variance equations of the estimated GARCH model for each country are $r_t = \mu + \sum_{n=1}^{12}\phi_n r_{t-n} + \varepsilon_t$, $\varepsilon_t|\Omega_{t-1} \sim N(0,\sigma_t^2)$ and $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{k=1}^{4}\psi_1^k nbf_{t-k} + \sum_{k=1}^{4}\psi_2^k nef_{t-k}$, respectively. r_t, nbf_{t-k}, and nef_{t-k} are log changes of Asian currencies in units of US dollars multiplied by 100, net bond inflows, and net equity inflows, respectively. Robust standard errors are reported in parentheses (.). The lag length of the model is selected using the Akaike information criterion (AIC), subject to correction for serial correlation by the inclusion of further lags. $Q(p)$ and $Q^2_{(p)}$ are respectively the Ljung and Box (1978) tests for the pth order autocorrelations in the standardised and squared standardised residuals; p-values are reported in square brackets [.].

[a] Statistical significance at the 1% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 10% level.

and exchange rates. In fact the residuals exhibit strong heteroscedasticity in most cases, indicating that the linear model does not fit the data well. By contrast, the GARCH models (see Table 3) appear to be well-specified: there is no linear or nonlinear dependence in the residuals, and the ARCH (α) and GARCH (β) parameters are significant in all cases. Regarding the impact of flows on volatility, the results suggest that bond inflows from the Asian countries toward the US lead to a decrease in the volatility of the US dollar exchange rate vis-a-vis the currencies of the Asian countries. This holds in all cases (ψ_1 being negative and significant), except for Taiwan where bond inflows are found to increase the volatility of the exchange rate (ψ_1 being positive and significant for this case). By contrast, equity inflows from the Asian countries toward the US are found to lead to higher volatility of the US dollar exchange rate vis-a-vis the currencies of these countries (i.e., ψ_2 is positive and significant in all cases).

Next, we check the robustness of these findings by including some control variables, namely interest rate differentials (between the US and each of the Asian countries) and changes in the VIX volatility index, since these variables are known to be associated with exchange rate volatility in emerging economies.[10] For example, both Frankel and Rose (1996) and Chen (2006) found that higher nominal interest rates increase the probability of switching to an exchange rate crisis regime. Further, Ananchotikul and Zhang (2014) recently concluded that global risk aversion, proxied by the VIX, has a significant impact on the volatility of asset prices, including the exchange rates, using data from 17 emerging countries. Our results suggest that the interest rate differential has a negative and significant effect in Indonesia and the Philippines, and a positive and significant one in India, Pakistan and South Korea (see λ_1 in Table 4). Changes in the VIX volatility index have a positive and significant effect in Indonesia, Pakistan, Taiwan and Thailand, but insignificant ones in the rest of the countries (see λ_2 in

[10] The data sources for interest rates and the VIX volatility index are the IMF's International Financial Statistics (IFS) and Datastream respectively. We also considered export growth in the Asian countries as a control, but found only a weak effect on volatility in most countries.

Table 4
Estimated GARCH models with additional control variables.

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
Conditional mean equation							
μ	−0.159 (0.175)	−0.051 (0.442)	−0.301[b] (0.142)	−0.056 (0.124)	0.142 (0.404)	−0.067 (0.086)	−0.038 (0.263)
ϕ_1	0.108 (0.092)	0.175 (0.163)	0.248[a] (0.080)	0.105 (0.084	−0.065 (0.130)	0.128[b] (0.062)	0.043 (0.143)
ϕ_2	−0.051 (0.064)	0.030 (0.156)	0.015 (0.125)	0.013 (0.062)	−0.098 (0.154)		
ϕ_3	0.166[b] (0.067)	−0.134 (0.119)	0.114 (0.072)	0.106 (0.072)	0.040 (0.095)		
ϕ_4	−0.127[b] (0.053)	0.095 (0.085)		−0.148[b] (0.062)			
ϕ_5		−0.067 (0.095)		0.042 (0.068)			
ϕ_6		0.016 (0.084)		0.128[c] (0.066)			
Conditional variance equation							
ω	2.767[a] (0.922)	7.683[a] (2.222)	0.906[a] (0.154)	0.327 (0.354)	13.85[a] (2.510)	0.225[b] (0.089)	6.837[a] (1.951)
α	0.200[b] (0.101)	0.436[a] (0.102)	0.070[a] (0.026)	0.326[a] (0.103)	0.168[a] (0.055)	0.044[c] (0.024)	0.211[c] (0.119)
β	0.296[c] (0.159)	0.361[a] (0.089)	0.675[a] (0.042)	0.461[a] (0.108)	0.477[a] (0.060)	0.864[a] (0.050)	0.501[a] (0.129)
ψ_1^1	−0.102[c] (0.061)	−1.938[a] (0.610)	−0.069[a] (0.010)	−0.137 (0.172)	−3.382[a] (0.839)	0.098 (0.069)	−0.145[c] (0.081)
ψ_1^2							
ψ_1^3							
ψ_1^4							
ψ_2^1	0.213[b] (0.105)	1.621[a] (0.287)		0.105 (0.100)	1.676[a] (0.330)	0.133[a] (0.036)	2.663[a] (0.605)
ψ_2^2							
ψ_2^3							
ψ_2^4			0.125[a] (0.019)				
λ_1	0.048[a] (0.016)	−0.879[b] (0.353)	0.035[a] (0.011)	−0.192[a] (0.072)	0.406[c] (0.241)	0.004 (0.015)	−0.207 (0.186)
λ_2	0.048 (0.066)	1.269[b] (0.498)	0.098[b] (0.038)	0.089 (0.117)	0.380 (0.529)	0.115[b] (0.049)	0.434[b] (0.216)
LogLik	−536.97	−759.44	−475.72	−571.62	−713.30	−483.93	−667.68
$Q_{(6)}$	8.822 [0.184]	9.889 [0.129]	4.151 [0.656]	5.555 [0.475]	6.288 [0.392]	8.225 [0.222]	8.968 [0.175]
$Q_{(12)}$	13.65 [0.323]	12.71 [0.390]	16.35 [0.176]	11.63 [0.476]	16.66 [0.163]	15.32 [0.224]	11.97 [0.447]
$Q^2_{(6)}$	4.850 [0.563]	5.814 [0.444]	3.879 [0.693]	7.309 [0.293]	7.846 [0.250]	7.865 [0.248]	7.537 [0.274]
$Q^2_{(12)}$	9.473 [0.578]	11.90 [0.453]	13.37 [0.342]	7.873 [0.795]	15.04 [0.239]	11.39 [0.495]	14.66 [0.260]

Notes: The conditional mean and variance equations of the estimated GARCH model for each country are respectively given by $r_t = \mu + \sum_{n=1}^{12} \phi_n r_{t-n} + \varepsilon_t$, $\varepsilon_t|\Omega_{t-1} \sim N(0, \sigma_t^2)$ and $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{k=1}^{4}\psi_1^k nbf_{t-k} + \sum_{k=1}^{4}\psi_2^k nef_{t-k} + \lambda_1 (i - i^*)_{t-1} + \lambda_2\, vix_{t-1}$. r_t, nbf_{t-k}, nef_{t-k}, vix_{t-1} and $(i - i^*)_{t-1}$ are log changes of Asian currencies in units of US dollars multiplied by 100, net bond inflows, net equity inflows, changes in the Chicago Board Options Exchange volatility index (VIX), and interest rate differential between the US and the corresponding Asian countries, respectively. Robust standard errors are reported in parentheses (.). The lag length of the model is selected using the Akaike information criterion (AIC), subject to correction for serial correlation by the inclusion of further lags. $Q(p)$ and $Q^2_{(p)}$ are respectively the Ljung and Box (1978) tests for the pth order autocorrelations in the standardised and squared standardised residuals; p-values are reported in square brackets [.].

[a] Statistical significance at the 1% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 10% level.

Table 4). These results are broadly in line with those of Ananchotikul and Zhang (2014), who found that more managed currencies show less sensitivity to global risk aversion. Overall, the inclusion of the control variables in the conditional variance equation in the GARCH specifications (Table 4) confirms the presence of a significant impact of bond flows on exchange rate volatility with one lag, except for the Philippines and Taiwan where bond inflows are found insignificant at any lags. The largest impact occurs in the case of South Korea ($\psi_1^1 = -3.382$) and the smallest in the case of Pakistan ($\psi_1^1 = -0.069$). Equity flows have a significant effect in all countries but the Philippines. The largest effect, at lag one, is estimated for Thailand ($\psi_2^1 = 2.663$), followed by South Korea ($\psi_2^1 = 1.676$), and the smallest is found for Taiwan ($\psi_2^1 = 0.133$). It takes four months for this effect to materialise in the case of Pakistan ($\psi_2^4 = 0.125$).

The general conclusion from these findings is that equity and bond inflows have significant effects on exchange rate volatility; specifically, equity (bond) inflows increase (decrease) it in all countries, except Taiwan (no effects of bond flows are found in this case) and the Philippines (where neither types of flows has significant effects).

4.2. Markov regime-switching results

GARCH models only examine the direct effects of flows on volatility. Further insights into the linkages between flows and exchange rate volatility can be gained by analysing whether flows affect the transition probabilities of volatility states using

Table 5
Markov-switching state dimension: Hansen test.

Country	Standard. LR test	Linearity vs two-states	Two states vs three-states
India	LR	4.231	0.316
	$M = 0$	[0.0009]	[0.5564]
	$M = 1$	[0.0018]	[0.5987]
	$M = 2$	[0.0045]	[0.6242]
	$M = 3$	[0.0088]	[0.7004]
Indonesia	LR	3.998	0.354
	$M = 0$	[0.0010]	[0.5871]
	$M = 1$	[0.0021]	[0.6012]
	$M = 2$	[0.0046]	[0.6591]
	$M = 3$	[0.0063]	[0.6998]
Pakistan	LR	4.446	0.332
	$M = 0$	[0.0012]	[0.6213]
	$M = 1$	[0.0024]	[0.6549]
	$M = 2$	[0.0058]	[0.6988]
	$M = 3$	[0.0064]	[0.7131]
Philippines	LR	4.852	0.491
	$M = 0$	[0.0008]	[0.6341]
	$M = 1$	[0.0019]	[0.6671]
	$M = 2$	[0.0049]	[0.7005]
	$M = 3$	[0.0062]	[0.7214]
South Korea	LR	3.759	0.667
	$M = 0$	[0.0013]	[0.6008]
	$M = 1$	[0.0025]	[0.6573]
	$M = 2$	[0.0055]	[0.6895]
	$M = 3$	[0.0063]	[0.7265]
Taiwan	LR	3.476	0.883
	$M = 0$	[0.0012]	[0.6221]
	$M = 1$	[0.0021]	[0.6879]
	$M = 2$	[0.0048]	[0.7031]
	$M = 3$	[0.0061]	[0.7391]
Thailand	LR	4.006	0.129
	$M = 0$	[0.0011]	[0.6417]
	$M = 1$	[0.0023]	[0.6913]
	$M = 2$	[0.0050]	[0.7227]
	$M = 3$	[0.0059]	[0.7664]

Note: The Hansen's Standardised Likelihood Ratio (LR) test *p*-values, reported in square brackets [.], are calculated according to the method described in Hansen (1992), using 1000 random draws from the relevant limiting Gaussian processes and bandwidth parameter $M = 0, 1, \ldots, 3$.

regime-switching models. The null hypothesis of linearity against the alternative of Markov regime-switching cannot be tested directly using a standard Likelihood Ratio (LR) test. Therefore we test for multiple equilibria (more than one regime) against linearity using Hansen's (1992) standardised likelihood ratio test. Testing requires the evaluation of the likelihood function across a grid of different values for the transition probabilities and for each state-dependent parameter.[11] The standardised Likelihood Ratio statistics (Table 5) provide strong evidence in favour of a two-state Markov switching specification for all seven currencies. We also test for the presence of a third state, but this is rejected for all series.[12]

The maximum likelihood estimates are reported in Table 6. The standardised residuals show no sign of either linear or nonlinear dependence of the estimated models. Further, the periods of high and low volatility seem to be identified accurately by the smoothed probabilities. The Markov process is driven by switching in the variance rather than the mean. Statistically significant low and high levels of the variances are identified for all countries considered. The mean appears to be significant only in the cases of Pakistan in both states, and India in the high volatility state.

Figs. 1–7 show plots of exchange rate changes, r_t, the estimated smoothed probabilities (SP), net bond inflows, nbf_t, net equity inflows, nef_t, and the time-varying transition probabilities (TVTP) for India, Indonesia, Pakistan, the Philippines, South Korea, Taiwan and Thailand, respectively. The smoothed probabilities indicate that switches are not very frequent in most cases. The process is in the high volatility state for 167 months (62.31%) in India, 64 months (23.52%) in Indonesia, 70 months (26.82%) in Pakistan, 139 months (51.29%) in the Philippines, 32 months (11.85%) in South Korea, 147 months (53.84%) in Taiwan, and 35 months (12.86%) in Thailand. Exchange rate changes are characterised by low volatility for the remainder of the sample. The high volatility periods are associated with the Asian financial crisis of 1997–1998 and the global financial crisis of 2008–2009 in most cases, the exchange rate for the US dollar against the currencies of India, Pakistan and the Philippines being the most volatile over recent years.

[11] P-values are calculated using the method described in Hansen (1992), with 1,000 random draws from the relevant limiting Gaussian processes and bandwidth parameter $M = 0, 1, \ldots, 3$ (see Hansen (1992) for details).

[12] Note that this result does not rule out the possibility of alternative nonlinear models being able to capture the dynamics of the series under investigation.

Table 6
Estimated Markov-switching models.

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
μ_1	−0.387[b] (0.196)	−2.295 (1.990)	−1.400[a] (0.339)	−2.528 (1.656)	−1.971 (1.733)	−0.090 (0.171)	−1.310 (1.760)
μ_2	0.034 (0.039)	−0.091 (0.129)	−0.140[a] (0.033)	−0.045 (0.138)	0.135 (0.130)	−0.063 (0.115)	0.016 (0.174)
ϕ_1	0.094[c] (0.055)	0.132[b] (0.060)		0.093[c] (0.056)	−0.080 (0.054)	0.104[c] (0.054)	0.103[c] (0.059)
ϕ_2	0.036 (0.044)			0.071 (0.050)	−0.009 (0.041)		
ϕ_3	0.041 (0.036)			0.057 (0.054)	0.073 (0.049)		
ϕ_4	−0.044 (0.032)				−0.129[a] (0.042)		
ϕ_5	−0.005 (0.030)						
ϕ_6	0.063[b] (0.027)						
σ_1	2.427[a] (0.059)	15.30[a] (0.093)	2.776[a] (0.092)	6.016[a] (1.141)	10.08[a] (1.139)	1.936[a] (0.085)	8.723[a] (0.148)
σ_2	0.311[a] (0.104)	1.738[a] (0.057)	0.381[a] (0.092)	1.669[a] (0.303)	1.862[a] (0.571)	0.499[a] (0.029)	1.593[a] (0.050)
LogLik	−461.23	−701.54	−332.39	−561.89	−642.45	−479.46	−575.71
$Q_{(6)}$	2.287 [0.891]	9.086 [0.169]	8.390 [0.211]	9.480 [0.148]	6.363 [0.384]	10.36 [0.110]	5.512 [0.480]
$Q_{(12)}$	3.470 [0.991]	14.92 [0.246]	15.80 [0.200]	14.85 [0.250]	13.79 [0.314]	17.27 [0.140]	6.961 [0.860]
$Q^2_{(6)}$	1.395 [0.966]	0.968 [0.987]	0.915 [0.989]	7.860 [0.249]	4.898 [0.557]	7.082 [0.313]	7.076 [0.314]
$Q^2_{(12)}$	5.093 [0.955]	5.478 [0.940]	2.340 [0.999]	17.24 [0.141]	14.60 [0.264]	11.45 [0.490]	7.437 [0.827]
Estimated transition probabilities – high state							
γ_0	2.722[a] (0.573)	2.874[a] (0.709)	1.041[a] (0.388)	1.734[c] (0.960)	3.925[c] (2.112)	0.809[c] (0.426)	3.015 (1.944)
γ_1^1				−1.623[b] (0.810)	−1.484 (1.101)		
γ_1^2			0.065 (0.084)			0.351 (0.309)	
γ_1^3	−0.594[b] (0.241)	0.139 (0.280)					−3.124[c] (1.750)
γ_1^4							
γ_2^1	−0.437 (0.348)			0.095 (0.592)	2.171[c] (1.290)		0.816 (1.088)
γ_2^2		0.515[b] (0.266)				0.393[c] (0.223)	
γ_2^3							
γ_2^4			0.500[b] (0.260)				
Estimated transition probabilities – low state							
η_0	1.651[a] (0.415)	4.222[a] (0.759)	2.172[a] (0.337)	4.092[a] (0.762)	3.083[a] (0.448)	−0.183 (1.002)	4.387[a] (0.807)
η_1^1				0.067 (0.332)	0.280[c] (0.159)		
η_1^2			0.284[b] (0.130)			0.727[b] (0.366)	
η_1^3	0.322 (0.261)	0.709[b] (0.286)					0.030 (0.079)
η_1^4							
η_2^1	−0.692[c] (0.372)			−0.060 (0.189)	−0.378 (0.368)		−0.632[c] (0.344)
η_2^2		−0.475[c] (0.265)				0.390 (0.400)	
η_2^3							
η_2^4			−0.273[c] (0.148)				

Notes: Autocorrelation and heteroscedasticity-consistent standard errors are reported in parentheses (.). The time varying transition probabilities evolve according to $p_t^l = \frac{\exp\{\eta_0+\sum_{k=1}^4 \eta_1^k nbf_{t-k}+\sum_{k=1}^4 \eta_2^k nef_{t-k}\}}{1+\exp\{\eta_0+\sum_{k=1}^4 \eta_1^k nbf_{t-k}+\sum_{k=1}^4 \eta_2^k nef_{t-k}\}}$ and $p_t^h = \frac{\exp\{\gamma_0+\sum_{k=1}^4 \gamma_1^k nbf_{t-k}+\sum_{k=1}^4 \gamma_2^k nef_{t-k}\}}{1+\exp\{\gamma_0+\sum_{k=1}^4 \gamma_1^k nbf_{t-k}+\sum_{k=1}^4 \gamma_2^k nef_{t-k}\}}$, where $\eta_1^k(\eta_2^k)$ and $\gamma_1^k(\gamma_2^k)$ measure the effects of net bond (equity) inflows for the kth lag on the probability to remain in the low and high exchange rate volatility regimes respectively. The lag length of the model is selected using the Akaike information criterion (AIC), subject to correction for serial correlation by the inclusion of further lags. $Q(p)$ and $Q^2_{(p)}$ are respectively the Ljung and Box (1978) tests for the pth order autocorrelations in the standardised and squared standardised residuals; p-values are reported in square brackets [.].

[a] Statistical significance at the 1% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 10% level.

Furthermore, the time-varying transition probabilities suggest that net equity and net bond portfolio inflows drive the switches between the two states for a selected number of exchange rates. In particular, higher exchange rate volatility is found to be associated with larger equity inflows. For example, γ_2 is positive and significant in Indonesia, Pakistan, South Korea, and Taiwan, hence equity inflows increase the probability of remaining in the high volatility regime in these cases, while η_2 is negative and significant in India, Indonesia, Pakistan, and Thailand, indicating that equity inflows decrease the probability of staying in the low volatility regime in such cases. By contrast, larger bond inflows are found to be associated with lower exchange rate volatility. For instance, γ_1 is negative and significant in India, the Philippines and Thailand, whereas

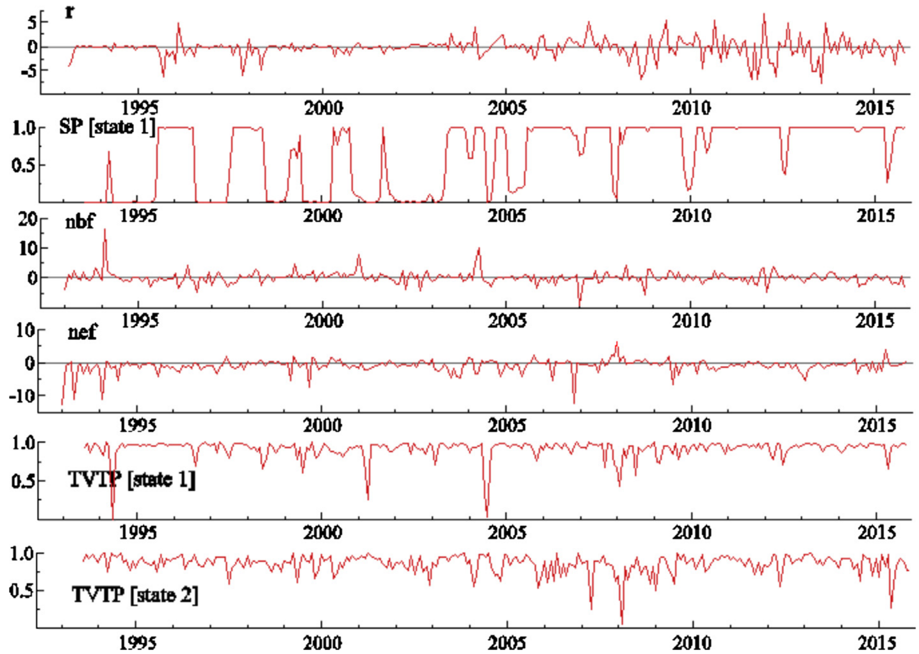

Fig. 1. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in India.

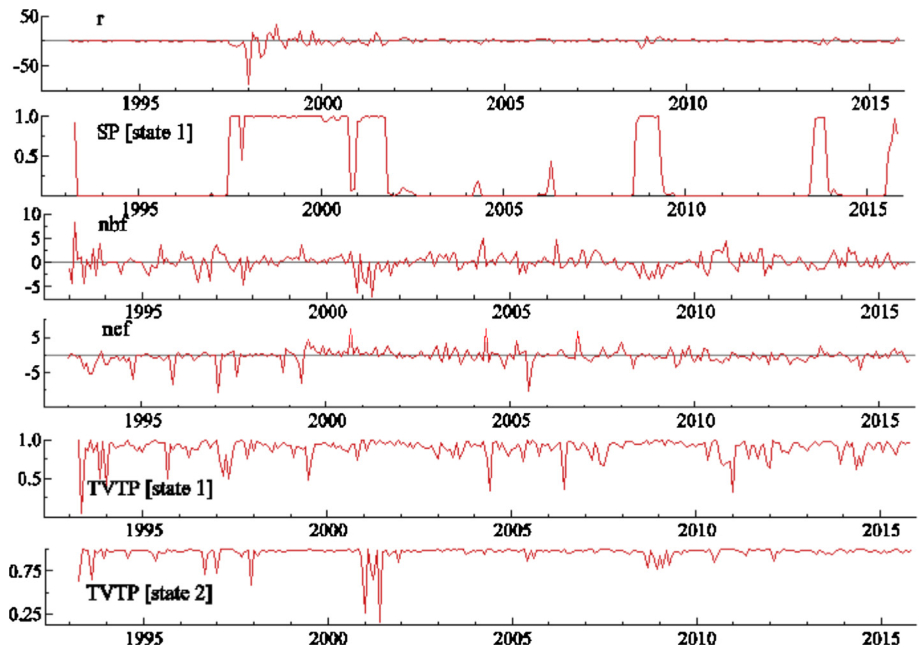

Fig. 2. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in Indonesia.

η_1 is positive and significant in Indonesia, Pakistan, South Korea, and Taiwan, suggesting that bond inflows decrease (increase) the probability of remaining in the high (low) volatility regime in the former three cases (the latter four cases).

We also carry out a robustness check for these findings by including interest rate differentials and changes in the VIX volatility index (defined earlier) as controls in the Markov time-varying transition probabilities, Eq. (3). The results, presented in Table 7, confirm that high exchange rate volatility is associated with higher global risk aversion, proxied by

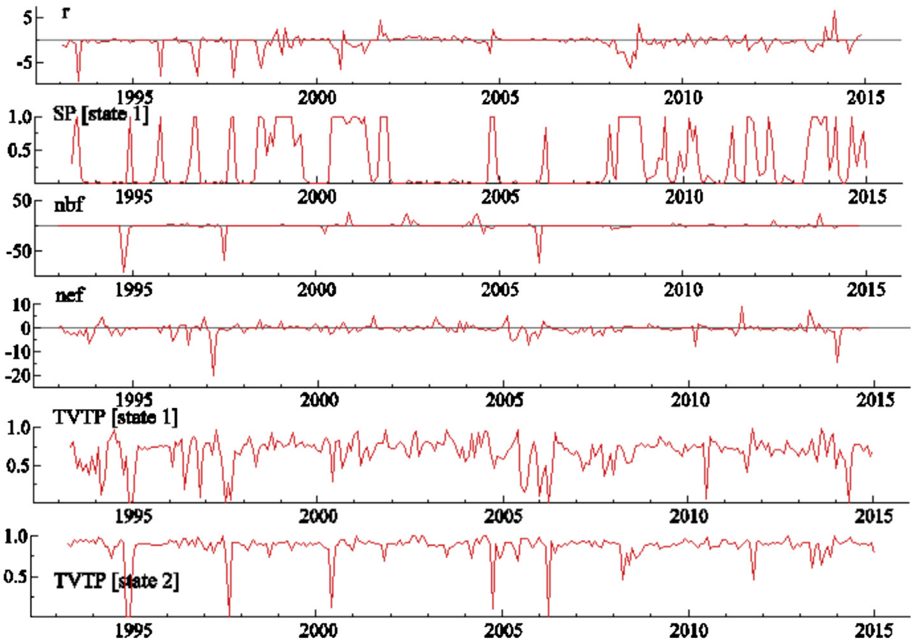

Fig. 3. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in Pakistan.

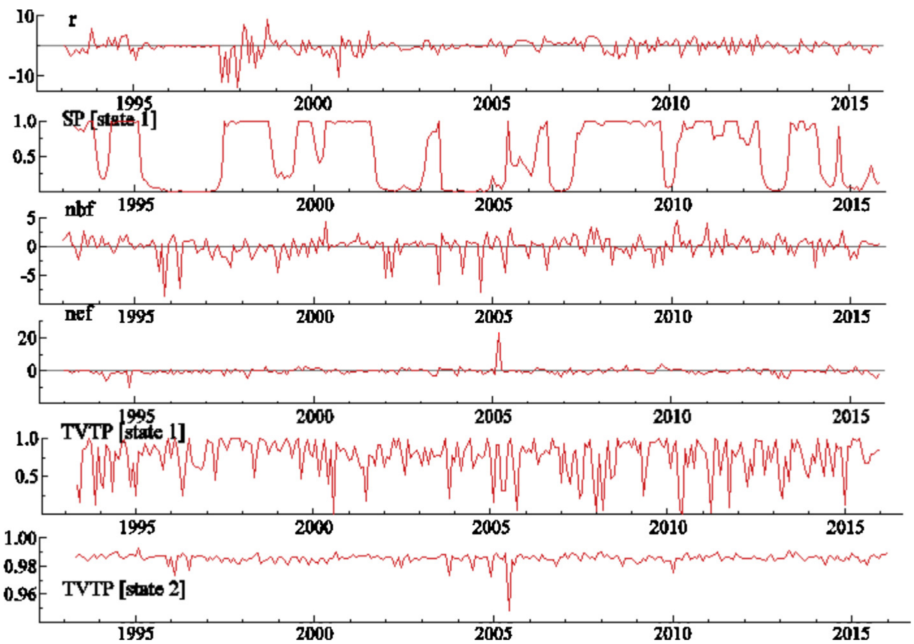

Fig. 4. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in the Philippines.

changes in the VIX (γ_4 is positive and significant in India, Thailand, and the Philippines, while η_4 is negative and significant in Indonesia, Pakistan, South Korea and Thailand); these findings are broadly in line with the GARCH ones and those of Ananchotikul and Zhang (2014). Further, a higher interest rate differential increases the probability of the exchange rate in Pakistan and the Philippines remaining in the low volatility regime (η_3 is positive and significant), decreases the probability of the exchange rate of South Korea staying in the low volatility regime (η_3 is negative and significant), and decreases the probability of the exchange rate of Taiwan and Thailand remaining in the high volatility regime (γ_3 is negative and sig-

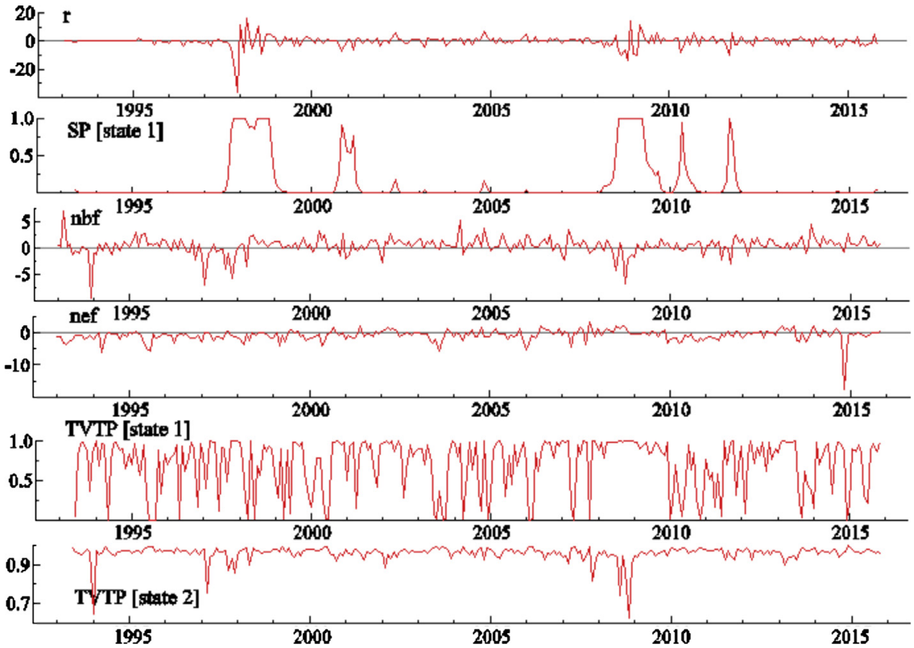

Fig. 5. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in South Korea.

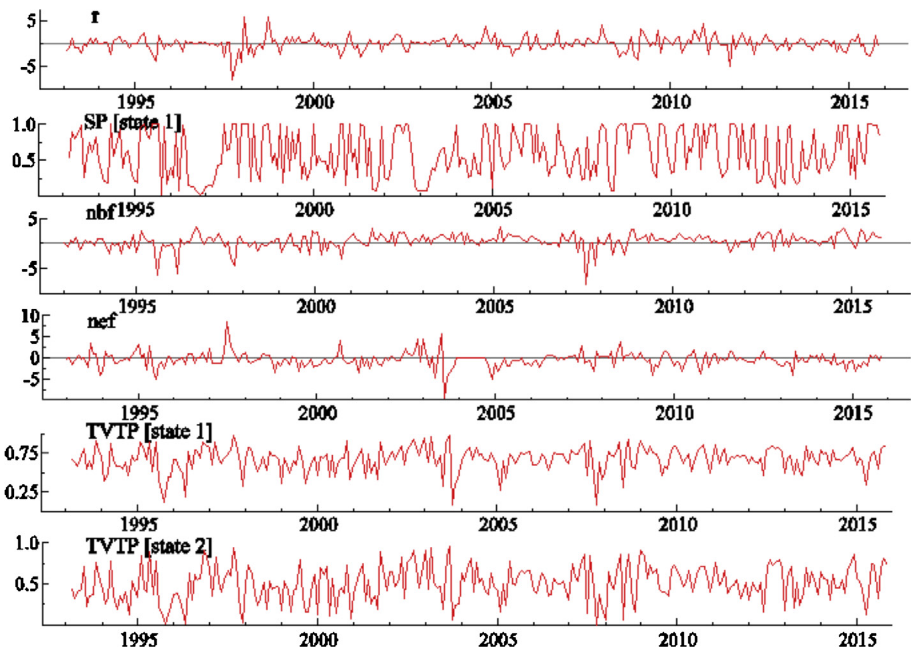

Fig. 6. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in Taiwan.

nificant). These results differ from those of Chen (2006), who reported instead that higher exchange rate volatility is associated with higher interest rates. As for the effects of flows, the additional results corroborate the previous conclusion that net equity (bond) inflows increase the probability of remaining in, or switching to, the high (low) volatility regime of exchange rates. This is true in all cases, the only exception being the Philippines where the coefficients on flows become insignificant when the control variables are included. This implies that exchange rate volatility in this country is driven

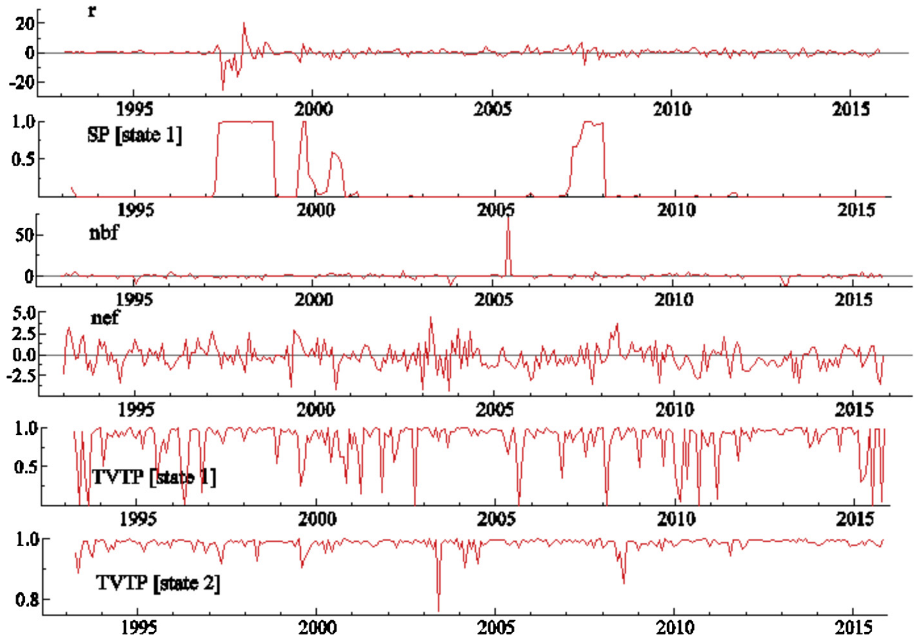

Fig. 7. Exchange rate changes (r_t), smoothed probabilities (SP), net bond inflows (nbf_t), net equity inflows (nef_t), and time-varying transition probabilities (TVTP) for high (state 1) and low (state 2) volatility in Thailand.

Table 7
Estimated Markov-switching models with additional control variables.

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
μ_1	−0.404[b] (0.201)	−2.228 (2.053)	−1.247[a] (0.286)	−0.849 (0.906)	−2.093 (1.806)	−0.077 (0.133)	−0.959 (1.310)
μ_2	0.021 (0.040)	−0.107 (0.127)	−0.115[a] (0.029)	−0.063 (0.115)	0.142 (0.131)	−0.116[b] (0.057)	0.019 (0.135)
ϕ_1	0.089[c] (0.046)	0.124[b] (0.062)		0.135[b] (0.055)	−0.050 (0.061)	0.131[b] (0.064)	0.091 (0.058)
ϕ_2	0.011 (0.039)	0.004 (0.028)		0.099 (0.063)			
ϕ_3	0.039 (0.039)	0.026 (0.056)					
ϕ_4	−0.049 (0.034)						
ϕ_5	−0.008 (0.036)						
ϕ_6	0.072[a] (0.027)						
σ_1	2.447[a] (0.060)	15.53[a] (0.096)	2.583[a] (0.080)	5.160[a] (0.142)	10.26[a] (0.128)	1.855[a] (0.060)	7.637[a] (0.127)
σ_2	0.330[a] (0.093)	1.747[a] (0.059)	0.334[a] (0.078)	1.551[a] (0.056)	1.952[a] (0.052)	0.348[a] (0.169)	1.432[a] (0.055)
LogLik	−459.15	−695.87	−326.75	−565.92	−638.62	−479.13	−566.35
$Q_{(6)}$	4.283 [0.638]	5.205 [0.518]	9.601 [0.142]	7.740 [0.258]	9.017 [0.173]	4.360 [0.628]	5.953 [0.428]
$Q_{(12)}$	7.748 [0.804]	16.06 [0.188]	17.77 [0.122]	16.96 [0.151]	12.55 [0.402]	17.75 [0.123]	7.709 [0.807]
$Q^2_{(6)}$	1.412 [0.965]	2.784 [0.733]	0.627 [0.996]	1.756 [0.941]	3.108 [0.795]	5.702 [0.457]	0.403 [0.999]
$Q^2_{(12)}$	7.771 [0.803]	16.13 [0.185]	4.125 [0.981]	2.171 [0.998]	9.414 [0.667]	9.269 [0.680]	0.629 [1.000]
Estimated transition probabilities – high state							
γ_0	2.929[a] (0.659)	1.414 (1.395)	1.565[b] (0.601)	10.14[c] (5.251)	2.172 (1.561)	1.115[a] (0.42)	1.113[b] (0.494)
γ_1^1				−0.328 (0.967)	−1.649 (1.213)		
γ_1^2			0.073 (0.093)			−0.072 (0.216)	
γ_1^3	−0.432[b] (0.195)	0.158 (0.289)					−0.814[a] (0.276)
γ_1^4							
γ_2^1	−0.608 (0.437)			1.833 (1.242)	4.721[c] (2.917)		0.897[b] (0.404)
γ_2^2		0.387 (0.288)				0.396[b] (0.197)	
γ_2^3							
γ_2^4			0.484[b] (0.247)				

(*continued on next page*)

Table 7 (*continued*)

	India	Indonesia	Pakistan	Philippines	South Korea	Taiwan	Thailand
γ_3	0.056 (0.070)	−0.122 (0.148)	0.060 (0.072)	0.469 (0.357)	−0.755 (0.527)	−0.312[c] (0.189)	−0.498[a] (0.153)
γ_4	0.158[c] (0.082)	0.117 (0.138)	−0.005 (0.039)	0.809[c] (0.473)	0.220 (0.146)	0.028 (0.061)	0.548[b] (0.263)
Estimated transition probabilities – low state							
η_0	1.242[b] (0.537)	4.480[a] (1.160)	5.187[a] (1.404)	6.703[a] (2.000)	5.708[a] (1.514)	−1.126[c] (0.683)	3.403[a] (0.455)
η_1^1				0.205 (0.289)	0.807[a] (0.295)		
η_1^2			0.446[a] (0.155)			0.924[b] (0.461)	
η_1^3	0.502[c] (0.288)	0.758[b] (0.357)					0.009[a] (0.002)
η_1^4							
η_2^1	−0.644[c] (0.385)			−0.095 (0.154)	−0.266[c] (0.155)		−0.156[a] (0.040)
η_2^2		−0.478[c] (0.284)				0.807 (0.566)	
η_2^3							
η_2^4			−0.278 (0.234)				
η_3	−0.176 (0.145)	−0.012 (0.096)	0.372[a] (0.142)	0.358[c] (0.184)	−0.424[b] (0.197)	−0.640 (0.446)	−0.817 (0.770)
η_4	−0.083 (0.104)	−0.233[b] (0.114)	−0.401[c] (0.214)	−0.324 (0.249)	−0.901[a] (0.248)	0.001 (0.029)	−0.150[a] (0.041)

Notes: Autocorrelation and heteroscedasticity-consistent standard errors are reported in parentheses (.). The time varying transition probabilities (Eq. (3)) are extended now accounting for the additional control variables, and hence evolve as follows: $p_t^l = \frac{\exp\{\eta_0 + \sum_{k=1}^{4}\eta_1^k nbf_{t-k} + \sum_{k=1}^{4}\eta_2^k nef_{t-k} + \eta_3 (i-i^*)_{t-1} + \eta_4 \, vix_{t-1}\}}{1+\exp\{\eta_0 + \sum_{k=1}^{4}\eta_1^k nbf_{t-k} + \sum_{k=1}^{4}\eta_2^k nef_{t-k} + \eta_3 (i-i^*)_{t-1} + \eta_4 \, vix_{t-1}\}}$ and $p_t^h = \frac{\exp\{\gamma_0 + \sum_{k=1}^{4}\gamma_1^k nbf_{t-k} + \sum_{k=1}^{4}\gamma_2^k nef_{t-k} + \gamma_3 (i-i^*)_{t-1} + \gamma_4 \, vix_{t-1}\}}{1+\exp\{\gamma_0 + \sum_{k=1}^{4}\gamma_1^k nbf_{t-k} + \sum_{k=1}^{4}\gamma_2^k nef_{t-k} + \gamma_3 (i-i^*)_{t-1} + \gamma_4 \, vix_{t-1}\}}$, where $nbf_{t-k}, nef_{t-k}, vix_{t-1}$, and $(i-i^*)_{t-1}$ are net bond inflows, net equity inflows, changes in the Chicago Board Options Exchange volatility index (VIX), and interest rate differential between the US and the corresponding Asian countries, respectively. The lag length of the model is selected using the Akaike information criterion (AIC), subject to correction for serial correlation by the inclusion of further lags. $Q(p)$ and $Q^2_{(p)}$ are respectively the Ljung and Box (1978) tests for the $p$thorder autocorrelations in the standardised and squared standardised residuals; p-values are reported in square brackets [.].

[a] Statistical significance at the 1% level.
[b] Statistical significance at the 5% level.
[c] Statistical significance at the 10% level.

by global risk aversion and interest rate differentials rather than flow changes, which is consistent with the GARCH evidence. Furthermore, the estimated lag structure shows that, in the cases of India, South Korea and Thailand, equity flows affect the transition probabilities between the high- and low-volatility regimes after one month, whilst it takes longer elsewhere. Instead in the case of bond flows it takes between two and three months for this effect to materialise, with the only exception of South Korea where the probability to remain in the low regime $(\eta_1^1 = 0.807)$ is affected after one month.

Overall, the results are mixed for most countries, either bond or equity flows in turn affecting exchange rates volatility and possibly at different lags. A clear pattern emerges only for South Korea and the Philippines. Specifically, the currency of the former appears to be the most responsive to equity and bond flows, where decades of financial repression had constrained the financial system, and the subsequent capital account liberalisation programme affected the response to the 1997–1998 crisis. Despite the considerable reforms undertaken since then, concerns remain about both South Korea's lending culture and ability to regulate a more complex financial system (Noland, 2005). As for the Philippines, our finding that the effects of flows are insignificant can be explained by the restrictive measures (especially on outflows) introduced by the central bank to avoid an excessive appreciation of the peso and maintain overall stability in the foreign exchange market as well as develop the domestic capital market (Gonzales, 2008).

5. Conclusions

In this paper we have investigated the effects of equity and bond portfolio inflows on exchange rate volatility, using monthly bilateral data for the US *vis-a-vis* seven Asian developing and emerging countries, namely India, Indonesia, Pakistan, the Philippines, South Korea, Taiwan and Thailand over the period 1993:01–2015:11. Both GARCH and time-varying transition probability Markov-switching specifications have been employed to model respectively the volatility of exchange rates and also switches between high and low volatility regimes as a function of stochastic information arrivals in the form of simple portfolio (bond and equity) shifts. Further, robustness checks have been carried out by including exogenous control variables such as global risk aversion and interest rate differentials.

The empirical results suggest that net equity and net bond portfolio inflows affect significantly exchange rate volatility in most countries, the Philippines being the exception. In particular, the results of the GARCH estimation show that equity inflows increase exchange rate volatility, while bond inflows decrease it. Moreover, the Markov switching results suggest that net equity and net bond portfolio inflows affect significantly the transition probabilities between the high and low volatility states; specifically, equity inflows increase the probability of remaining in, or switching to, the high exchange rate volatility, whereas bond inflows increase the probability of staying in, or switching to, the low volatility regime. The Philippines are the only exception once again, whilst South Korea is the most responsive country.

The impact of net equity flows can be plausibly attributed to the exchange rate response to a more volatile demand for equities in emerging markets. As for net bond flows, cross-border bond acquisitions in emerging countries are usually hedged, because bonds denominated in the local currency in emerging markets are relatively less liquid (Gadanecz et al., 2014). Therefore, lower exchange rate volatility is associated with larger bond inflows. Finally, our findings have important policy implications: in countries where net equity and net bond portfolio flows appear to affect exchange rate volatility, capital controls imposed on them could be an effective tool for policy-makers and financial regulators aiming to stabilise the foreign exchange market.

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