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Abstract

This paper attempts to provide evidence of "shift-volatility" transmission in the East Asian equity markets. By "shift-volatility", we mean the volatility shifts from a low level to a high level, corresponding respectively to tranquil and crisis periods. We examine the interdependence of equity volatilities between Hong Kong, Indonesia, Japan, Malaysia, the Philippines, Singapore, Thailand and the United States. Our main issue is whether shift-volatility needs to be considered as a regional phenomenon, or from a more global perspective. We find that the timing/spans of high volatility regimes correspond adequately to years historically documented as those of crises (the Asian crisis and the years following the 2008 crisis). Moreover, we suggest different indicators that could be useful to guide the investors in their arbitrage behavior in the different regimes: the duration of each state, the sensitivity of the volatility in a market following a change in the volatility in another market. Finally, we are able to identify which market can be considered as leading markets in terms of volatility.

Keywords: Regime shifts, Equity Volatility, East Asia, TVPMS
JEL: R31,G15,C32

1. Introduction

This paper attempts to provide evidence of "shift-volatility" transmission in the East Asian equity markets. By "shift-volatility", we mean that in these markets, the volatility shifts from a low level to a high level, usually corresponding respectively to tranquil and crisis periods. We investigate which of the markets, regional or global, are the most influential in driving the volatility into different regimes. The optimal equity portfolio is likely to be different in calm and turbulent periods, thereby implying that exploiting regime switching may lead to shift assets from one market to another when a bull or a bear market is expected. The presence of different states in the volatility can be explained by a diversity of factors, among which the heterogeneity of arbitrageurs, the rigidity of price adjustment,

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jumps in the asset allocation reflected for instance by time-varying betas (Ang and Bekaert , 2002), and asymmetric correlation phenomena (Ang and Chen , 2002; Longin and Solnik , 2001).

Most empirical papers considering such possibilities focus on the asymmetric nature of volatility, and cross-market second-order moment correlations, using nonlinear models. These models can be divided into two categories, depending on whether they identify *a priori* the different regimes, or whether they are based on an endogenous identification from the data. The first category of models include nonlinear VARs, threshold autoregressive models (TAR), nonlinear multivariate GARCH models (see e.g. Chou et al. , 1994; Hamao et al. , 1990). The second type of models is based on Markov-switching models where a hidden state variable follows a Markov chain. These models have been designed as a way of doing "identification through heteroskedasticity" (see Rigobon , 2003) where the timing of changes from low to higher volatility regimes is endogenously determined. Examples of papers are Ang and Bekaert (2002), Billio et al. (2005), Fratzscher (2003) and Gravelle et al. (2006). The present paper is based on the second approach. Unlike many previous papers, we do not consider standard Markov-switching models (Hamilton , 1989, 1990) where the probabilities of moving from one regime to another are fixed over time. Instead, we assume that the regime-shifts are conditioned by the dynamics of the volatility in another influent market, which is a good way of capturing volatility spillover effects. We accordingly refer to the framework originally proposed by Filardo (1994) and explore time-varying probability Markov-switching models (TVPMS).

We propose to examine the interdependence of equity volatilities between Hong Kong, Indonesia, Japan, Malaysia, the Philippines, Singapore, Thailand and the United States. In doing this exercise, our main issue is whether shift-volatility needs to be considered as a regional phenomenon, or from a more global perspective. It has been shown that the US market is more influential than the Japanese market in transmitting the volatility to the other Asian markets (Liu and Pan , 1997), but that during the 1997 and 1998 Asian crisis, the regional transmission played a significant role due to an increased co-movement of the Asian markets in turbulent periods (In et al. , 2001; Jang and Sul , 2002). Moreover, the impact of the Japanese market is found to be important whatever the state of the volatility, low or high (Chuang et al. , 2007). In this paper, we investigate these issues by considering data that include both the years of the Asian crisis (at the end 1990s) and those of the more recent financial crisis (after 2008).Within this framework we analyze to what extent the influence of regional markets volatility is more significant than that of international markets (notably the US market).

This sheds some light on the extent to which investors could benefit or not from portfolio diversification within the East Asian region. We find that international influence is not necessarily more important than regional influence in certain countries, although convincing evidence of different volatility regimes is obtained for all markets. The main contributions of the paper are the following. Firstly, the timing/spans of high volatility regimes identified by our model correspond adequately to years historically documented as those of crises (the Asian crisis and the years following the 2008 crisis). Secondly, our paper goes beyond finding just volatility regimes, since we suggest different indicators that could be useful to guide the investors in their arbitrage behavior in the different regimes: the duration of each state, the sensitivity of the volatility in a market following a change in the volatility in another market. Finally, we are able to identify which market can be considered as leading markets in terms of volatility.

The remainder of the paper is as follows. In section 2, we briefly review some previous empirical studies on volatility spillovers and contagion in East Asian stock markets. In section 3 we describe the empirical model. Section 4 presents and discusses the results. Section 5 concludes.

2. Volatility spillovers and contagion in East Asian stock markets

Over the last decades, East Asian economies have emerged as a pole of economic growth. The key factors underlying the catching-up process relate to greater economic openness and globalization. These economies have indeed undertaken substantial reforms aiming at liberalizing their capital account and their domestic financial system, opening up additional channels for cross-border linkages. Indeed, with the removal of restrictions, markets participants have found considerable opportunities to reduce the risk of their portfolio through international diversification strategy (see e.g. Grubel , 1968; Levy and Sarnat , 1970). Strictly speaking, Asian countries attracted about 57% of total financial inflows, such as FDI and FPI, to emerging market economies since 1990. Financial liberalization has contributed to more diversified and deepened linkages at both global and regional levels, which in turn, has given rise to a higher degree of stock market co-movement. For instance, Bekaert and Harvey (1997) examine the effects of financial liberalization and find that capital market reforms in emerging markets often increase the correlation between local stock returns and the world market without drive up local market volatility. This view is shared by some researchers for whom financial liberalization has either a reducing impact or no impact on volatility (see e.g. De Santis and Imrohoroglu , 1997; Hargis , 2002; Umutlu et al. , 2010).

On the other hand, intensified financial linkages in a world of high capital mobility may also harbor the risk of volatility spillovers, especially during episodes of financial stress. Accordingly, the tighter linkages among East Asian countries, and with the rest of the world, have enlarged the scope of spillover from global and regional shocks. This weakness was confirmed by the fact that these countries have experienced huge variations of their stock market volatility during both the 1997/1998 crisis and the 2008 global financial turmoil. The intrinsic vulnerability of these countries confronted to external shocks finds its causes in the lack of financial market depth which limit their capacity to absorb capital inflows but also in the heavy dependence on global financial intermediation conducted in international reserve currencies. Consequently, an abrupt swing in market sentiment and a sudden change in liquidity conditions could provoke a currency crisis (see e.g. Radelet and Sachs , 1998; Chang and Velasco , 1998). One important feature of financial crisis is that market turbulence can spread rapidly to other countries when the markets are highly integrated. The recurrence as well as the magnitude of financial crisis during the 1990s has spurred numerous empirical studies which attempt to identify whether the spillovers are the results of contagion effects or rather the expression of strong linkages and interdependencies among markets (see e.g. Forbes and Rigobon , 2002).

The interaction between stock market volatilities in East Asia has been widely studied in the literature. Several econometric approaches have been applied such as, among other, VAR and cointegration analysis, GARCH class of models or Granger-causality methodology. In a recent study, Engle et al. (2012) use a MEM-Based approach to model the volatility spillovers in eight East Asian stock markets before, during, and after the Asian currency crisis. The authors find significant interdependencies within the region where Hong Kong has a crucial role in influencing other markets. Using a spillover index methodology (see e.g. Diebold and Yilmaz , 2009) for ten East Asian countries, Yilmaz (2010) shows that the volatility spillover index experiences significant bursts during major episodes of financial stress, including both the East Asian and the recent global financial crises. Worthington and Higgs (2004) use a Multivariate GARCH model to identify the source and magnitude of spillovers during the period 1988 to 2000 for a panel of nine Asian countries, including both developed and emerging equity markets. While they find evidences that these markets are highly integrated, the authors suggest that volatility spillovers from changes in domestic market conditions are generally higher than cross-volatility spillovers for all markets, but especially for the emerging markets. Otranto (2005) proposes another approach in which the dynamics of the regime volatility of a variable depends on the dynamics of the regime volatility of the other variables. Gallo and Otranto (2007, 2008) apply this multi-chain Markov switching (MCMS) model to volatilities of several Asian stock markets and found that such model is also appropriate to estimate both contagion and co-movements. Nonetheless, their methodology implies to determinate the market from which the shock originates. Accordingly, this assumption excludes the possibility, for the dominated market, to influence the dominant market. Empirical studies on the extent of contagion and interdependence across East Asian countries during the 1997-98 crisis has also been conducted by Khan and Park (2009), Ratanapakorn and Sharma (2002) and Chiang and Doong (2001), among other.

Other studies have focused on the interactions between the US and East Asian equity markets to trace the influence of world and regional factors on market volatility. For instance, Cheung et al. (2007) show that the US market leads the daily equity returns on Hong Kong, Korea Singapore and Taiwan markets before, during and after the 1997 Asian financial crisis and the opposite is true only during the crisis period. In a comparative analysis, Miyakoshi (2003) estimates a volatility spillover model to examine whether Asian stock markets are influenced by the world factor (namely the US market) or by the regional factor (the Japanese market). The author shows that the volatility of the Asian market is more influenced by the Japanese market than by the US one. Conversely, Ng (2000) finds significant volatility spillovers inside the region, e.g. a regional shock originating from Japan is transmitted to most of the Pacific-Basin countries. In the context of the recent US financial crisis, the analysis of volatility spillovers has been conducted by Morales and Andreosso-O'Callaghan (2012). According to these authors, the US crisis does not generate contagious effects in East Asia although they find strong evidence of volatility transmission suggesting that these markets are highly integrated. Another recent study conducted by Samarakoon (2011) shows that interdependence is driven more by US shocks, while contagion is driven more by emerging market shocks.

In this paper, we focus on both emerging and developed East Asian stock markets that are the Stock Exchange of Thailand (SET), the Straits Time Index of Singapore (STI), the Philippines Stock Exchange Index (PSEI), the Kuala Lumpur Composite Index (KLCI), the Jakarta Composite Index (JCI), the Hang Seng Index (HSI) and the Nikkei 225 (NKY). Since we are interested in the transmission of stock market volatility from developed markets and US market to emerging markets, we also consider the Standard & Poor's 500 (SPX). In line with many studies, we use the range-based volatility as a proxy for the true volatility (see e.g. Christensen and Podolskij , 2007; Martens and Van Dijk , 2007; Engle et al. , 2012). Therefore, the integrated volatility is constructed based on daily range and is calculated according to the following formula:

$$r_{t,i} = \ln\left(\frac{h_{t,i}}{l_{t,i}}\right) \tag{1}$$

with $r_{t,i}$, the daily range measure defined as the difference between the highest ($h_{t,i}$) and the lowest ($l_{t,i}$) log security prices over a day, with $i = \{SET, STI, PSEI, KLCI, JCI, HSI, NKY, SPX\}$. The sample covers 18 July 1995 to 29 November 2012.

3. The empirical model

In order to investigate shift-volatility transmission, we adopt the framework initially proposed by Filardo (1994). We assume that there are two volatility regimes with a given variable driving the data into either one or the other regimes. The transition between the two regimes is governed by a time-varying transition probability matrix. Though the choice of two regimes is made here for simplicity's sake, another argument for not considering a higher number of states in exploring the volatility dynamics is that, in general, they provide little improvement in the likelihood (see e.g. Ardia , 2009; Henneke et al. , 2011). The model we explore has the following parametric form:

$$y_t = \alpha_{s_t} + \beta_{s_{t-1}}(y_{t-1} - \alpha_{s_{t-1}}) + \sigma^2_{s_t}\varepsilon_t, \qquad s_t = \{1, 2\}, \qquad \varepsilon_t \sim i.i.d.\ N(0, 1), \qquad t = 1, \ldots, T \tag{2}$$

The endogenous variable, y_t, is assumed to visit the two states of a hidden variable s_t that follows a first-order Markov chain, over the T observations. s_t is assumed to satisfy regularity conditions such as aperiodicity, irreducibility and ergodicity. Denoting z_t the driving (or transition) variable, we define the following transition probability functions,

$$p_{11}(z_{t-1}) = \frac{\exp(\gamma_{11} + \gamma_{12}z_{t-1})}{1 + \exp(\gamma_{11} + \gamma_{12}z_{t-1})}, \qquad p_{22}(z_{t-1}) = \frac{\exp(\gamma_{21} + \gamma_{22}z_{t-1})}{1 + \exp(\gamma_{12} + \gamma_{22}z_{t-1})} \tag{3}$$

where $p_{11}(z_{t-1})$ and $p_{22}(z_{t-1})$ are elements of the following transition probability matrix

$$P(z_{t-1}) = \begin{pmatrix} p_{11}(z_{t-1}) & p_{12}(z_{t-1}) \\ p_{21}(z_{t-1}) & p_{22}(z_{t-1}) \end{pmatrix} \tag{4}$$

with $p_{21}(z_{t-1}) = 1 - p_{11}(z_{t-1})$, $p_{12}(z_{t-1}) = 1 - p_{22}(z_{t-1})$. $p_{ij}(z_{t-1})$ is the probability of moving from state j to state i at time t, one day ahead following a change in the transition variable. For purpose of comparison we also consider the fixed probability model (Hamilton , 1990) as a benchmark. In this second model, the transition probability functions are defined as $p_{11}(\theta_{11}) = \exp(\theta_{11}/(1 + \exp(\theta_{11}))$ and $p_{22}(\theta_{22}) = \exp(\theta_{22}/(1 + \exp(\theta_{22}))$. In Eqs. (3), the coefficients γ_{12} and γ_{22} make explicit the link between the transition variable and the probability of remaining in or leaving regime

1 and regime 2. If there is no statistically meaningful impact of the volatility in a leading market on the volatility in other markets, then the TVPMS model converges to the Hamilton fixed probability model. In this case we may have shift-volatility due to other factors than cross-market correlation. The unconditional log likelihood function of y_t is defined as

$$L(y_t;\Theta) = \sum_{t=1}^{T}\sum_{i=1}^{2}\sum_{j=1}^{2} \ln\left[f(y_t|s_t = i, s_{t-1} = j, \Omega_t, \xi_{t-1};\Theta) \times \mathbb{P}(s_t = i, s_{t-1} = j|\Theta_t, \xi_{t-1};\Theta)\right] \tag{5}$$

$$= \sum_{t=1}^{T} \ln f(y_t|\Omega_t, \xi_{t-1};\Theta) \tag{6}$$

where $\xi_t = (y_t, y_{t-1}, \ldots, y_t)$ and $\Omega_t = (Y'_{t-1}, Z'_{t-1})$ denotes the vector of observations of y and z up to $t-1$. Considering the normality assumed in Eq. (2), the regime-dependent densities are defined as

$$f(y_t|\Omega_t, \xi_{t-1};\Theta) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(\frac{-\left(y_t - \alpha_i - \beta_j(y_{t-1} - \alpha_j)\right)^2}{2\sigma_i^2}\right) \tag{7}$$

The estimation of such a model is not trivial and can be achieved by employing three different methodologies. The first combines the gradient method and the Hamilton's filter and relies on the maximum likelihood (ML). The second relies on the so-called expectation-maximization (EM) algorithm. The third relies on a Bayesian approach and uses the Gibbs sampler. In this paper, we estimate the model applying the ML method for mixtures of Gaussian distributions, which provides efficient and consistent estimates under the normality assumption (see e.g. Kim et al. , 2008). Applying the Bayes' rule, the weighting probabilities are computed recursively. We start from the following relation,

$$\mathbb{P}(s_t = i, s_{t-1} = j|\Omega_t, \xi_{t-1};\Theta) = \mathbb{P}(s_t = i, s_{t-1} = j|z_t;\Theta)\mathbb{P}(s_{t-1} = j|\Omega_t, \xi_{t-1};\Theta) \tag{8}$$

$$= p_{ij}(z_t)\mathbb{P}(s_{t-1} = j|\Omega_t, \xi_{t-1};\Theta) \tag{9}$$

Then, we deduce the unconditional density of y_t in each regime and finally obtain the following unconditional probability:

$$\mathbb{P}(s_t = i, s_{t-1} = j|\Omega_t, \xi_{t-1};\Theta) = \frac{\sum_j f(y_t|s_t = i, s_{t-1} = j, \Omega_t, \xi_{t-1};\Theta)\mathbb{P}(s_t = i, s_{t-1} = j|\Omega_t, \xi_{t-1};\Theta)}{f(y_t|\Omega_t, \xi_{t-1};\Theta)} \tag{10}$$

4. Standard analysis of results

The transition variable (z_t) is chosen to be the volatility in some leading markets: we take alternatively the Standard and Poor's (SPX), the Nikkei (NKY), the Hang Seng (HSI) and the STI of Singapore indices. These time series

Table 1: Estimation results of FTP and TVTP models for dependent variables HSI, STI and NKY

y_t	HSI				STI				NKY			
z_t	FTP	SPX	Nikkei	STI	FTP	SPX	Nikkei	HSI	FTP	SPX	STI	HSI
α_1	0,005	0,005	0,005	0,005	0,004	0,005	0,004	0,004	0,005	0,006	0,006	0,006
t-stat	(72,30)	(75,17)	(75,80)	(77,50)	(67,76)	(68,57)	(68,04)	(62,47)	(76,01)	(72,71)	(71,84)	(67,38)
α_2	0,011	0,011	0,011	0,011	0,010	0,010	0,010	0,010	0,011	0,010	0,010	0,010
t-stat	(41,77)	(44,02)	(44,23)	(48,33)	(37,35)	(36,43)	(37,49)	(37,12)	(36,64)	(42,11)	(36,43)	(31,83)
β_{11}	0,242	0,248	0,250	0,263	0,445	0,489	0,453	0,459	0,426	0,569	0,565	0,558
t-stat	(9,72)	(10,50)	(10,86)	(11,47)	(20,63)	(21,26)	(20,90)	(18,92)	(20,11)	(25,18)	(22,42)	(17,53)
β_{21}	0,403	0,398	0,398	0,396	0,463	0,480	0,467	0,461	0,344	0,419	0,411	0,400
t-stat	(17,25)	(17,57)	(22,42)	(17,28)	(19,32)	(20,15)	(19,47)	(18,60)	(12,04)	(21,14)	(17,49)	(12,78)
σ_1	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002
t-stat	(52,64)	(54,35)	(55,83)	(54,58)	(47,23)	(48,21)	(48,12)	(50,38)	(50,21)	(39,47)	(36,34)	(32,07)
σ_2	0,005	0,005	0,005	0,005	0,005	0,006	0,005	0,005	0,006	0,005	0,006	0,006
t-stat	(47,47)	(50,05)	(47,90)	(45,50)	(42,77)	(39,56)	(41,76)	(39,91)	(35,22)	(34,59)	(29,79)	(26,80)
θ_{11}	3,963				3,142				2,970			
t-stat	(22,22)				(23,99)				(20,15)			
θ_{12}	-3,328				-1,987				-1,482			
t-stat	-(15,41)				-12,765				-8,018			
γ_{11}		3,712	3,837	3,474		2,553	3,025	2,629		1,669	1,807	1,867
t-stat		(20,83)	(21,62)	(20,69)		(18,34)	(21,62)	(20,54)		(13,89)	(11,58)	(9,09)
γ_{21}		2,969	3,175	2,731		0,899	1,779	1,145		-0,825	-0,649	-0,588
t-stat		(15,95)	(14,93)	(13,94)		(4,58)	(9,36)	(5,81)		-(4,96)	-(2,72)	-(1,76)
γ_{12}		-0,696	-0,849	-1,369		-1,188	-0,626	-1,033		-0,607	-0,321	-0,378
t-stat		-(4,77)	-(5,30)	-(6,27)		-(10,18)	-(6,26)	-(7,47)		-(7,35)	-(3,50)	-(4,45)
γ_{22}		0,544	-0,060	0,415		0,628	0,053	0,571		0,793	0,420	0,476
t-stat		(2,35)	-(0,45)	(1,66)		(4,19)	(0,49)	(2,54)		(5,47)	(4,15)	(3,49)
p_{11}	0,981	0,971	0,986	0,991	0,959	0,899	0,966	0,973	0,951	0,815	0,890	0,901
p_{11}	0,965	0,958	0,961	0,914	0,879	0,749	0,852	0,651	0,815	0,359	0,264	0,264
LL	19904,4	19916,3	19912,9	**19921,3**	20334,2	**20408,4**	20348,8	20381,0	19962,2	**20028,2**	19974,3	19981,8
LR signif.		0,000	0,000	0,000		0,000	0,000	0,000		0,000	0,000	0,000

are standardized in the transition functions in order to get an easiest interpretation and comparison of the estimated parameters. Tables 1, 2 and 3 contain our estimation results. The models very often dichotomize between two regimes of respectively low and high volatility (compare the intercepts in each regime). For instance, in the case of the HSI index, any change in the standardized volatility of the SPX index is expected to yield a high volatile regime characterized by a mean volatility of 1.1% per day, or a low volatile regime with a mean volatility equal to only 0.5% per day. Therefore shift in volatility is caused by "jumps" in the volatility of the leading market equities. The Hang Seng Index (HSI) is chosen to illustrate graphically the relationships between the volatility of Asian markets and the volatility related to alternative leading markets: the United States and Singapore[3].

These relationships are respectively depicted in the first graphic of the Figure 1 where the shaded areas refer to the high volatility regime of the transition variables. The HSI clearly exhibits volatility clustering and important episodes of extreme volatility, particularly during the Asian financial crisis and the recent global financial turmoil. Figures 1 and 2 display the smoothed posterior probability of regime 2 (high volatility) for the stock market volatility of HSI according to the transition variables. Obviously, regime 2 appears to be quite persistent over the sample

[3]To save place, other similar graphs for the other countries are not reported, but available upon request to the authors.

Table 2: Estimation results of FTP and TVTP models for dependent variables KLCI and PSEI

y_t	KLCI					PSEI				
z_t	FTP	SPX	Nikkei	STI	HSI	FTP	SPX	Nikkei	STI	HSI
α_1	0,004	0,004	0,004	0,004	0,004	0,005	0,005	0,005	0,005	0,005
t-stat	(58,83)	(57,63)	(55,07)	(56,01)	(52,18)	(82,11)	(83,48)	(81,48)	(84,80)	(90,47)
α_2	0,009	0,009	0,009	0,009	0,009	0,010	0,010	0,010	0,010	0,010
t-stat	(28,47)	(29,34)	(30,27)	(29,33)	(29,53)	(40,51)	(42,33)	(43,98)	(42,12)	(47,26)
β_{11}	0,558	0,559	0,572	0,567	0,575	0,356	0,363	0,353	0,368	0,365
t-stat	(27,54)	(27,23)	(29,43)	(30,78)	(29,73)	(14,63)	(14,54)	(14,90)	(15,64)	(15,74)
β_{21}	0,622	0,623	0,625	0,628	0,623	0,257	0,265	0,260	0,270	0,254
t-stat	(28,71)	(30,13)	(29,56)	(32,37)	(32,25)	(11,89)	(12,89)	(12,42)	(12,78)	(15,32)
σ_1	0,002	0,002	0,002	0,001	0,001	0,002	0,002	0,002	0,002	0,002
t-stat	(58,69)	(59,03)	(57,31)	(60,61)	(58,18)	(45,66)	(44,51)	(46,05)	(46,26)	(46,95)
σ_2	0,007	0,007	0,007	0,007	0,007	0,005	0,005	0,005	0,005	0,005
t-stat	(34,96)	(38,39)	(37,14)	(35,32)	(36,78)	(40,12)	(41,88)	(41,71)	(42,37)	(43,36)
θ_{11}	3,362					2,200				
t-stat	(26,04)					(20,26)				
θ_{12}	-1,848					-0,694				
t-stat	-(11,32)					-(4,58)				
γ_{11}		3,351	3,254	3,165	3,171		2,107	2,164	1,961	1,962
t-stat		(25,48)	(26,07)	(27,28)	(26,01)		(19,50)	(20,23)	(19,23)	(20,19)
γ_{21}		1,766	1,619	1,546	1,376		0,487	0,631	0,274	0,246
t-stat		(10,72)	(9,70)	(9,00)	(8,03)		(3,50)	(4,18)	(1,84)	(1,88)
γ_{12}		-0,466	-0,526	-0,835	-0,713		-0,531	-0,157	-0,518	-0,423
t-stat		-(6,38)	-(2,94)	-(7,40)	-(8,36)		-(6,77)	-(2,13)	-(6,03)	-(4,88)
γ_{22}		-0,006	0,031	0,037	0,310		0,149	0,360	0,528	0,815
t-stat		-(0,06)	(0,16)	(0,48)	(2,51)		(1,46)	(3,40)	(4,57)	(6,30)
p_{11}	0,966	0,961	0,971	0,980	0,979	0,900	0,875	0,904	0,919	0,913
p_{11}	0,864	0,854	0,832	0,819	0,749	0,667	0,630	0,611	0,451	0,378
LL	20775,9	20790,5	20788,5	20802,5	**20806,5**	20259,5	20290,1	20269,0	20298,3	**20306,5**
LR signif.		0,000	0,000	0,000	0,000		0,000	0,000	0,000	0,000

and periods characterized by a high probability of being in a turbulent stock market regime are recurrent and long-lived. When examining jointly the integrated volatility of HSI and the smoothed probabilities, the results offer fairly convincing evidence that clusters of extreme values in the volatility can be precisely identified by the TVTP model. For instance, the smoothed probabilities indicate high volatility regimes during the major events of financial stress, such as the financial crises in emerging markets in the late 1990s, the global economic downturn in 2001, the subprime mortgage crisis of 2007, the collapse of Lehman brother in 2008 and the EU sovereign debt crisis in 2011. Further, these graphs also show that volatility transmission from United States to Hong Kong is clearly identified since the smoothed probabilities are highly correlated with the shaded areas corresponding to shocks emanating from United States. We obtain similar conclusion for STI. This suggests that the volatility in the Hong Kong and Singapore equity markets evolves in line with the volatility in the US market. We also observe that the time-varying probabilities are function of the volatility in the leading markets. Figures 3 and 4 plot the values of p_{11} and p_{22} implied by the changes in the volatility of SPX, and STI, respectively. Figure 3 shows that when the volatility of SPX is maintained at his sample mean value (i.e. $z_{t-1} = 0$)[4] the probability of staying in the calm regime is approximately 0.95. We find similar

[4]Note that z_t are standardized in the transition functions.

results with STI. However, as the volatility in the leading markets increases above his average level, the probability p_{11} decreases, thereby suggesting that a positive increase in z_{t-1} makes a feedback to a high volatility regime more likely. This effect is particularly rapid for STI but less than SPX.

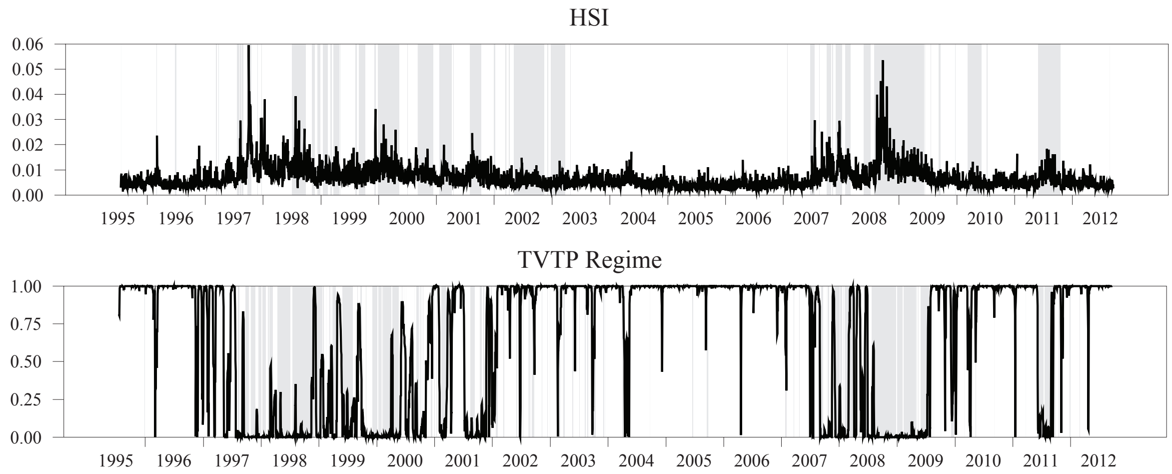

Figure 1: Range-based volatility of HSI market and the TVTP of being in regime 1 with SPX as information market.

Turning to the estimated coefficients in the Tables 1, 2 and 3, we see that they are very often statistically significant at the 1% level of significance,and that the LR tests (which test the null hypothesis of a fixed transition probability matrix against the alternative hypothesis of a time-varying one) yield to reject the Hamilton constant probability model. In both cases of constant and time varying probabilities models, the transition probabilities p_{11} and p_{22} show that the expected duration of "calm" periods - associated with regime 1 - is longer than the duration of "turbulent" periods or high volatility regime associated with regime 2. Inspection of the model's log-likelihood value reveals some "preferred models", in the sense that their log-likelihood is superior to other specifications: (1) HSI and STI regime-shifts in volatility are both influenced by the SPX market and mutually interrelated; (2) JCI regime-shifts in volatility is influenced by SPX and STI; (3) KLCI, PSEI and SET are influenced by HSI and STI; (4) NKY is influenced by SPX.

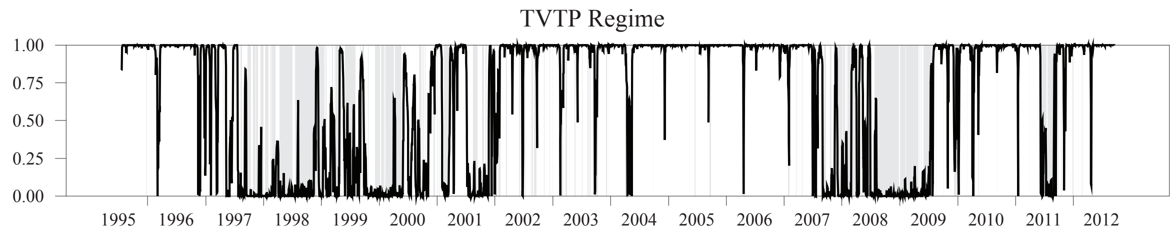

Figure 2: TVTP of being in regime 1 with STI as information market.

Table 3: Estimation results of FTP and TVTP models for dependent variables SET and JCI

y_t	SET					JCI				
z_t	FTP	SPX	Nikkei	STI	HSI	FTP	SPX	Nikkei	STI	HSI
α_1	0,006	0,006	0,006	0,006	0,006	0,006	0,006	0,006	0,006	0,006
t-stat	(67,64)	(77,96)	(72,89)	(71,42)	(71,55)	(71,77)	(71,10)	(68,48)	(70,31)	(72,00)
α_2	0,012	0,012	0,012	0,012	0,012	0,013	0,012	0,012	0,012	0,012
t-stat	(40,18)	(43,52)	(41,64)	(39,25)	(39,67)	(28,50)	(32,67)	(30,93)	(29,87)	(30,41)
β_{11}	0,423	0,434	0,439	0,442	0,436	0,491	0,513	0,503	0,501	0,505
t-stat	(18,79)	(20,53)	(19,60)	(19,70)	(19,77)	(22,76)	(25,41)	(24,66)	(22,96)	(24,60)
β_{21}	0,330	0,328	0,334	0,333	0,333	0,380	0,422	0,405	0,408	0,406
t-stat	(13,48)	(12,94)	(13,58)	(11,99)	(12,12)	(9,42)	(12,28)	(10,78)	(10,35)	(11,39)
σ_1	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002	0,002
t-stat	(49,60)	(54,26)	(50,44)	(50,42)	(53,17)	(48,17)	(47,45)	(49,80)	(49,36)	(48,26)
σ_2	0,006	0,006	0,006	0,006	0,006	0,008	0,008	0,008	0,008	0,008
t-stat	(39,95)	(44,84)	(45,52)	(44,82)	(46,55)	(39,96)	(43,33)	(39,98)	(40,85)	(43,60)
θ_{11}	3,141					2,651				
t-stat	(24,59)					(22,18)				
θ_{12}	-2,130					-1,270				
t-stat	-14,198					-(9,04)				
γ_{11}		3,071	2,990	2,929	2,974		2,477	2,538	2,407	2,430
t-stat		(24,83)	(23,73)	(22,89)	(23,85)		(21,96)	(22,81)	(21,69)	(21,50)
γ_{21}		1,952	1,830	1,734	1,732		0,891	1,078	0,827	0,812
t-stat		(13,22)	(12,29)	(11,29)	(11,66)		(6,57)	(7,55)	(5,32)	(5,68)
γ_{12}		-0,346	-0,603	-0,718	-0,884		-0,680	-0,430	-0,812	-0,562
t-stat		-(3,38)	-(4,94)	-(5,67)	-(7,32)		-(7,64)	-(5,81)	-(8,05)	-(6,49)
γ_{22}		0,456	0,280	0,584	0,364		0,308	0,130	0,302	0,557
t-stat		(3,37)	(1,86)	(3,25)	(2,22)		(2,45)	(1,29)	(2,84)	(4,26)
p_{11}	0,959	0,951	0,964	0,973	0,978	0,934	0,906	0,940	0,958	0,950
p_{11}	0,894	0,890	0,844	0,771	0,802	0,781	0,728	0,734	0,636	0,575
LL	19361,2	19374,0	19377,7	19391,1	**19397,5**	19200,5	**19246,9**	19212,9	19244,6	19238,5
LR signif.		0,000	0,000	0,000	0,000		0,000	0,000	0,000	0,000

5. State-dependent indicators

5.1. *The expected duration of each state (ED)*

Assume that the transition variable is permanently maintained at his sample mean, that is $z_{t-1} = 0$ since z_{t-1} is the standardized volatility in the leading market. From Eqs. (3), we can infer the following transition probabilities

$$p_{ii}(z = 0) = \frac{\exp(\gamma_{i1})}{1 + \exp(\gamma_{i1})}, \qquad i = \{1, 2\}. \tag{11}$$

and thus, the expected duration (ED) of each state, which is expressed in number of days, can be easily computed as :

$$ED_i(0) = \frac{1}{1 - p_{ii}(z = 0)}, \qquad i = \{1, 2\}. \tag{12}$$

Since regime 1 corresponds to the calm period and regime 2 represents the turbulent period - as shown by the estimated constant in each regime - the first indicator measures the expected number of days of staying in the low volatility regime and the second one the expected number of days of staying in the high volatility regime. As shown in Tables 4, 5 and 6, the HSI index is characterized by the longer ED during the calm periods (33 days if the STI is taken as the leading market and 41 days if the SPX is the leading market), followed by the KLCI (about 25 days) and the SET (about 20 days). At the opposite, the shortest ED in low volatility regime is found in PSEI and NKY markets (about 7 to 8 days).The longer ED related to turbulent periods is observed in the HSI market (about 20 days). In the other markets, the ED during regime 2 is found to be very short: it varies between 1.5 days in the NKY market and about 7 days in SET and KLCI markets.

Table 4: State dependent indicators for dependent variables HSI, STI and NKY

y_t	HSI			STI			NKY		
z_t	SPX	Nikkei	STI	SPX	Nikkei	HSI	SPX	STI	HSI
MMP_1	-0,174	-0,212	-0,342	-0,297	-0,156	-0,258	-0,152	-0,080	-0,095
MMP_2	0,136	-0,015	0,104	0,157	0,013	0,143	0,198	0,105	0,119
z_M^1	5,335	4,522	2,538	2,148	4,833	2,545	2,748	5,628	4,934
z_M^2	-5,454	53,024	-6,580	-1,431	-33,429	-2,004	1,041	1,546	1,235
$ED_1(0)$	41,917	47,393	33,268	13,842	21,594	14,864	6,308	7,094	7,467
$ED_2(0)$	20,464	24,936	16,353	3,456	6,923	4,141	1,438	1,523	1,555
VED_1	-20,510	-26,536	-24,060	-8,929	-9,581	-8,930	-2,416	-1,674	-2,037
VED_2	14,081	-1,391	7,900	2,147	0,324	2,420	0,530	0,273	0,339
$MP_1(0)$	-0,016	-0,018	-0,040	-0,080	-0,028	-0,065	-0,081	-0,039	-0,044
$MP_2(0)$	0,025	-0,002	0,024	0,129	0,007	0,105	0,168	0,095	0,109

5.2. *The variation of expected duration of each state (VED)*

Assume that, from the situation where $z_{t-1} = 0$, the volatility in the leading market is permanently increased by one standard-deviation. Thus, due to the standardization, it results that $z_{t-1} = 0$ and we have the following transition probabilities

$$p_{ii}(z = 1) = \frac{\exp(\gamma_{i1} + \gamma_{i2})}{1 + \exp(\gamma_{i1} + \gamma_{i1})}, \qquad i = \{1, 2\}. \tag{13}$$

Following this permanent shock of one standard deviation in the volatility of the leading market we can compute a new set of two expected durations (ED):

$$ED_i(1) = \frac{1}{1 - p_{ii}(z = 1)}, \qquad i = \{1, 2\}. \tag{14}$$

These indicators enable us to calculate the variation of the ED's resulting from a permanent increase (or decrease, because of local symmetry) of one standard deviation in the volatility of the leading market:

$$VED_i = ED_i(1) - ED_i(0), \qquad i = \{1, 2\}. \tag{15}$$

These indicators capture the impact of a change in volatility occurring in the leading market in terms of expected duration of each regime. In the cases of our preferred specifications (see Tables 4, 5 and 6), we obtain the following conclusions.

- The HSI and STI markets. A permanent increase of one standard deviation in the volatility of the SPX index decreases the expected duration of the low volatility regime by 20.5 days in the HSI market and 9 days in the STI market. Conversely, a decrease of one standard deviation in the volatility of the SPX index decreases the duration of the high volatility regime by 14 days in the HSI market and only 2 days in the STI market. The VED indicator makes clear an asymmetrical influence of the SPX index, since the HSI market appears to be much exposed to its variations than the STI market. Regarding the interactions between these two Asian markets, we can note that the index STI is influenced quite similarly by the two indices HSI and SPX. Conversely, at least during periods of high volatility (regime 2), the HSI market is less sensitive to changes in volatility on the STI market in comparison to those which affect the SPX market.

Table 5: State dependent indicators for dependent variables JCI and KLCI

y_t	JCI				KLCI			
z_t	SPX	Nikkei	STI	HSI	SPX	Nikkei	STI	HSI
MMP_1	-0,170	-0,108	-0,203	-0,140	-0,116	-0,131	-0,209	-0,178
MMP_2	0,077	0,032	0,076	0,139	-0,002	0,008	0,009	0,078
z_M^1	3,640	5,900	2,964	4,327	7,194	6,188	3,793	4,445
z_M^2	-2,890	-8,321	-2,738	-1,458	278,936	-51,648	-41,232	-4,436
$ED_1(0)$	12,900	13,657	12,101	12,363	29,525	26,897	24,692	24,840
$ED_2(0)$	3,438	3,939	3,286	3,253	6,850	6,046	5,692	4,958
VED_1	-5,874	-4,425	-6,172	-4,884	-10,621	-10,591	-13,408	-12,159
VED_2	0,881	0,407	0,806	1,681	-0,037	0,161	0,179	1,439
$MP_1(0)$	-0,049	-0,029	-0,062	-0,042	-0,015	-0,019	-0,032	-0,028
$MP_2(0)$	0,064	0,025	0,064	0,119	-0,001	0,004	0,005	0,050

- The JCI market. This market is identically influenced by the SPX and STI markets. A permanent increase of one standard deviation in the volatility of the SPX or the STI index decreases the expected duration of the low volatility regime by about 6 days in the JCI market. A decrease of one standard deviation in the volatility of the SPX or the STI index decreases the expected duration of the high volatility regime by less than 1 day.

- The KLCI, PSEI and SET markets. The three markets are influenced similarly by STI and HSI markets. In the case of KLCI and SET indices, we can notice a strong effect of the leading markets upon the expected duration in regime 1, but not in regime 2. In the case of the PSEI market, the influence of the leading markets is weak in both regimes in terms of VED. Nevertheless, since the PSEI market is characterized by a short expected duration in both regimes, we could not expect to get ahigh value of the VED.

5.3. *The marginal probability (MP)*

A limitation of the VED measure is that the expected duration in the high volatility regime is often very low, and thus it is also necessarily the case of the VED in this regime. We can thus suggest a related measure of the impact of an increase of one standard-deviation in the volatility of the leading market based on the first derivative of the probability function with respect to z_{t-1}:

Table 6: State dependent indicators for dependent variables PSEI and SET

y_t	PSEI				SET			
z_t	SPX	Nikkei	STI	HSI	SPX	Nikkei	STI	HSI
MMP_1	-0,133	-0,039	-0,130	-0,106	-0,086	-0,151	-0,179	-0,221
MMP_2	0,037	0,090	0,132	0,204	0,114	0,070	0,146	0,091
z_M^1	3,965	13,756	3,782	4,638	8,888	4,956	4,080	3,364
z_M^2	-3,275	-1,752	-0,519	-0,302	-4,278	-6,540	-2,967	-4,761
$ED_1(0)$	9,223	9,707	8,108	8,113	22,570	20,878	19,707	20,564
$ED_2(0)$	2,627	2,879	2,316	2,279	8,046	7,233	6,663	6,650
VED_1	-3,390	-1,267	-2,876	-2,454	-6,302	-9,004	-9,583	-11,481
VED_2	0,261	0,814	0,916	1,612	4,076	2,012	4,497	2,478
$MP_1(0)$	-0,051	-0,015	-0,056	-0,046	-0,015	-0,028	-0,035	-0,041
$MP_2(0)$	0,035	0,082	0,130	0,201	0,050	0,033	0,075	0,046

$$\frac{\partial p_{ii}(z_{t-1})}{\partial z_{t-1}} = \gamma_{i2}\frac{\exp(\gamma_{i1} + \gamma_{i2} z_{t-1})}{(1 + \exp(\gamma_{i1} + \gamma_{i1}))^2}, \qquad i = \{1, 2\}. \tag{16}$$

These expressions give a measure of the marginal transition probabilities (MP) associated with a variation in z_{t-1} and the value taken by these derivatives depends on the specific value of the transition variable. It is thus easy to compute the MP at $z_{t-1} = 0$, i.e. at the sample mean of the transition variable, which we denote $MP_i(0)$ for $i = 1, 2$:

$$MP_i(0) = \gamma_{i2}\frac{\exp(\gamma_{i1})}{(1 + \exp(\gamma_{i1}))^2}, \qquad i = \{1, 2\}. \tag{17}$$

In this case, $MP_i(0)$ measures the variation in the transition probability induced by an increase (or a decrease because of local symmetry) of one standard deviation from the sample mean in the volatility of leading market. As shown in Tables 4, 5 and 6, in most cases (JCI, PSEI, SET) the $MP_i(0)$ indicator is about -0.05 in regime 1, which means that, starting from its sample mean, an increase of one standard deviation of the volatility in the leading market (SPX, HSI, or JCI) leads to a 0.05 decrease in the probability to stay within the same regime of low volatility at the next period. In some cases, this marginal probability reaches higher values, for instance -0.08 in the STI and NKY market when SPX is used as leading market. Finally, KLCI and HSI markets appear to be less sensitive in terms of marginal probability (less than -0.03 in the first case and less than -0.02 in the second one when SPX is taken as leading market). In these cases, results are somewhat at odds with those obtained using the VED indicator. Moreover, one interesting point concerns the potential asymmetry between the $MP_i(0)$ over the two regimes. It appears clearly in most cases (PSEI, STI, NKY and - depending on the chosen leading market - JCI, SET and KLCI) that the marginal probability is greater in regime 2 (high volatility) than in regime 1. In those cases, a decrease of one standard deviation in the leading market's volatility (starting from its sample mean) leads to a decrease of about 0.1 of the probability to stay in the same regime of high volatility at the next period. Although this point is not confirmed in the case of the HSI market, these results leads us to conclude that, overall, a variation of the volatility in the leading market has greater effects in terms of marginal probability during high volatility periods than during calm periods.

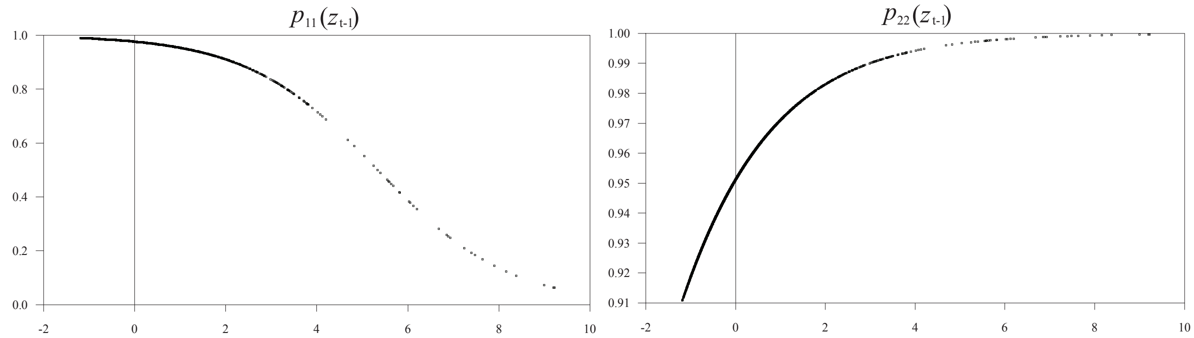

Figure 3: Logistic transition function of HSI regime switches with information market SPX.

5.4. The maximum marginal probability (MMP)

It is known that the curves of the transition probability functions have an inflection point which corresponds to $p_{11} = 0.5$ and $p_{22} = 0.5$. This specific point is associated to the maximum marginal probability, which means that a given variation of the transition variable will result in a maximum change in the transition probability. The maximum marginal probability (MMP) is the slope of the tangent at the inflexion point. In the case of the logistic function used as the transition probability function, we have:

$$MMP_i = \gamma_{i2}\frac{1}{4}, \qquad i = \{1, 2\}. \tag{18}$$

Accordingly, the value of the transition variable corresponding to this MMP is given by

$$z_M^i = -\gamma_{i1}\frac{1}{\gamma_{i2}}, \qquad i = \{1, 2\}. \tag{19}$$

The interpretation is as follows: if the transition variable increases of one standard deviation from the specific value z_M^i, then the probability to stay in the regime 1 increases by the value of MMP_i Reg.1. Since $p_{ii} = 0.5$ when $z_{t-1} = z_M^i$ it results that p_{ii} will be equal to $0.5+MMP_i$ after the shock occurs.Inspection of empirical results (Tables 4, 5 and 6) reveals some interesting features: in all cases except the PSEI and NKY indices, one can find a maximal marginal probability measure heavily asymmetric and greater (in absolute value) during low volatility regimes. This result is in sharp contrast with the $MP_i(0)$ indicator. However, if we refer to the value z_M^i at which the MMP_i is calculated, we must admit that there is little chance that the value of MMP_i is actually reached (besides the negative values of the indicator are so strong that they correspond to the negative volatility). As a consequence, we have to admit that the MMP_i measure is not relevant in this case.

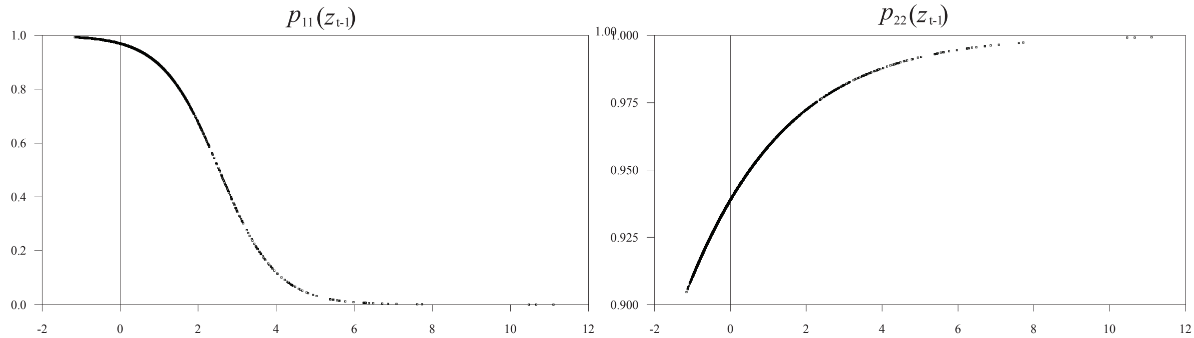

Figure 4: Logistic transition function of HSI regime switches with information market STI.

6. Final comments

The results in this paper suggest several features regarding shift-volatility caused by cross-market interdependence. Firstly, based on the model's likelihood, the Asian emerging markets can be segmented into two groups: the first one composed by HSI, STI, and JSI, appears to be positively influenced by the volatility in the U.S. market (SPX), while the second group composed by KLCI, PSEI and SET are primarily influenced by the others Asian emerging markets (namely HSI and STI). This suggests that, in Hong Kong, Singapore, and Japan, the existing linkage of the second moments between these markets and the US market, should provide less incentive towards an international equity diversification because of volatility's co-movements. On the contrary, the equities in Indonesia, Malaysia and the Philippines could be viewed as safer assets since the risk they incorporate is immune from the US equity risks. Secondly, though very different from one market to another, the expected duration is much longer in the low volatility regime than in the turbulent one. Thirdly, the VED measure appears to be directly related to the expected duration in each regime: a variation in the volatility of the leading market will induce a reduction of the expected duration of a given regime as much stronger than the initial duration of this regime is high. Accordingly, an increase in the volatility of the leading market will thus reduce heavily the expected duration of the calm regime. However, the observed heterogeneity of expected durations between markets makes it difficult to compare the results related to the VED measure.In this respect, the marginal probability (MP) indicator provides useful additional information. In the specific case of the HSI market, a variation of the volatility in the leading market starting from the sample mean, is found to have greater effects in terms of marginal probability during low volatility periods (regime 1) than during turbulent periods (regime 2), but this conclusion is reversed in all of the others markets. Thirdly, it appears finally that the influence of the leading market on the transition probabilities depends on the initial starting value of the volatility in the leading market. The maximum marginal probability (MMP) indicator shows that, in most cases, an increase in volatility of the leading market starting from a high initial value implies a sharp reduction in the probability to stay in a low volatility regime, and thus provides some evidences of the financial contagion hypothesis. Nevertheless in the case of high volatility regime the inflexion point of the transition function corresponds to implausible values of the transition variable and thus makes the MMP indicator inappropriate in this case.

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