

How volatile are East Asian stocks during high volatility periods?*

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Abstract

This study reports the estimates of the magnitude of volatility during abnormal times relative to normal periods for seven East Asian economies using a rudimentary univariate Markov-switching ARCH method. The results show that global and regional events like the 1990 gulf war and the 1997 Asian currency crisis led to high volatility episodes whose magnitude relative to normal times differ from country to country. Country-specific events like the opening up of country borders in the mid-1990s are also observed to lead to high volatility periods. Additional insights are obtained when volatility was assumed to evolve according to a three-state Markov regime switching process.

Keywords: volatility index, Markov-regime switching ARCH, East Asian stock markets

JEL classification: G10

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1 Introduction

There is no doubt that the changes in the global economic environment that occurred in the past decade and the rapid developments in technology have stimulated East Asian economies in a variety of ways. The financial markets of the so-called “emerging market” economies of East Asia, most of them liberalized during this period, attracted international investors as they provided alternative assets that offered competitive rates of return. Hence, volume of transactions increased as foreign funds flowed in to the capital markets in the early 1990s. The flow of funds however suddenly reversed as the structural weaknesses of these economies became apparent, leading to the Asian currency crisis of 1997. In both episodes when capital poured in and flowed out, the stock markets experienced heightened volatility as prices rose and plunged precipitously.

This paper reports the results of volatility estimates of East Asian stock markets during the events described above. The main interest of this study is to determine the extent of volatility of these markets relative to their tranquil periods. The study computes for the index of volatility states and attempts to date the high volatility periods in seven East Asian economies using a rudimentary univariate Markov-switching-ARCH regression analysis due to Hamilton and Susmel (1994). Weekly stock return data for Hong Kong, Korea, Indonesia, Singapore, Malaysia, Philippines and Thailand from 1988 to 2003 are used in this study. The next section presents the methodology. The third section discusses the estimation results. The last section offers some concluding remarks.

2 Methodology

Since the seminal article of Engle (1982) on ARCH modeling, quite a number of extensions and generalizations of the method have been published in academic journals and are currently being used by practitioners in Finance as a way of estimating the volatility of financial assets.¹ Bollerslev's (1986) generalization of Engle's original univariate model to ARMA processes led to further refinements but the extensions by Cai (1994) and Hamilton and Susmel (1994) to account for endogenous switches in the volatility regime assumed that the conditional variance follows an AR process. The GARCH specification was avoided mainly because of path dependence problems associated with using Markov-regime-switching methods in ARMA processes. Gray (1996) avoided the path dependence problem by using the expected value of the past conditional variance instead, which is not regime dependent. In his study, the mean and the conditional variance were allowed to evolve according to a two-state Markov process. He compared its forecasting prowess with other models of volatility to demonstrate its superiority. The present study's objective is not to forecast volatility ex ante but only modestly seeks to determine the magnitude of volatilities in abnormal times relative to normal periods. Hence the basic switching ARCH model of Hamilton and Susmel is adequate for this study's purpose.

The switching-ARCH model used in this study is described by the following equations:

$$(1) \quad r_t = \phi_0 + \phi_1 r_{t-1} + e_t$$

$$(2) \quad e_t | \Omega_{t-1} \sim N(0, h_t)$$

$$(3) \quad \frac{h_t}{g(s_t)} = \alpha_0 + \sum_{i=1}^q \alpha_i \frac{e_{t-i}^2}{g(s_{t-i})}$$

r_t , the stock return, is assumed to follow a first order AR process. The ARCH family of models assumes a non-constant conditional variance for stock returns. ARCH techniques differ on how

¹ See Bollerslev et al (1992) for a review.

the error process, e_t , is modeled, that is, how volatility is measured. In the switching-ARCH framework, the error process is described by equations (2) and (3) above.

It is clear from the above that $g(s_t)$ is a variance factor that serves to scale the ARCH process. This factor depends on the state variable, $s_t = 1, 2, \dots, K$, that indexes the “volatility regime.” The move from one state to another represents a change in the scale of the volatility process. In this specification one of the factors is unidentified and a normalization is imposed such that $g(1) = 1$ and $g(s_t) \geq 1$ for $s_t = 2, \dots, K$. Effectively, state 1 is assigned as the state with the lowest volatility and hence may be viewed as representing the normal state of the market. For $s_t \neq 1$, $g(s_t)$ indicates the magnitude of volatility at s_t relative to state 1. Equations (1) to (3) describes a regime-switching-ARCH(K, q) model. Note that when $K = 1$, the model reduces to the plain ARCH(q) model.

The volatility state is assumed to be the outcome of an unobserved first-order K -state Markov process, which can be described by transition probabilities, $P(s_t = j | s_{t-1} = i) = p_{ij}$. Each probability number, p_{ij} , is the probability that state j follows state i . One of the objectives of switching-ARCH estimation is to predict the probability of occurrence of a state for each period. This is obtained using a non-linear Markov-switching filter due to Hamilton (1989). Aside from the Hamilton and Susmel paper, the only other application of this method is Bautista (2003).

3 Data and estimation results

The study makes use of weekly stock price data of seven economies – Hong Kong, Korea, Indonesia, Singapore, Malaysia, Philippines and Thailand – from January 1988 to March 2003. Most of the stock price indices come from Datastream; the Philippine stock price series comes from the Philippine Stock Exchange. Returns are computed as the first differences of their logarithms. Descriptive statistics are shown in Table 1. It is seen that these returns have non-

normal distributions and are characterized by fat tails. Figure 1 shows the graphs of the stock price index and stock return for each of the seven countries.

Table 2 presents the estimation results where two volatility states, a low and a high state, are assumed. Figure 2 shows the graph of the smoothed probability of being in a high volatility state. The shaded portion of the diagrams covers the start of the Asian crisis up to the end of the study's sample period. The estimates seem reasonable as most of the coefficients are significantly different from zero. Except for Hong Kong, the coefficient estimates satisfactorily show the presence of ARCH effects in the countries under study.

For the period covered by this study, there were two events that could have caused volatility in all countries to almost simultaneously rise significantly above normal levels. These were the gulf war that took place at the beginning of the 1990 decade and the Asian crisis of 1997. As can be seen in Figure 2, all countries had high volatility episodes during the Asian crisis. Note that for the Thai stock market, the high volatility episode began even before the commencement of the 1997 crisis. Only the Indonesian and the Korean stock markets seemed not to have been affected by the gulf war.

The growth and development of the capital markets in Asia is a reflection of the trend towards globalization where trade and financial liberalization programs were launched by developing economies who wish to participate more fully in the expanding world marketplace. The liberalization of the Asian capital markets that began during the late 1980s until just before the 1997 Asian crisis however did not occur simultaneously across countries and were done in stages and at different speeds. For example, Indonesia's stock market which was a dormant market during the 1970s was liberalized in the late 1980s while Malaysia which had the earliest start in the 1870s began liberalization in the early 1990s (See ___, 1994). As seen in the diagrams of Fig. 2, high volatility states in the mid-1990s can be observed for Thailand, Malaysia and the

Philippines and this can be attributed in part to the sudden flow of foreign money into these capital markets.

The results show that Indonesia has the highest volatility level relative to normal at 15.4 times. A look at the diagram for Indonesia in Figure 1 however reveals that this estimate may be due to a single event in 1988 when the Indonesian stock market was given a boost by new regulations that stimulated the market. This led to an increase in the number of listed companies in the Jakarta stock exchange from 24 in 1988 to 57 in 1989 (See Reksohadiprodjo, 1993).

A two state assumption for stock market volatility might be too restrictive for some countries like Korea. Clearly, the two-state model is unable to capture the opening of the Korean stock market to foreign investors in January 3, 1992; it also shows that the market is in a high volatility state since the commencement of the Asian crisis up to the end of the sample period of this study. To remedy this, the study re-computes the volatility estimates assuming it evolves according to a three-state Markov process. With this, volatility can be in a low, a moderate or a high state; volatility indices are derived as before.

The estimates of the parameters of the 3-state model are shown in Table 3. Estimating a 3-state model is more complicated and difficult when compared to the previous 2-state computation. This is because convergence is difficult to obtain when the algorithm bumps into boundary values of some parameters. A way out of this is to restrict these parameters, the transition probabilities, to zero in the succeeding estimations. Imposing the restriction, say, $p_{13} = 0$ is essentially an assumption that state 1, the low volatility state, is never followed by state 3, the high volatility state. The transition probability matrices are given in Table 4. As shown, three probabilities were restricted in the Hong Kong, Philippines and Thailand estimates; two were restricted in the Indonesia, Korea, Malaysia and Singapore estimates.

Because volatility is classified into finer states, the index for the highest volatility state should be higher when compared to estimates that assume a 2-state process. As can be gleaned from Table 3, Indonesia's high volatility index now stands at 34 times its normal level. An interesting result that is obtained in the estimates is the indices derived for Malaysia and Singapore. The numbers indicate that the relative magnitudes of moderate and high volatility states are very close for the two economies. A possible explanation may lie in their history. In this case the result would not be surprising if one notes that Singaporean and Malaysian firms are cross-listed in both of these economies stock exchanges until January 1, 1990 when a formal separation of exchanges was effected.

Unlike in the 2-state model, the estimates for Korea indicate that the market was moderately volatile (twice that of the normal period) in 1992 when the market was opened to foreign investors and a few months before the beginning of the Asian crisis. For the Philippines, Malaysia, Thailand and Korea, the computed probabilities of moderate and high volatility states might be a good indicator of a forthcoming crisis. For these countries, stock market volatility was moderate to high during the months prior to the onset of the 1997 Asian crisis.

4 Concluding Remarks

This paper examines the magnitude of stock market volatility relative to normal periods in seven Asian economies. The paper shows that the volatility patterns that emerge in the estimation adequately characterize events that transpired in the East Asian region. It also to some extent highlights unique characteristics of the individual country markets.

Figure 1
Stock Prices and Returns

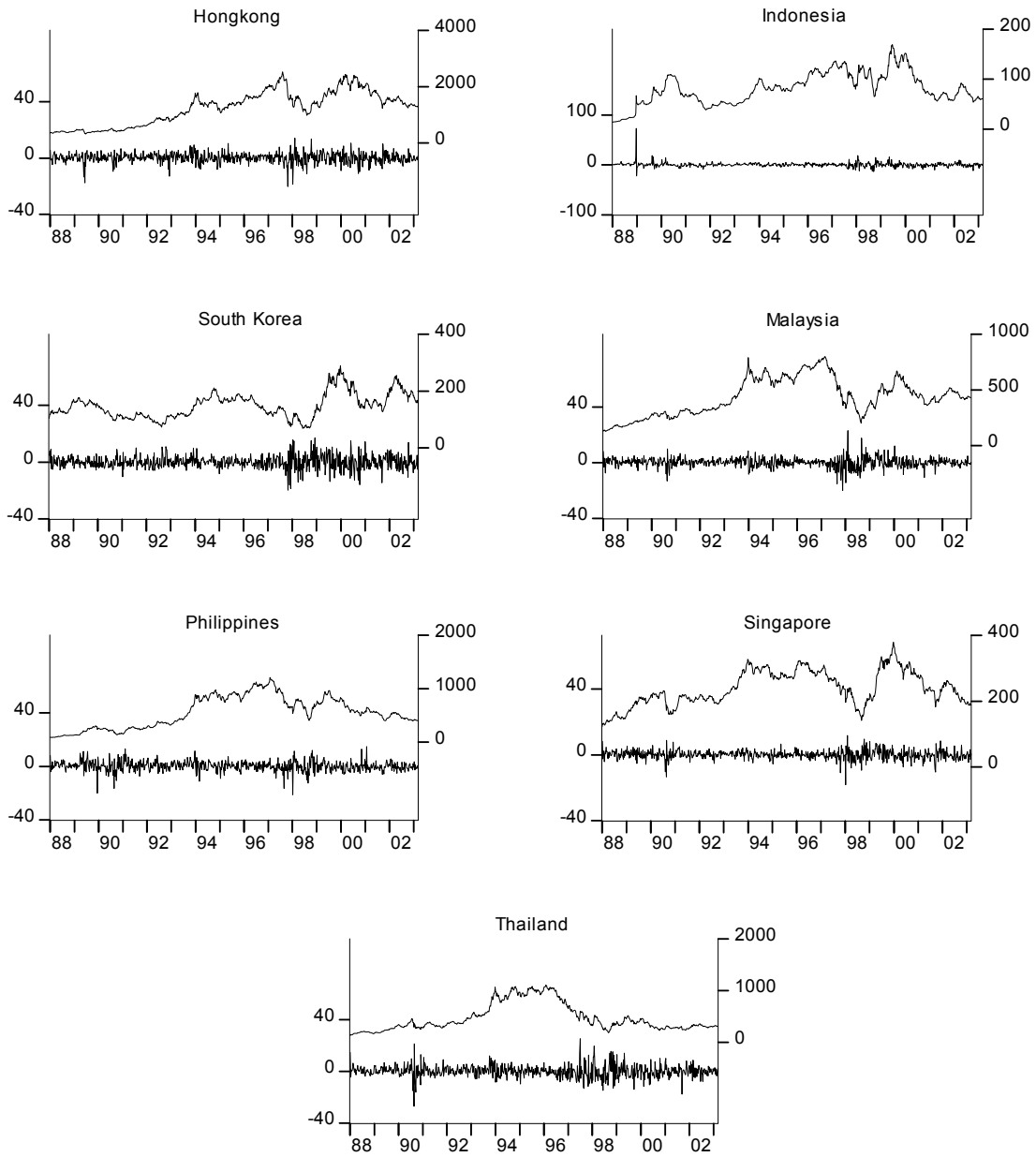


Figure 2
Smoothed probabilities of a high volatility state from a 2-state regime-switching ARCH

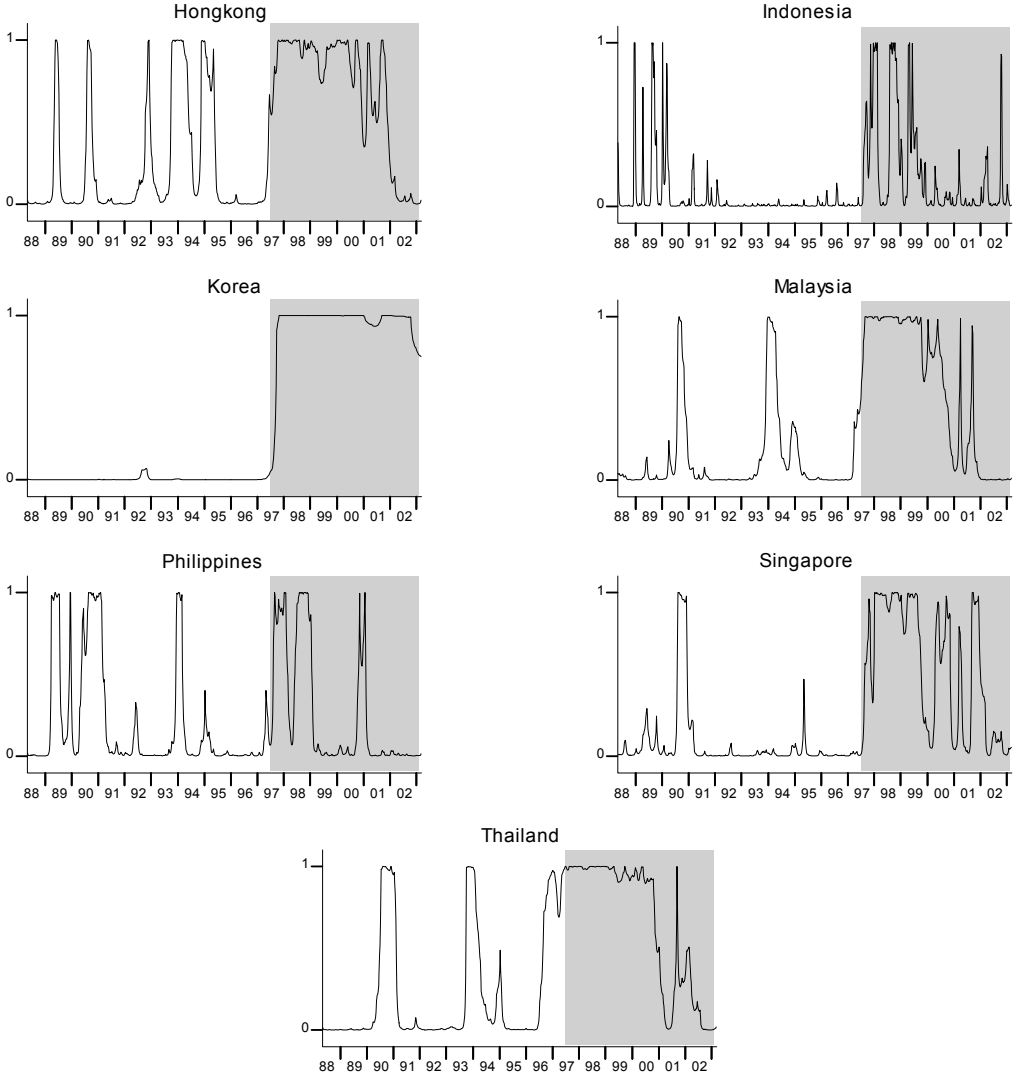
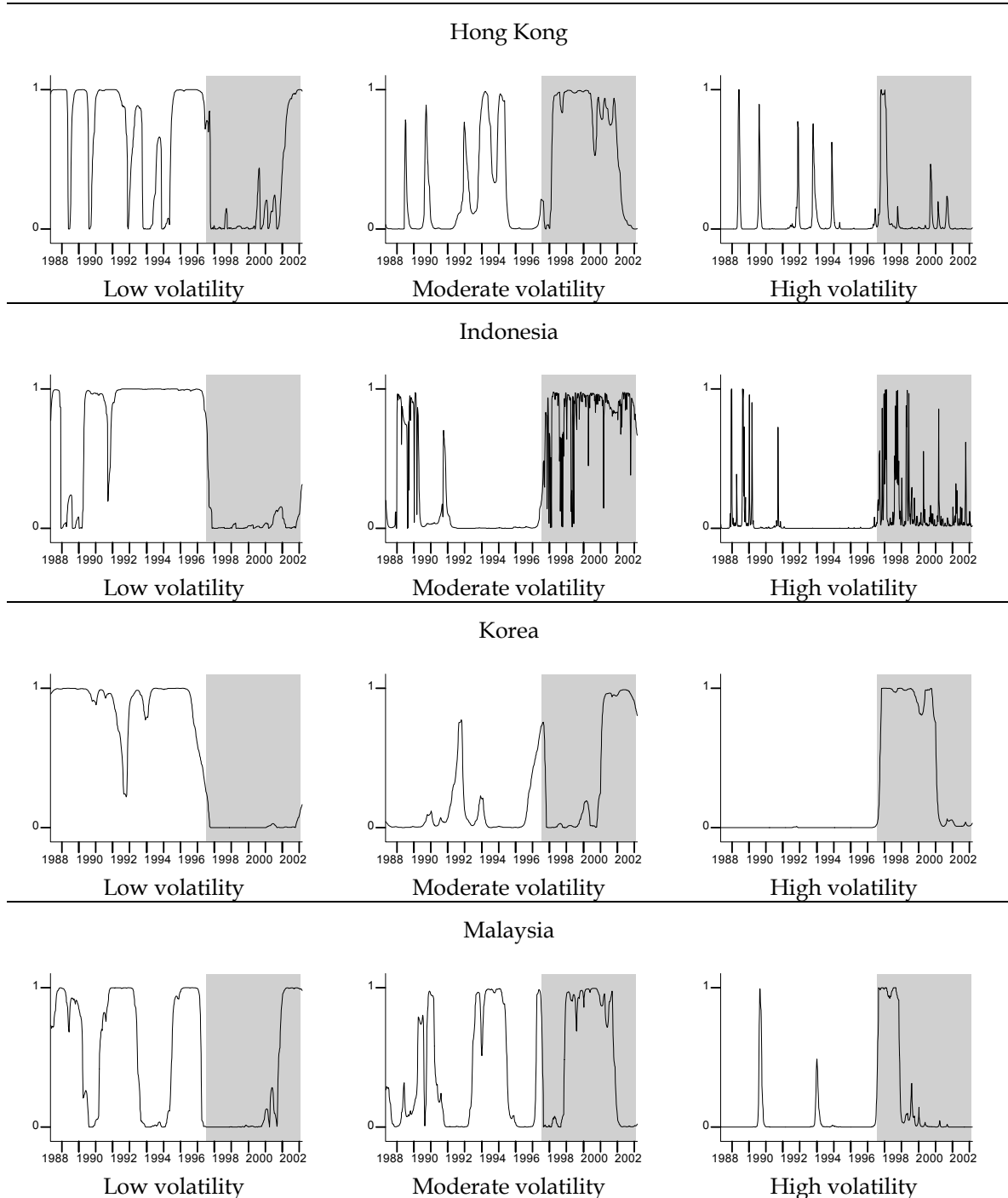
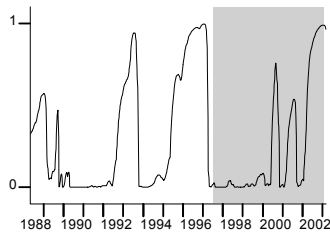


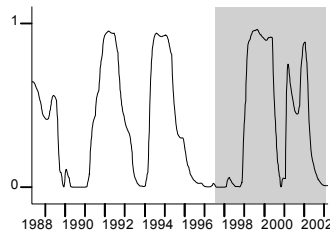
Figure 3
Smoothed probabilities from a 3-state regime-switching ARCH



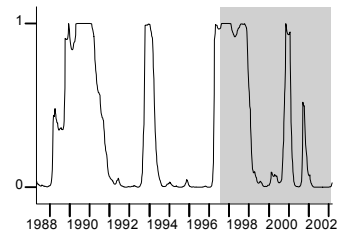
Philippines



Low volatility

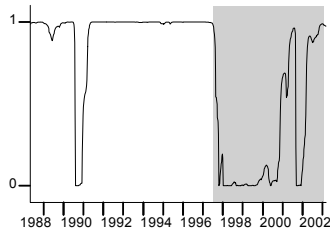


Moderate volatility

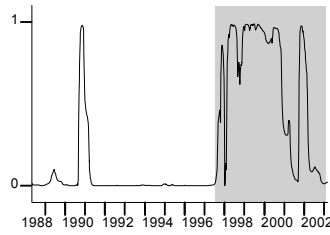


High volatility

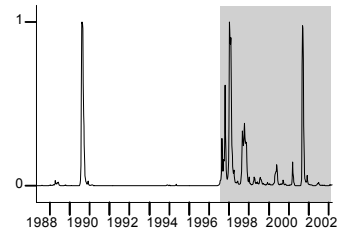
Singapore



Low volatility

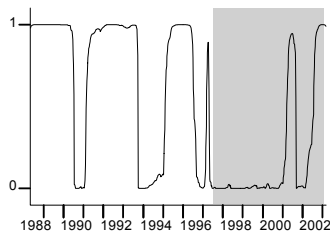


Moderate volatility

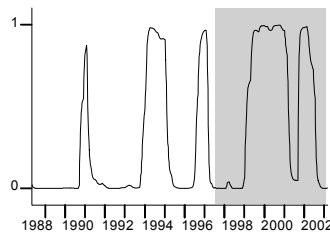


High volatility

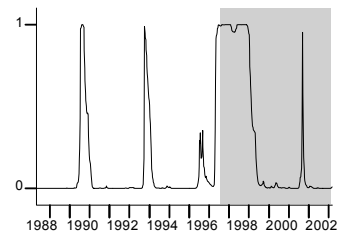
Thailand



Low volatility



Moderate volatility



High volatility

Table 1
Stock returns – Descriptive statistics

	Hong Kong	Indonesia	Korea	Malaysia	Philippines	Thailand	Singapore
Mean	0.154	0.166	0.033	0.132	0.174	0.068	0.037
Median	0.266	0.151	-0.123	0.214	0.116	-0.030	0.048
Maximum	14.061	73.286	16.947	23.058	14.741	25.267	11.740
Minimum	-20.215	-22.191	-19.575	-19.941	-21.135	-26.885	-18.281
Std. Dev.	3.583	4.513	4.474	3.431	3.697	4.685	2.747
Skewness	-0.634	5.597	0.005	-0.109	-0.394	0.118	-0.526
Kurtosis	6.568	92.845	5.082	9.132	7.030	6.966	7.489
Jarque-Bera	463	264710	140	1216	545	510	686
Observations	775	775	775	775	775	775	775

Table 2
2-state regime-switching ARCH regressions

	Hong Kong		Indonesia		South Korea		Malaysia		Philippines		Singapore		Thailand	
	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE
ϕ_0	0.337	0.109	0.070	0.092	<u>-0.061</u>	0.109	0.295	0.094	<u>0.022</u>	0.075	0.049	0.083	<u>0.188</u>	0.130
ϕ_1	<u>0.049</u>	0.038	0.386	0.040	<u>0.006</u>	0.027	0.075	0.037	0.296	0.035	0.074	0.041	0.117	0.040
α_0	5.299	0.543	2.992	0.471	8.802	0.678	3.872	0.465	5.248	0.780	2.680	0.658	6.771	0.876
α_1	<u>0.000</u>	0.029	0.176	0.058	0.094	0.039	<u>0.022</u>	0.036	<u>-0.001</u>	0.035	<u>0.011</u>	0.043	0.125	0.048
α_2	<u>0.041</u>	0.046	0.176	0.077			<u>0.043</u>	0.039	0.136	0.063	<u>0.073</u>	0.055	0.085	0.046
α_3			<u>0.000</u>	0.024			<u>-0.002</u>	0.024			<u>0.080</u>	0.059		
α_4			0.222	0.075			0.162	0.054			0.124	0.091		
p_{11}	0.979	0.010	0.975	0.012	0.998	0.002	0.987	0.007	0.982	0.014	0.984	0.012	0.987	0.007
p_{22}	0.967	0.017	0.809	0.106	0.997	0.004	0.965	0.019	0.962	0.027	0.949	0.038	0.977	0.012
$g(2)$	4.178	0.508	15.419	4.772	3.913	0.462	5.097	0.867	3.624	0.590	5.403	0.948	4.742	0.666

Underlined coefficients are insignificant.

Table 3
3-state regime-switching ARCH regressions

	Hong Kong		Indonesia		South Korea		Malaysia		Philippines		Singapore		Thailand	
	coef	SE	coef	SE	coef	SE	coef	SE	coef	SE	Coef	SE	Coef	SE
ϕ_0	0.331	0.105	<u>0.046</u>	0.082	<u>-0.058</u>	0.289	0.258	0.090	<u>0.019</u>	0.062	<u>0.074</u>	0.082	<u>0.193</u>	0.120
ϕ_1	<u>0.043</u>	0.047	0.362	0.037	<u>0.007</u>	0.036	0.103	0.038	0.293	0.034	<u>0.055</u>	0.037	0.104	0.039
α_0	5.442	1.064	-2.784	0.427	8.312	1.190	-3.456	0.382	3.645	0.695	-3.556	0.323	6.440	0.661
α_1	<u>0.000</u>	0.257	0.179	0.076	<u>0.064</u>	0.042	<u>-0.015</u>	0.037	<u>0.000</u>	0.045	<u>0.006</u>	0.036	0.081	0.047
α_2			-0.187	0.073					0.126	0.057	<u>-0.040</u>	0.049		
p_{11}	0.983	0.014	0.992	0.007	0.995	0.008	0.988	0.009	0.974	0.016	0.993	0.004	0.987	0.006
p_{22}	0.973	0.035	0.917	0.075	0.980	0.015	0.973	0.015	0.979	0.012	0.966	0.025	0.977	0.010
P_{33}	0.853	0.091	<u>0.512</u>	0.357	0.990	0.011	0.956	0.034	0.976	0.013	0.774	0.157	0.960	0.018
p_{12}			<u>0.011</u>	0.012	<u>0.012</u>	0.014	0.016	0.010			0.021	0.012		
$g(2)$	3.043	0.938	2.619	0.591	2.191	0.392	3.135	0.479	1.945	0.353	3.144	0.731	2.911	0.407
$g(3)$	9.760	4.527	33.962	16.479	5.519	1.012	14.450	3.041	5.227	1.139	14.060	8.573	9.383	1.687

Underlined coefficients are insignificant.

Table 4
Transition probability matrices
3-state models

	1	2	3
Hong Kong			
1	0.983	0.027	0.000
2	0.000	0.973	0.147
3	0.017	0.000	0.853
Indonesia			
1	0.992	0.011	0.000
2	0.000	0.917	0.488
3	0.008	0.072	0.512
S. Korea			
1	0.995	0.012	0.000
2	0.005	0.980	0.010
3	0.000	0.008	0.990
Malaysia			
1	0.988	0.016	0.000
2	0.012	0.973	0.044
3	0.000	0.011	0.956
Philippines			
1	0.974	0.021	0.000
2	0.000	0.979	0.024
3	0.026	0.000	0.976
Singapore			
1	0.993	0.021	0.000
2	0.000	0.966	0.226
3	0.007	0.013	0.774
Thailand			
1	0.987	0.023	0.000
2	0.000	0.977	0.040
3	0.013	0.000	0.960

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