GLOBAL AND REGIONAL SOURCES OF RISK IN EQUITY MARKETS: EVIDENCE FROM FACTOR MODELS WITH TIME-VARYING CONDITIONAL SKEWNESS

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First draft: January 2002
This draft: April 2003

Abstract: We examine the influence of global and regional factors on the conditional distribution of stock returns from six Asian markets, using factor models in which unexpected returns comprise global, regional and local shocks. The models allow for conditional heteroskedasticity and time-varying conditional skewness, and permit mean, variance and skewness spillovers to be measured. We find that the pattern of spillovers changed in the late 1990s. When spillovers are allowed to vary with the type of news arriving in a market, we find that local news reduces mean spillovers but increases variance spillovers. News about regional countries increases skewness spillovers.

Keywords: Asymmetries, Skewness, Volatility, Spillover, Stock returns, News.

JEL Classification: G15, C53

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1. Introduction

A thorough understanding of the sources of risk in equity markets is useful for important financial market activities such as risk management, asset allocation, and the development and implementation of regulatory frameworks. We contribute to this understanding by presenting new measurements of the relative importance of global, regional and local components of risk in equity markets. Our measurements are new in two ways: first, we re-estimate volatility spillover using a factor model that, unlike previous models used for this purpose, allows for time-varying conditional skewness. Second, we present additional evidence that distinguishes between downside and upside risks; specifically, we present measurements of spillover in skewness. The evidence we present is from six Asian equity markets, namely Hong Kong, Korea, Malaysia, Singapore, Taiwan and Thailand, using weekly data from the 1990s.

Research into interlinkages between stock markets has focused on co-movements in the mean and volatility of returns across stock markets, and has uncovered evidence of spillovers. Eun and Shim (1989), using a VAR model, find interdependence among the daily returns of leading stock markets of the world, with the US stock market being the most influential market. Kasa (1992) finds a common trend driving weekly and monthly returns from the US, Japanese, UK, German and Canadian markets. Hamao et al. (1990) study the interdependence of returns volatility across the US, UK and Japanese stock markets and find that volatility spills over mainly from the US market to the Japanese market, but not the other way around. Lin et al. (1994) find bi-directional dependency between the US and Japanese markets; daytime returns in one market are correlated with overnight returns in the next market to open. Koutmos and Booth (1995) study the US, UK and Japanese markets but differentiate between good and bad news and find, as did Booth et al. (1997) in a study of Scandinavian markets, that volatility spillovers are greater when news is bad, i.e., when the price movement in the latest market to trade prior to opening is a decline.

Evidence of co-movements in the mean and volatility of equity returns suggests that factor models, such as those developed in Bekaert and Harvey (1997) and Ng (2000), are useful ways of modeling the behavior of stock returns. Specifying unexpected return to depend on a world factor as well as an idiosyncratic shock, Bekaert and Harvey (1997) find evidence that emerging market volatility is affected by a world factor, and that the influence of the world factor varies considerably over time. Extending this approach to include both a world factor and a regional factor, Ng (2000) finds evidence of spillovers in volatility from the US and Japanese markets to the same six stock markets that we study, with the US market exerting a stronger influence, although the external shocks appear to explain only a small fraction of volatility in these markets. Both Bekaert and Harvey (1997) and Ng (2000) find that liberalization of equity markets changes the proportion of variance caused by external factors.

Past studies of mean and/or volatility spillovers have assumed the conditional distribution of stock returns to be symmetric about its conditional mean. Recent work, however, suggests that dynamics in the conditional third moment is an empirically relevant feature of stock returns. Using a model that allows for autoregressive third moments, Harvey and Siddique (1999) present evidence of skewness in the conditional distributions of daily stock index returns in the US, German, Japanese, Chilean, Mexican, Taiwanese and Thai markets, and that this asymmetry in the shape of the distribution depends on the degree of skewness in previous periods. Harvey and Siddique (2000) and Chen, Hong and Stein (2001) are detailed studies into the determinants and economic significance of skewness in stock returns; stocks that are experiencing relatively high turnover and/or unusually high returns over previous periods tend to be more negatively skewed. Stock capitalization also appears to be important in explaining the degree of skewness in stock returns. Perez-Quiros and Timmermann (2001) relate time-varying skewness to business cycle variation. The skewness in stock returns is economically significant; Chen, Hong and Stein (2001) demonstrate this by showing that the asymmetry they find in stock returns changes options prices substantially. Harvey and Siddique (2000) incorporate time-varying conditional skewness into an asset pricing model and find that doing so helps to explain pricing errors in portfolio returns using other asset pricing models. Our calculations, reported in section 2, suggest that ignoring conditional distributional asymmetries can lead to substantial mis-measurements of the probability of large negative returns.

The presence of time-varying conditional skewness in equity returns raises a few questions concerning the measurement of the influence of global, regional and local factors on individual stock markets. For instance, will incorporating time-varying skewness into an analysis of spillovers provide substantially different measurements of the relative importance of world and regional factors on the volatility of domestic equity returns? Furthermore, can we improve our understanding of volatility spillovers by measuring spillovers in downside-risk and upside-"risk", where downside-risk is measured by the probability of large unexpected negative returns relative to the probability of similarly-sized unexpected positive returns, i.e., distributional asymmetries?

In this paper, we investigate spillover effects from three perspectives, all within the context of a factor model with time-varying conditional skewness; first, we assume that the spillover effects are constant over time. Next, in the light of previously reported evidence that liberalization and other changes in the environment in which stock markets operate influence the extent of spillovers, we consider a model where spillover effects vary with important developments in the six markets. Partly in response to the results obtained from the latter model, we further explore spillovers using a model that allows spillovers to vary according to the nature of news arriving in the market. By the nature of news, we mean whether the news pertains to the country under investigation, or to a regional country. We begin with some preliminary data analysis in section 2, where we document evidence of time-varying asymmetry in the markets that we study. The evidence we present here justifies our use of a time-varying skewness framework for studying spillover effects. The evidence also highlights the importance of studying the extent of spillovers in skewness. The models that we employ for studying spillovers are described in detail in Section 3. These models are similar to those employed by Bekaert and Harvey (1997) and Ng (2000) in that unexpected returns comprise world, regional and local shocks, with the difference that these shocks are now characterized not just by time-varying conditional volatility, but also by time-varying conditional skewness. Empirical results are presented and discussed in Section 4, and Section 5 concludes.

2. Data and Summary Statistics

2.1 Data

We use weekly equity market index returns from the first week of January 1990 to the last week of December 2000.[1] The data are obtained from Datastream, and the weekly percentage returns are calculated as the difference of log closing prices on Tuesdays (multiplied by 100); we choose Tuesdays for calculating weekly returns as this is the day with the fewest holidays in our sample. The indexes used for the Pacific-Basin markets included in this study are the Hang Seng Price Index, Korea SE Composite,

[1] While an understanding of spillovers at the daily (and higher frequencies) is useful, we could not find opening and closing prices for the Asian markets. The use of weekly data also avoids problems with day-of-the-week and holiday effects.

Singapore Straits Times Index, Taiwan SE Weighted Price Index, Kuala Lumpur Composite and Bangkok S.E.T.. In Section 3, we construct spillover models where each of these returns series is driven by a world factor and a regional factor. For the world factor we use weekly returns on the MSCI World Index. For each country, a market-capitalization weighted average of weekly returns of the Asian markets in our study, excluding the market under investigation, will be used as a proxy for the regional factor.[2] For instance, when studying the Hong Kong market, the regional index will be computed as

$$r_{g(HK),t} = \frac{\sum_{j \neq HK} w_{j,t}\, r_{j,t}}{\sum_{j \neq HK} w_{j,t}} \ , \ \ j = HK, KOR, MAS, SNG, TWN, THL;$$

where $r_{g(HK),t}$ is the regional return excluding Hong Kong, $w_{j,t}$ is the market capitalization for country *j*, and $r_{j,t}$ is the return for country *j*. There are 573 observations in our sample. From this point on, we will refer to the regional return as $r_{g,t}$ when referring to the regional factor generically.

Table 1a contains summary statistics of the weekly returns on the world index, the six country indexes and, to economize on space, only the regional index which excludes Hong Kong. The Jarque-Bera test statistic clearly indicates that the returns are non-Normal, and in all cases this is due to the presence of skewness and excess kurtosis (except possibly in the case of Korean returns where excess kurtosis is the main deviation from normality). A comparison of the mean and median suggests that the World, Region ex Hong Kong, Hong Kong, Singapore and Taiwan index returns are skewed to the left, whereas the Malaysian and Thai index returns are skewed to the right. This is confirmed

[2] This follows the strategy employed in Bekaert, Harvey and Ng (2002). We thank an anonymous referee for bringing this paper to our attention.

by the coefficient of skewness. The returns series all display statistically significant excess kurtosis, which is very likely due, at least in part, to the presence of autoregressive conditional heteroskedasticity as evidenced by the prominent autocorrelations in the square of all the returns series. Significant autocorrelation in the returns taken to the third power is sometimes used as an indicator of the possible presence of autoregressive third moments. The first-order autocorrelation of returns to the third power would then indicate the possible presence of autoregressive skewness in Hong Kong, Malaysia and Singapore returns. Similar remarks concerning non-normality can be made of the regional returns that were omitted from Table 1a, with the skewness patterns varying in terms of direction and size.

Table 1b shows the correlation between the six individual markets with each other, and with the world and regional indexes. In all cases the correlations between the returns for the markets and the regional index is higher than between the markets and the world index. The pairwise correlations between the Hong Kong, Malaysia, Singapore and Thailand markets are all above 0.5 (or close to it) while the correlations involving Korea and Taiwan are all small. The correlations between the world index and the regional indexes (not shown in Table 1b) range from 0.492 to 0.592.

2.2 Time-Varying Skewness

To confirm the presence of time-variation in conditional skewness, and to assess the need for and the potential gains from using a framework that permits this, we fit univariate models of time-varying conditional skewness to these returns: the stock returns are modeled as following an AR - GARCH process, with the standardized residuals following a zero-mean unit-variance skewed t distribution developed in Hansen (1994).[3] Letting $r_{i,t}$ represent the time t return on the equity index of market i, with $i = w, g, 1, 2, \ldots, 6$ representing the world, regional, and the six individual Asian markets respectively, we model returns as:

$$r_{i,t} = \alpha_{i,0} + \alpha_{i,1} r_{i,t-1} + \varepsilon_{i,t}, \ \varepsilon_{i,t} = \sigma_{i,t} z_{i,t}, \tag{2.1}$$

$$\sigma_{i,t}^2 = \beta_{i,0} + \beta_{i,1} \sigma_{i,t-1}^2 + \beta_{i,2} \varepsilon_{i,t-1}^2 + \beta_{i,3} \left[\max(0, \varepsilon_{i,t-1})\right]^2 \tag{2.2}$$

$$z_{i,t} \sim g\left(z_{i,t} \middle| \eta_i, \lambda_{i,t}\right) \tag{2.3}$$

where the conditional distribution of the standardized residuals is as follows:

$$g\left(z_{i,t} \middle| \eta_i, \lambda_{i,t}\right) = \begin{cases} b_{i,t} c_i \left(1 + \frac{1}{\eta_i - 2}\left(\frac{b_{i,t} z_{i,t} + a_{i,t}}{1 - \lambda_{i,t}}\right)^2\right)^{-\frac{\eta_i + 1}{2}} & \text{when } z_{i,t} < -a_{i,t}/b_{i,t} \\ b_{i,t} c_i \left(1 + \frac{1}{\eta_i - 2}\left(\frac{b_{i,t} z_{i,t} + a_{i,t}}{1 + \lambda_{i,t}}\right)^2\right)^{-\frac{\eta_i + 1}{2}} & \text{when } z_{i,t} \geq -a_{i,t}/b_{i,t} \end{cases} \tag{2.4}$$

with $a_{i,t}$, $b_{i,t}$ and c_i defined as:

$$a_{i,t} = 4\lambda_{i,t} c_i \left(\frac{\eta_i - 2}{\eta_i - 1}\right) \tag{2.5}$$

$$b_{i,t}{}^2 = 1 + 3\lambda_{i,t}{}^2 - a_{i,t}{}^2 \tag{2.6}$$

$$c_i = \frac{\Gamma\left(\frac{\eta_i + 1}{2}\right)}{\sqrt{\pi\left(\eta_i - 2\right)}\,\Gamma\left(\frac{\eta_i}{2}\right)} \tag{2.7}$$

The distribution described in (2.4) through (2.7) is obtained by modifying a standardized student t distribution (see Hansen, 1994; Jondeau and Rockinger, 2002). It is

[3] The proof that a random variable with this distribution has zero mean and unit variance is in Hansen (1994).

characterized by two parameters: $\lambda_{i,t}$ determines the degree of asymmetry in the distribution and is restricted to $-1 < \lambda_{i,t} < 1$; η_i is a degree of freedom parameter that is restricted to $2 < \eta_i < \infty$. The distribution is skewed to the left (right) when $\lambda_{i,t}$ is less (greater) than 0, and reduces to the student's *t* density when $\lambda_{i,t}$ is equal to zero.[4] This is illustrated in Figure 1. Time-varying conditional skewness is obtained by specifying $\lambda_{i,t}$ as following an autoregressive specification:

$$\lambda_{i,t} = f(\lambda_{i,t-1}, \varepsilon_{i,t-1}, \max(0, \varepsilon_{i,t-1})) \ . \qquad (2.8)$$

The autoregressive specification allows current skewness to depend on past skewness, thus permitting some degree of persistence in the shape of the distribution. This follows previous work documenting time-varying conditional skewness, and fits our data well, as we show presently.[5] In addition, recent theoretical work in this area suggests an autoregressive structure. For instance, Cao, Coval and Hirshleifer (2002) show that the presence of fixed transactions costs 'side-lines' some investors who wait until price movements validate their private signals, and that this leads to time-varying skewness which depends on past price movements, a pattern which is captured by our autoregressive specification.

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[4] We refer to $\lambda_{i,t}$ as the "asymmetry parameter" or the "skewness parameter" as this parameter determines whether the distribution is symmetric or not. This parameter is, however, not the same as the coefficient of skewness; the relationship between η_i and $\lambda_{i,t}$ and the skewness coefficient and kurtosis of $z_{i,t}$ is given in Jondeau and Rockinger (2002).

[5] The specification in (2.8) does differ from previous applications of the Hansen (1994) model in that we allow for negative shocks and positive shocks to have different effects not just on volatility (the usual "leverage effect") but also on skewness.

In fitting the model[6], we impose the restrictions $-1 < \lambda_{i,t} < 1$ and $2 < \eta_i < \infty$ using the logistic transformations:

$$\lambda_{i,t} = -1 + \frac{2}{1+\exp\left(-\lambda'_{i,t}\right)} \tag{2.9}$$

$$\eta_i = 2 + \frac{30}{1+\exp\left(-\eta'_i\right)} \tag{2.10}$$

and specify (2.8) as

$$\lambda'_t = \gamma_0 + \gamma_1 \lambda'_{t-1} + \gamma_2 \varepsilon_{t-1} + \gamma_3 \max(0, \varepsilon_{i,t-1}) \ .$$

In (2.9) and (2.10) $\lambda'_{i,t}$ and η'_i are the unrestricted values of the skewness and degrees of freedom parameters respectively, and $\lambda_{i,t}$ and η_i are their restricted versions.[7]

To get an idea of how well each of the models fit the data, we use the result in Diebold, Gunther and Tay (1998) that if a series of probability density forecasts correctly describes the data generating process, then

$$q_t = \int_{-\infty}^{y_t} p_{t|t-1}(u_t)\ du_t \overset{i.i.d}{\sim} U[0,\ 1] \text{ if } p_{t|t-1}(y_t) = f_{t|t-1}(y_t)$$

where $f_{t|t-1}(y_t)$ is the true conditional distribution of y_t, and $p_{t|t-1}(y_t)$ is the probability density forecast. If our models fit well, then q_t will be distributed *iid*

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[6] The models are estimated by maximum likelihood using the BFGS Quasi-Newton method as implemented in the MATLAB function *fminunc*.

[7] Although η_i in principal should be allowed to take any value above two, numerical maximization of the likelihood function was easier with an upper bound imposed on η_i. All the fitted values of η_i lie well below 30 so there does not appear to be any problem with this restriction.

Uniform [0,1].[8] While the test of the *iid* Uniformity of q_t was developed as a forecast evaluation tool, we do not interpret it as such in this paper, since we will be applying the tests in-sample. Instead we treat the *iid* Uniformity of q_t as a measure of goodness-of-fit. Diebold, Gunther and Tay (1998) emphasize a visual evaluation by plotting the histogram of z_t and the autocorrelation functions of the powers of $z_t - \overline{z}$. To conserve on space, we will instead report the Kolmogorov-Statistic as a measure of Uniformity, and report the autocorrelation and the Ljung-Box Q statistic of $z_t - \overline{z}$ through to $(z_t - \overline{z})^4$ at lags 1 and 10 respectively.

The results from this estimation exercise are shown in Table 2, where again we leave out the results for the regional indexes except for the index ex Hong Kong. The standard errors reported are the quasi-MLE "robust" standard errors. The estimates of the mean and variance equations show very reasonable results, and the goodness-of-fit measures for all returns series suggest that the models capture the dynamics of the returns well; the Kolmogorov-Smirnov test does not reject the null of Uniformity in all cases, and the autocorrelations and Ljung-Box Q statistics show that, to a large extent, all the dynamics in the data have been accounted for. There is substantial evidence of time-varying conditional skewness despite the small sample sizes. Both the returns on the world and regional ex Hong Kong indexes show clear statistical evidence of time variation in conditional skewness. The parameters $\gamma_{i,1}$, $\gamma_{i,2}$ and $\gamma_{i,3}$ in the asymmetry equation are mostly statistically significant at 5%. A Wald test on the joint significance of these parameters in each of the equations rejects the null that the parameters are zero. The

[8] All the formulas for obtaining cdf values, quantiles and random numbers from the skewed t-distribution, can be found in Jondeau and Rockinger (2002) and Hashmi and Tay (2001).

evidence for the individual markets in our study is a little weaker. Individual and joint tests on the parameters $\gamma_{i,1}$ and $\gamma_{i,2}$ of the asymmetry equation show mixed results[9].

We can perhaps gain a better perspective on the degree of variation in the asymmetry parameter over time by evaluating these values directly. Table 3 gives the maximum and minimum values of the asymmetry series for the world and regional factor (ex Hong Kong), as well as the individual markets; Recall that these parameters lie between -1 and 1. The world and Thai returns display only negative conditional skewness, although the degree of negative skewness varies substantially over the sample. The other returns also show substantial variation in the shape of the conditional distribution, with perhaps Malaysia displaying the least variation.

To gain some idea of the importance of the asymmetries implied by the model for various values of η and λ_t, we make a comparison between the probabilities of large negative returns when the distribution is skewed versus the corresponding probabilities when asymmetries are ignored. Figure 2 plots the value $\text{Prob}(z_t \leq -2)$, i.e., the probability of an unexpected return falling more than two standard deviations below the mean, for various values of η and λ_t. Comparing the value of $\text{Prob}(z_t \leq -2)$ over the entire range of λ_t against the same probability when $\lambda_t = 0$ suggests that when time-variation in conditional skewness is neglected, it is possible to severely underestimate (or overestimate) the probability of large negative changes in the value of a portfolio. In our application to stock index returns, the values of λ_t in some cases falls below -0.8, and the implication is that $\text{Prob}(z_t \leq -2)$ could, for these stock market returns, be

[9] The inclusion of $\gamma_{i,3}$ in the univariate models for the individual markets resulted either in very small and insignificant values for $\gamma_{i,3}$, or in numerical problems when the likelihoods were being maximized. We therefore decided to leave out $\gamma_{i,3}$ when estimating the univariate models for the individual markets.

underestimated by half. There is also a potential for the probability of large negative returns to be severely overestimated if λ_t were positive. For instance, if λ_t were to be around 0.5 so that the conditional distribution is skewed to the right, the true value of $\text{Prob}(z_t \leq -2)$ would be just one-fifth of the value at $\lambda_t = 0$. These measurements highlight the importance of understanding the behavior of conditional third moments for risk management activities such as the calculation of Value-at-Risk (see Duffie and Pan, 1997, for a concise overview of VaRs.)[10]

Furthermore, the world, regional and individual market returns in our study (except for returns from the Taiwanese market) tend to be more negatively skewed during periods of high volatility. Table 4a displays the correlation between the degree of skewness as measured by $\lambda_{i,t}$ and $\sigma^2_{i,t}$, the conditional volatility of returns from the univariate models. The correlation of negative skewness with high volatility adds further weight to the economic importance of conditional skewness in the data, and the usefulness of refining our understanding of volatility spillovers to distinguish downside risks from overall volatility. The correlations, shown in Table 4b, between the estimated asymmetry parameters from the eight univariate models suggest that a factor model would be an appropriate framework for such an analysis. The correlations are all fairly large and positive (again, the exception is the Taiwanese market, for which the correlation is negative.)

[10] As η controls the fatness of the tails, it is a potentially important parameter when it comes to estimating the probability of extreme events. We note, however, that for values of η between 5 and 15 the value of $\text{Prob}(z_t \leq -2)$ does not differ much even at extreme values of λ_t. As our estimates of η all fall approximately in this range, even when η was allowed to be time varying, suggesting that restricting η to be constant may be of limited consequence in our application.

3. Spillover models

3.1 A Model with Constant Spillovers

The results from the univariate models strongly suggest that it would be productive to study the issue of volatility spillover using a factor model with time-varying conditional skewness. We construct, in the spirit of Bekeart and Harvey (1997) and Ng (2000), the following sequence of models for each of the six countries.[11] In each case, the world market returns series is assumed to follow the process described in (2.1) - (2.8), and is assumed to not depend on any of the individual markets in this study, or on the regional factor. The regional market returns series on the other hand is driven by a world shock, and a regional shock that is assumed to be independent of the world shock:

$$r_{g,t} = \alpha_{g,0} + \alpha_{g,1} r_{w,t-1} + \alpha_{g,2} r_{g,t-1} + \varepsilon_{g,t}, \tag{3.1}$$

$$\varepsilon_{g,t} = \phi_{g,1} \varepsilon_{w,t} + e_{g,t}, \quad e_{g,t} = \sigma_{g,t} z_{g,t} \tag{3.2}$$

$$z_{g,t} \sim g\left(z_{g,t} \middle| \eta_g, \lambda_{g,t}\right) \tag{3.3}$$

$$\sigma^2_{g,t} = \beta_{g,0} + \beta_{g,1} \sigma^2_{g,t-1} + \beta_{g,2} e^2_{g,t-1} + \beta_{g,3} \left[\max(0, e_{g,t-1})\right]^2 \tag{3.4}$$

$$\lambda'_{g,t} = \gamma_{g,0} + \gamma_{g,1} \lambda'_{g,t-1} + \gamma_{g,2} e_{g,t-1} + \gamma_{g,3} \max(0, e_{g,t-1}) \ . \tag{3.5}$$

The unexpected returns on individual markets are, in turn, assumed to depend on the world shock, the idiosyncratic portion of the regional shock, $e_{g,t}$, and a country-specific shock that is independent of both $e_{g,t}$ and $\varepsilon_{w,t}$:

$$r_{i,t} = \alpha_{i,0} + \alpha_{i,1} r_{w,t-1} + \alpha_{i,2} r_{g,t-1} + \alpha_{i,3} r_{i,t-1} + \varepsilon_{i,t} \ , \tag{3.6}$$

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[11] An alternative approach would be to model the individual market returns series using univariate conditional skewness models and link these through a copula, as in Rockinger and Jondeau (2001). The approach adopted in this paper allows us to directly measure the contribution of the world and regional factor to the variance and skewness of the individual returns series.

$$\varepsilon_{i,t} = \phi_{i,1}\,\varepsilon_{w,t} + \phi_{i,2}\,e_{g,t} + e_{i,t}\ ,\ e_{i,t} = \sigma_{i,t}\,z_{i,t} \tag{3.7}$$

$$z_{i,t} \sim g\left(z_{i,t} \middle| \eta_i, \lambda_{i,t}\right)\ , \tag{3.8}$$

$$\sigma_{i,t}^2 = \beta_{i,0} + \beta_{i,1}\,\sigma_{i,t-1}^2 + \beta_{i,2}\,e_{i,t-1}^2 + \beta_{i,3}\left[\max(0, e_{i,t-1})\right]^2 \tag{3.9}$$

$$\lambda'_{i,t} = \gamma_{i,0} + \gamma_{i,1}\,\lambda'_{i,t-1} + \gamma_{i,2}\,\varepsilon_{i,t-1}\ . \tag{3.10}$$

Throughout, the symbol ε is used to denote unexpected returns while e denotes the idiosyncratic shock. σ^2 and λ always denote the conditional variance and skewness of an idiosyncratic shock, while h will refer to the conditional volatility of unexpected returns (which combines the idiosyncratic shock with the external factors). λ and λ' are connected through (2.9). The world shock affects the volatility and skewness of unexpected regional returns only through (3.2), while the world shock and idiosyncratic regional shock influence the volatility and skewness of unexpected country returns through (3.7). These two equations are referred to as the factor equations.

For each market *i*, the multivariate likelihood function is

$$\begin{aligned}
&\prod_{t=1}^{T} f(r_{it}, r_{gt}, r_{wt} \mid I_{t-1}, \theta) \\
&\quad = \prod_{t=1}^{T} f(r_{it} \mid r_{gt}, r_{wt}, I_{t-1}, \theta_i, \theta_g, \theta_w) f(r_{gt} \mid r_{wt}, I_{t-1}, \theta_g, \theta_w) f(r_{wt} \mid I_{t-1}, \theta_w) \\
&\quad = \prod_{t=1}^{T} f(e_{it} \mid e_{gt}, \varepsilon_{wt}, I_{t-1}, \theta_i, \theta_g, \theta_w) f(e_{gt} \mid e_{wt}, I_{t-1}, \theta_g, \theta_w) f(r_{wt} \mid I_{t-1}, \theta_w)
\end{aligned}$$

where θ_w, θ_g and θ_i are the parameters appearing in equations (2.1) - (2.8), (3.1) - (3.5), and (3.6) - (3.10) respectively. I_{t-1} represents past values of the returns. We maximize the likelihood sequentially, starting with the likelihood for the world model $\prod_{t=1}^{T} f(r_{wt} \mid I_{t-1}, \theta_w)$ to obtain consistent estimates for θ_w, then maximize the regional likelihood $\prod_{t=1}^{T} f(e_{gt} \mid \hat{\varepsilon}_{wt}, I_{t-1}, \theta_g, \hat{\theta}_w)$, followed by the individual market likelihood

$\prod_{t=1}^{T} f(e_{wt} \mid \hat{e}_{gt}, \hat{\varepsilon}_{wt}, I_{t-1}, \theta_i, \hat{\theta}_g, \hat{\theta}_w)$. This process yields consistent though inefficient estimates, and we do not correct for sampling error in having replaced θ_w, ε_w, θ_g and e_g with $\hat{\theta}_w$, $\hat{\varepsilon}_w$, $\hat{\theta}_g$ and $\hat{e}_g$ in the second and third stages. The six individual models can also be viewed as a single model, if we assume as we have, that conditional on the regional and world factors the idiosyncratic country shocks are unrelated, that is

$$\begin{aligned}&\prod_{t=1}^{T} f(r_{1t}, \ldots, r_{6t}, r_{gt}, r_{wt} \mid I_{t-1}, \theta) \\ &= \prod_{t=1}^{T} \prod_{i=1}^{6} f(e_{it} \mid e_{gt}, \varepsilon_{wt}, I_{t-1}, \theta_i, \theta_g, \theta_w) f(e_{gt} \mid e_{wt}, I_{t-1}, \theta_g, \theta_w) f(r_{wt} \mid I_{t-1}, \theta_w).\end{aligned}$$

This allows the likelihood for the six countries to be maximized separately, although the regional proxy we use in each case is different.

Equations (3.9) and (3.10) capture dynamics in the volatility and skewness due to each market's idiosyncratic shock. The factor loadings $\phi_{i,1}$ and $\phi_{i,2}$, on the other hand, capture the impact of the global and regional factors on the volatility and skewness of country *i*'s return, and so in our analysis we consider the relative size and significance of these two parameters. To understand the economic significance of these factors, however, we calculate the proportion of variance and skewness in the market returns that is explained by the global and regional factors. Since the conditional variance of country *i*'s stock return is

$$E[\varepsilon_{i,t}^2 \mid I_{t-1}] = h_{i,t} = \phi_{i,1}{}^2 \sigma_{w,t}^2 + \phi_{i,2}{}^2 \sigma_{g,t}^2 + \sigma_{i,t}^2, \tag{3.11}$$

we estimate the proportion of country *i*'s volatility accounted for by the factors by the average values of

$$\widetilde{VR}_{i,t}^{w} = \frac{\hat{\phi}_{i,1}{}^2 \hat{\sigma}_{w,t}^2}{\hat{h}_{i,t}} \quad \text{and} \quad \widetilde{VR}_{i,t}^{g} = \frac{\hat{\phi}_{i,2}{}^2 \hat{\sigma}_{g,t}^2}{\hat{h}_{i,t}} \tag{3.12}$$

To measure the influence of global and regional factors on the shape of the conditional distribution of individual market returns, we use two statistics. First we estimate the skewness coefficients, at each period *t*, of the country specific shock $e_{i,t}$, the combination of the regional shock and the country-specific shock $\phi_{i,2} e_{g,t} + e_{i,t}$, and all the shocks combined $\varepsilon_{i,t} = \phi_{i,1} \varepsilon_{w,t} + \phi_{i,2} e_{g,t} + e_{i,t}$. This will show the cumulative effect of regional and global effects on the skewness of the conditional distribution of the individual market returns. We label these skewness coefficients as s_t^i, s_t^{i+g} and s_t^{i+g+w} respectively. The skewness coefficients are calculated by simulation: for each period *t*, we draw 1000 observations of $z_{i,t} = e_{i,t} / \sigma_{i,t}$ from $g\left(z_{i,t} \middle| \eta_i, \lambda_{i,t}\right)$. Denoting the random numbers as $\{z_{i,t}^{(r)}\}_{r=1}^{1000}$, the skewness coefficient of $e_{i,t}$ at time *t* is calculated as

$$s_t^i = \frac{1}{1000} \sum_{r=1}^{1000} \left(z_{i,t}^{(r)} \right)^3 \tag{3.13}$$

A similar procedure is used to obtain 1000 draws from $z_{g,t} = e_{g,t} / \sigma_{g,t}$ and $z_{w,t} = \varepsilon_{w,t} / \sigma_{w,t}$, and the sample skewness coefficients for $\phi_{i,2} e_{g,t} + e_{i,t}$ and $\phi_{i,1} \varepsilon_{w,t} + \phi_{i,2} e_{g,t} + e_{i,t}$ calculated as:

$$s_t^{i+g} = \frac{1}{1000} \sum_{r=1}^{1000} \frac{\left(\phi_{i,2} z_{g,t}^{(r)} \hat{\sigma}_{g,t} + z_{i,t}^{(r)} \hat{\sigma}_{i,t} \right)^3}{\left(\phi_{i,2}^2 \hat{\sigma}_{g,t}^2 + \hat{\sigma}_{i,t}^2 \right)^{3/2}} \equiv \frac{1}{1000} \sum_{r=1}^{1000} \left(z_{i+g,t}^{(r)} \right)^3 \tag{3.14}$$

$$s_t^{i+g+w} = \frac{1}{1000} \sum_{r=1}^{1000} \frac{\left(\phi_{i,1} z_{w,t}^{(r)} \hat{\sigma}_{w,t} + \phi_{i,2} z_{g,t}^{(r)} \hat{\sigma}_{g,t} + z_{i,t}^{(r)} \hat{\sigma}_{i,t} \right)^3}{\left(\phi_{i,1}^2 \hat{\sigma}_{w,t}^2 + \phi_{i,2}^2 \hat{\sigma}_{g,t}^2 + \hat{\sigma}_{i,t}^2 \right)^{3/2}}$$

$$\equiv \frac{1}{1000} \sum_{r=1}^{1000} \left(z_{i+g+w,t}^{(r)} \right)^3 \tag{3.15}$$

The other statistic we look at focuses on the left tail of the distribution of $e_{i,t}$, $\phi_{i,2}\, e_{g,t} + e_{i,t}$ and $\phi_{i,1}\, \varepsilon_{w,t} + \phi_{i,2}\, e_{g,t} + e_{i,t}$. For each market *i* and at each period *t*, we estimate the probability of obtaining a negative realization of $e_{i,t}$, $\phi_{i,2}\, e_{g,t} + e_{i,t}$ and $\phi_{i,1}\, \varepsilon_{w,t} + \phi_{i,2}\, e_{g,t} + e_{i,t}$ that is greater than 2 times the size of their respective period-*t* standard deviations, i.e.,

$$p_t^i = \widehat{\Pr}[e_{i,t} < -2\, s.d.(e_{i,t})] = \frac{1}{1000}\sum_{r=1}^{1000}\left(I\left(z_{i,t}^{(r)} < -2\right)\right) \tag{3.16}$$

$$\begin{aligned} p_t^{i+g} &= \widehat{\Pr}[\phi_{i,2}\, e_{g,t} + e_{i,t} < -2\, s.d.(\phi_{i,2}\, e_{g,t} + e_{i,t})] \\ &= \frac{1}{1000}\sum_{r=1}^{1000}\left(I\left(z_{i+g,t}^{(r)} < -2\right)\right) \end{aligned} \tag{3.17}$$

and

$$\begin{aligned} p_t^{i+g+w} &= \widehat{\Pr}[\phi_{i,1}\, \varepsilon_{w,t} + \phi_{i,2}\, e_{g,t} + e_{i,t} < -2\, s.d.(\phi_{i,1}\, \varepsilon_{w,t} + \phi_{i,2}\, e_{g,t} + e_{i,t})] \\ &= \frac{1}{1000}\sum_{r=1}^{1000}\left(I\left(z_{i+g+w,t}^{(r)} < -2\right)\right) \end{aligned} \tag{3.18}$$

where *I(.)* is an indicator function that takes the value one when its argument is true, and zero otherwise. This gives us an alternate means by which to measure how global and regional factors influence the probability of realizing large unexpected negative returns.

3.2 Allowing for Structural Changes

One of the lessons from previous work on the issue of volatility spillover is that significant changes to the environment in which a stock market operates influence the degree of spillovers from external factors into that market. Ng (2000), for instance, documents changes in the degree of linkages between stock markets as a result of certain events, such as the introduction of country funds. For the sample period that we study, all six markets underwent major changes, either as a result of, or as a response to the financial crisis that began in July 1997 (see for instance, Berg, 1999). Most countries in our sample, with the exception of Malaysia, undertook regulatory changes that can be viewed as contributing towards greater liberalization. Ignoring these developments might bias our measurement of the relative impact of the factors. We therefore re-specify our model to account for the structural changes arising from these various developments.

Given the limited number of post-crisis observations, attempting to account for specific developments would be demanding too much of the data. We therefore summarize the numerous developments into a single "post-crisis" dummy variable d_c, and allow for possible changes in the mean spillover parameters and in the factor loadings, i.e., for the individual markets, the equations in (3.6) and (3.7) are re-specified as

$$r_{i,t} = \alpha_{i,0} + (\alpha_{i,1} + \alpha_{i,2} d_c) r_{w,t-1} + (\alpha_{i,3} + \alpha_{i,4} d_c) r_{g,t-1} + \alpha_{i,5} r_{i,t-1} + \varepsilon_{i,t} \quad (3.6')$$

and

$$\varepsilon_{i,t} = (\phi_{i,1} + \phi_{i,2} d_c)\varepsilon_{w,t} + (\phi_{i,3} + \phi_{i,4} d_c) e_{g,t} + e_{i,t} \quad . \quad (3.7')$$

The change in the degree of influence of the global and regional factors on variance and skewness spillover will be reflected in the parameters $\phi_{i,2}$ and $\phi_{i,4}$. For this model, the variance ratios (3.12), and the skewness and probability estimates (3.13) - (3.15) and (3.16) - (3.18) for both the pre- and post-crisis sample periods are computed.[12] We will consider a third model which explores spillovers in relation to new arrivals, but first we discuss the results from these two models.

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[12] The exact date of the breakpoint for each market is found by estimating the model at different break points and choosing the point which maximizes the log-likelihood value. The breakpoint search was conducted over the period Feb 97 to end-Mar 98. In all cases, this breakpoint was found to be a few months after July 1997. The dates are 10/21/97, 11/25/97, 01/13/98, 10/28/97, 03/03/98, and 12/30/97 for Hong Kong, Korea, Malaysia, Singapore, Taiwan and Thailand respectively.

4. Empirical Results

We begin by discussing the parameter estimates from the constant spillover models, followed by the spillover model allowing for structural change. We follow this with a discussion of the relative influence of global and regional factors in downside risk in the individual markets implied by the skewness coefficients and probabilities from the spillover models with time-varying conditional skewness.

4.1 Parameter Estimates

Table 5 reports the results for the constant spillover models. In both cases, we obtain the usual results concerning mean spillovers (defined in our models, as in Ng (2000), as persistent effects on individual markets of past information in global and regional returns). The global market in general displays larger spillover effects in the mean than the regional factor in all markets. Mean spillover from the regional factor is small in all cases except Thailand where spillovers are large and negative. The variance equation, which captures the evolution of the conditional variance of the idiosyncratic country shock, continues to display asymmetric effects of past shocks on variance, and the asymmetry equation also shows time-variation in the skewness of the idiosyncratic shock. The parameter estimates of $\phi_{i,1}$ and $\phi_{i,2}$ in Table 5 show that the spillover effects of both the world and regional factors are not statistically significant, although we will see shortly that some of these numbers still translate to economically significant levels of volatility spillovers.

The parameters estimates for the spillover models with the post-crisis dummy are shown in Table 6. Only the estimates of the spillover coefficients in the mean and factor equation parameters are displayed to save space. We find that the mean spillover from the global factor increases substantially (albeit statistically insignificant) for all markets except Malaysia, where there is a large drop, and Taiwan, where there is little change. The large drop in global mean spillover for Malaysia may reflect the strict capital controls that were imposed there in September 1998. Mean spillover from the regional factor, however, increases substantially for Malaysia. This is also true for Hong Kong and Thailand, although in these cases the sign is negative. Surprisingly, in Singapore’s case there appears to be little mean spillover from the region, pre- or post-crisis.

Pre-structural break, only the coefficient on the world factor for Hong Kong is statistically significant. The estimates pertaining to the world and regional factors nonetheless seem substantial for the other countries (with the exception of the regional factor for Taiwan) and may translate to substantial variance and skewness spillovers. The signs are all positive for the world factor and, in all cases except Thailand, negative for the regional factor. The estimates post-structural break from the factor equation suggest that in general the world and regional factor becomes more important post-structural break, as might be expected given greater liberalization efforts in these markets. The exception is Hong Kong where both appear to have been reduced. In absolute terms, both the world and regional factors becomes more important post-structural break for Malaysia, Singapore and Taiwan. For Hong Kong they become much less important. There are marginal changes in the importance of the world factor for Korea, and the regional factors for Thailand, although in the latter case the sign changes.

4.2 Spillover Effects in Variance and Skewness

To gain some insight into the economic significance of these results, we calculate, for each market, the proportion of the movements in the conditional variance and the amount of skewness in unexpected returns that can be attributed to the world and regional factors. We are also interested in the degree and pattern of spillovers of downside risk in the six markets.

4.2.1 Variance Ratios

Table 7 shows the average of the period t variance ratios for the world and regional factors. The rows labeled 'World' and 'Region' respectively show the average value of $\widetilde{VR}_{i,t}^{w}$ and $\widetilde{VR}_{i,t}^{g}$ as described in (3.12). The variance ratios for two models are displayed: the top panel lists the variance ratio for the constant spillover model, and the bottom panel shows the variance ratios with the post-crisis control dummy. The ratios are listed for the pre- and post-crisis periods.

The spillover models without the post-crisis dummy show that the world factor plays an important role in explaining the variance of the unexpected returns for the Hong Kong market, whereas the regional factor accounts for an important fraction of the variance in the Singapore market. For the other markets, the proportion of variance due to both regional and world factors appears to be rather small. This profile also applies to the pre-crisis period when the structural change dummy is used. These patterns can perhaps be explained by the fact that the Hong Kong and Singapore markets are the most open of the six markets in our sample. Our estimates, however, show that their relationships with external factors are quite different, with Hong Kong more closely tied to the world factor, and Singapore to regional markets.

The post-crisis pattern is somewhat more difficult to interpret. Although there are more instances where either spillover from the world and/or the regional factors becomes more important, the pattern for each country is rather different. The world factor becomes completely unimportant for the variance in the Hong Kong market, and the influence of the regional factor becomes substantial for Korea, Malaysia and Singapore. The world factor becomes important for the Malaysian, Taiwan and Thailand markets.

4.2.2 *Pattern and Size of Skewness Spillovers*

To evaluate the pattern and size of spillovers in downside risks implied by our spillover models with time-varying skewness, we present for each market the skewness coefficient at time *t* for the idiosyncratic shock, s_t^i, the combination of the idiosyncratic shock with the regional factor, s_t^{i+g}, and the combination of the idiosyncratic, regional and world shocks, s_t^{i+g+w}, which represents the skewness coefficient of the total unexpected returns for each market. A comparison of these three skewness coefficients will show how much (or how little) the regional and world factors contribute to the skewness in each market's unexpected return.

Figure 3 shows the scatterplots of s_t^{i+g} against s_t^i, and s_t^{i+g+w} against s_t^{i+g} for all six markets. The plots for each country comprise two columns of scatterplots. The left column shows the plot of s_t^{i+g} against s_t^i, and the right column plots s_t^{i+g+w} against s_t^{i+g}. The first row for each country shows the figures for the constant spillover model. The second and third rows presents the scatter diagrams for the pre- and post-crisis samples respectively, obtained from the spillover model with the post-crisis dummy. Each scatter diagram is augmented with a 45° line; a scatter diagram with most of its points lying along this diagonal would indicate that the addition of the regional factor (for the diagrams in the left column) or the world factor (right column) contributes nothing to the shape of the distribution. Deviations from the diagonal will show the direction and strength of the influence of the regional or world factor in determining the shape of the distribution.

We begin by focusing on the Hong Kong market. For the constant spillover model, we see from the x-axis of panel (a) that the skewness coefficients for the idiosyncratic shock ranges from about –1.2 to 0.5, as does the skewness coefficient of unexpected returns (y-axis of panel (b)). Panel (a) shows that the regional factor increases skewness to the right very slightly (all the points lie just above the 45° line, and this is reinforced slightly by the world factor. Nonetheless, these effects are very small. A similar statement can be made for the pre-crisis period. Panels (e) and (f) show that the external factors have no influence on skewness post-crisis.

Looking at the figures for the remaining five countries, we find that the world and regional factors play little role in the shape of the distribution, with the following exceptions: Post-crisis, the regional factor appears to contribute more to the shape of the conditional distribution of the Malaysian market. This is offset slightly by the world factor, so that the overall variation is small. For the Singapore market, the influence of the regional factor is large, and more interestingly, the effect of the regional factor is opposite in direction to that of the local factor. When the local factor is negatively skewed, the combined regional and local factor is positive, and vice-versa. The world factor has zero influence. Post-structural break, the world factor largely offsets the effect of the regional factor in the Taiwan market. There is substantial variation in the shape of the local factor for Thailand, but this is also largely offset by the world factor, so that for Thailand (and Taiwan) the overall variation in shape is small.

We supplement these findings with the estimated probabilities of large negative unexpected returns. Table 8 shows the differences $p_t^{i+g} - p_t^i$ and $p_t^{i+g+w} - p_t^{i+g}$. As before, the top panel shows the ratios from the constant spillover models, and the bottom panel displays the differences from the pre- and post-crisis periods. The maximum and minimum values of the differences are reported, and we include the mean value of p_t^i as a benchmark with which to compare the size of the differences. With mean values in the range of 0.02 to 0.034, a difference in the probabilities of 0.01 can be considered large (approximately 30% to 50% difference evaluated at the mean). In both models, the world and regional factor can either increase or decrease the probabilities in the tail (the minimum values of changes in probabilities are all negative, and the maximum values all positive) but some interesting individual cases can be highlighted. We start with the constant spillover model. For Hong Kong, the world factor general increases the probability in the left tail (maximum of $p_t^{i+g+w} - p_t^{i+g}$ is positive, and much larger than the minimum of $p_t^{i+g+w} - p_t^{i+g}$ in absolute terms). In Korea, even though the influence of the regional factor to variance is small, it tends to reduce the probability in the left tail. In Singapore's case the regional factor causes the probability in the left tail to fluctuate substantially. Pre-crisis, the regional factor reduces left-tail probabilities in Hong Kong, Korea, and Malaysia. Post-crisis, the regional factor is important for Korea, Malaysia and Singapore. The world factor tends to increase left tail probabilities for Malaysia and Thailand.

As one of our aims is to evaluate how incorporating time-varying skewness into our analysis will affect the measurement of spillovers, we summarize in Tables 9a and b the mean and variance spillovers for the pre-/post-crisis model with alternative specifications in conditional skewness. The top panels of Table 9a and b show mean and variance spillovers in the model that restrict conditional skewness to be constant, i.e., the model where the world, regional and country returns are assumed to be generated by (2.1) – (2.4), (3.1) - (3.5), and (3.6) - (3.10) respectively, but where $\gamma_{i,j} = 0 \quad \forall j \geq 1$, $i = w, g, 1, \ldots, 6$. Panel b in both tables give the estimates from the same model, but this time assuming conditional symmetry, i.e., $\gamma_{i,j} = 0 \quad \forall j \geq 0$, $i = w, g, 1, \ldots, 6$.

The comparison of mean spillovers shows some differences between the time-varying skewness model, and the alternative models, mainly in Hong Kong and Korea. In the Hong Kong case, there is little difference between the conditional symmetry model and the time-varying conditional skewness model. The differences are a little more dramatic in the variance spillover profiles, especially for the cases of Korea, Taiwan and Thailand (in both models). Again, for Hong Kong, the variance spillover profile for the conditional symmetry model matches the time-varying skewness model (but the conditional skewness model produces different results). The consequence of ignoring time-varying skewness for the measurement of mean and variance spillover is thus unclear: it matters in some cases, and not in others. Of course, the constant skewness and conditional symmetry models cannot measure skewness spillovers from the world and regional factors.

To summarize, the influence of the world and regional factor vary substantially across countries, and its importance depends on whether we are considering mean, variance or skewness spillovers. Mean spillovers are predominantly from the world factor, although this profile changes in the late 1990s. Pre-crisis, variance spillover from the world is important for Hong Kong, and variance spillover from the regional factor is more important for Singapore. The world and regional variance spillovers become more important for more countries post-crisis. Skewness spillover is in general small, except for a few cases where there is a substantial skewness spillover from the regional factor. In some of these cases the world factor partially compensates for this effect.

4.3 Spillovers and the Arrival of News

A clearer picture may arise if we allow mean, variance and skewness spillovers to vary with the arrival of specific types of news. In particular, news that concerns the local economy may have a different impact on a market than news that concerns the markets in the region. In the post-crisis sample period, there was considerable uncertainty concerning the economies of the six countries and the political stability of countries in close proximity to them, and this may help explain the differences in mean, variance and skewness spillovers over the two periods. Kaminsky and Schmukler (1999), for instance, find evidence that foreign news had a smaller impact on movements in these markets than local or regional news in the period immediately after July 1997.

We further explore spillovers using a third model that allows mean, variance and skewness spillovers to vary according to the nature of news arriving in the market. We collected 'significant' news items concerning the six countries in our study. These news items are items that appear in the Financial Times during our sample period, and were collected from the Factiva news database.[13] We picked out daily macroeconomic news (releases of key economic data like unemployment rate, inflation, GDP forecasts, interest rates cuts/raises, speeches by significant individuals about the economy e.g. Presidents/Prime Ministers, budget issues and structural changes in the financial market, trade talks, signing of trade pacts, release of financial aid, imposition of sanctions and excessive trade surplus/deficits with trade partners), and political news (e.g. reshuffling of cabinet ministers, appointing/resigning/sacking of key ministers, coups, investigation of corruption charges, elections). Commentaries and analyses, and the 'usual' daily equity market news reports were not considered.

A day that contained significant news is assigned a value of 1, and 0 otherwise. These are then compiled into weekly data, each week taking value 1 if it contained a day with news. Six weekly 'local news' dummies are thus created. From these six local news dummies, we created six 'regional' news dummies corresponding to the six regional

[13] The construction of any data series representing news inevitably entails some subjectivity. Our decision to use a single publication with international coverage, with the assumption that a particular news item would not appear in that publication unless it is important, is an attempt to filter out 'important' news in a somewhat objective fashion. Other methods (different choice of periodical, occurrence of a news item in multiple periodicals, etc) are of course possible.

indexes. The regional index for country *i* takes value 1 if for that week there was a news item in any of the other five countries. Over the entire 573 observation sample there were 236, 281, 157, 65, 141 and 210 news items for Hong Kong, Korea, Malaysia, Singapore, Taiwan and Thailand respectively. There are certainly many more regional news items than local news items: there were 456, 441, 472, 483, 464 and 454 news items for the corresponding regional indexes. The regional news index largely, but not completely subsumes the local news index; for the six countries, there are 29, 44, 13, 2, 21 and 31 local news that occurred in weeks without regional news items.

We incorporate the arrival of news items from different sources by respecifying equations (3.6) and (3.7) as

$$\begin{aligned} r_{i,t} = \alpha_{i,0} &+ (\alpha_{i,1} + \alpha_{i,2} d_g + \alpha_{i,3} d_i) r_{w,t-1} \\ &+ (\alpha_{i,4} + \alpha_{i,5} d_g + \alpha_{i,6} d_i) r_{g,t-1} + \alpha_{i,7}\, r_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{3.6''}$$

and

$$\varepsilon_{i,t} = (\phi_{i,1} + \phi_{i,2} d_g + \phi_{i,3} d_i)\varepsilon_{w,t} + (\phi_{i,4} + \phi_{i,5} d_g + \phi_{i,6} d_i) e_{g,t} + e_{i,t} \tag{3.7''}$$

where d_g and d_i refers to the regional and local news dummies respectively. The results from this exercise are displayed in Tables 10a and b and Figure 4.

Table 10a shows how mean spillovers change with the arrival of regional news and local news respectively. The three sets of numbers show mean spillovers when there is no regional or local news, when there is regional news, and when there is local news respectively. In the baseline case, mean spillovers from the world and region seem large although only in Singapore's case is there a statistically significant spillover. An interesting pattern emerges from the parameters corresponding to the local news dummy: in all cases where there are substantial mean spillovers from an external source, the presence of local news reduces that spillover (in absolute terms). In the case of Singapore and Thailand, the presence of local news items also increases mean spillovers from the region and world respectively whereas in the baseline case there are no spillovers from those sources. The pattern for regional news items is much less clear.

Table 10b gives the average variance ratios for the baseline no regional/local news case, and for the cases where there is regional news, and local news items. Again, no clear pattern emerges from the regional news cases. Regional news increases variance spillover from the world factor for Hong Kong and Taiwan, and reduces it for Singapore, but has virtually no effect on spillovers from the region. The lack of a clear pattern for regional news may reflect different degrees of linkages among the different countries, and so the regional news index contains relevant and irrelevant news items. There is, on the other hand, a clear pattern in spillovers with the arrival of local news: in all cases, the arrival of local news *increases* variance spillovers from the world factor (although for Taiwan and Thailand the increase is small at 6% and 7% respectively). In the case of Singapore and Thailand, the arrival of local news also increases spillovers from the region. This is a surprising result, as it seems reasonable to expect local news events to reduce variance spillovers from the world factor, as it does in the case of mean spillovers.

The relationship between skewness spillover and the arrival of news is summarized in Figure 4 which shows the scatterplots of s_t^{i+g} against s_t^i, and s_t^{i+g+w} against s_t^{i+g} for all six markets. In the case of Hong Kong and Korea, skewness spillover from the regional factor is similar when there is regional or local news. The regional factor is clearly more important for skewness in the Korean market than in the world factor. In the case of Malaysia and Singapore, skewness spillover is clearly correlated with the arrival of regional news. This may be the result of the close relationship between these two markets (since local news for Singapore is regional news for Malaysia and vice versa). Skewness in the Taiwanese market seems entirely driven by the regional factor: there is little variation in the skewness of the idiosyncratic shock, and little contribution from the world factor. This pattern is uncorrelated with the presence of regional or local news. World and regional factors do not have a strong influence variance and skewness in Thai returns, except when there is regional news.

5. Concluding Comments

We present new measurements of the relative importance of global, regional and local components of risk in equity markets, an issue with implications for important financial market activities, using a factor model that allows for time-varying conditional skewness. The evidence is from six Asian markets, namely Hong Kong, Korea, Malaysia, Singapore, Taiwan and Thailand, using weekly data from the 1990s, and using world and regional indexes as proxies for world and regional factors.

We explore spillovers in terms of mean, volatility and skewness. We estimate a constant spillover model, and two models which allow spillover effects to vary over time. In one model we permit the degree of spillover to change in the post-financial crisis period to control for possible structural change as a result of regulatory and other changes that took place during this period. We use a third model to explore the relationship between the sources of spillovers (regional or world) and the sources of news arriving in a market (regional news or local news). Local news reduces mean spillovers, but increases variance spillovers from the world factor. The regional factor seems to be much more important for skewness spillover than the world factor, and in some cases, skewness spillover is clearly correlated with the arrival of regional news. The drastic changes in the source of risk in equity markets in our sample period re-emphasize the need to allow for time-varying spillovers, as in Bekeart and Harvey (1997) and Ng (2000).

One interesting avenue for future research is to explore how spillovers might be related to the type of news (macroeconomic, political, etc) arriving in a market. This can be easily done in the framework that we present here, but as we are interested in global versus regional sources of risk, this issue does not fall within the scope of this paper. In addition, an investigation of spillover effects with time-varying conditional skewness at the daily (or higher frequencies) would be useful. Finally, more research into the economic reasons behind asymmetry in the conditional distribution of stock returns is needed. Our lack of knowledge of the causes of time-varying conditional skewness notwithstanding, the results in this paper show that studies of spillovers and linkages between equity markets will benefit from incorporating predictability in conditional skewness.

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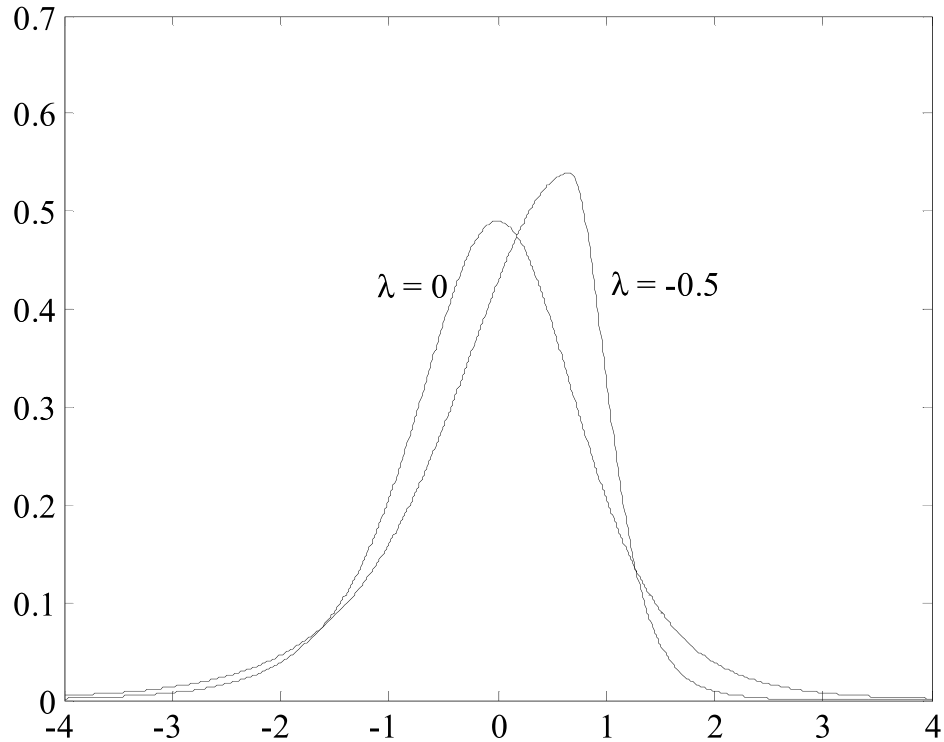
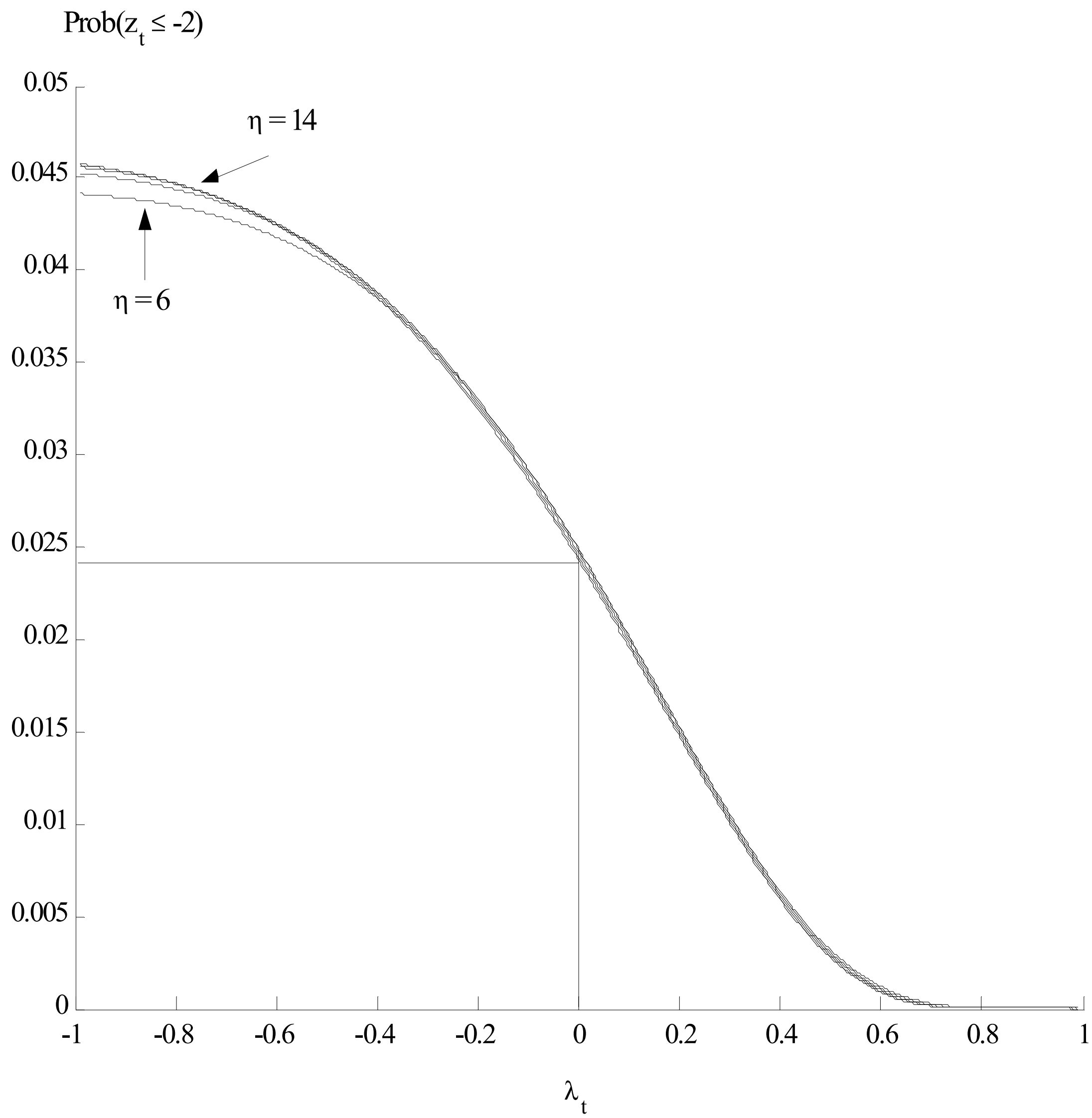
Figure 1 Hansen Skewed-t Distribution [a]



[a] The Hansen skewed-t distribution as described in equations (2.4) through (2.7) for $\eta = 5$ and $\lambda = -0.5$ and $\lambda = 0$.

Figure 2 Prob$(z_t \leq -2)$ at Various Values of η and λ [a]



[a] Each line is a plot of $\int_{-\infty}^{-2} g(z_t \mid \lambda_t, \eta)\, dz_t$ against λ_t for various values of η .

Figure 3 Scatterplots of Skewness Coefficients

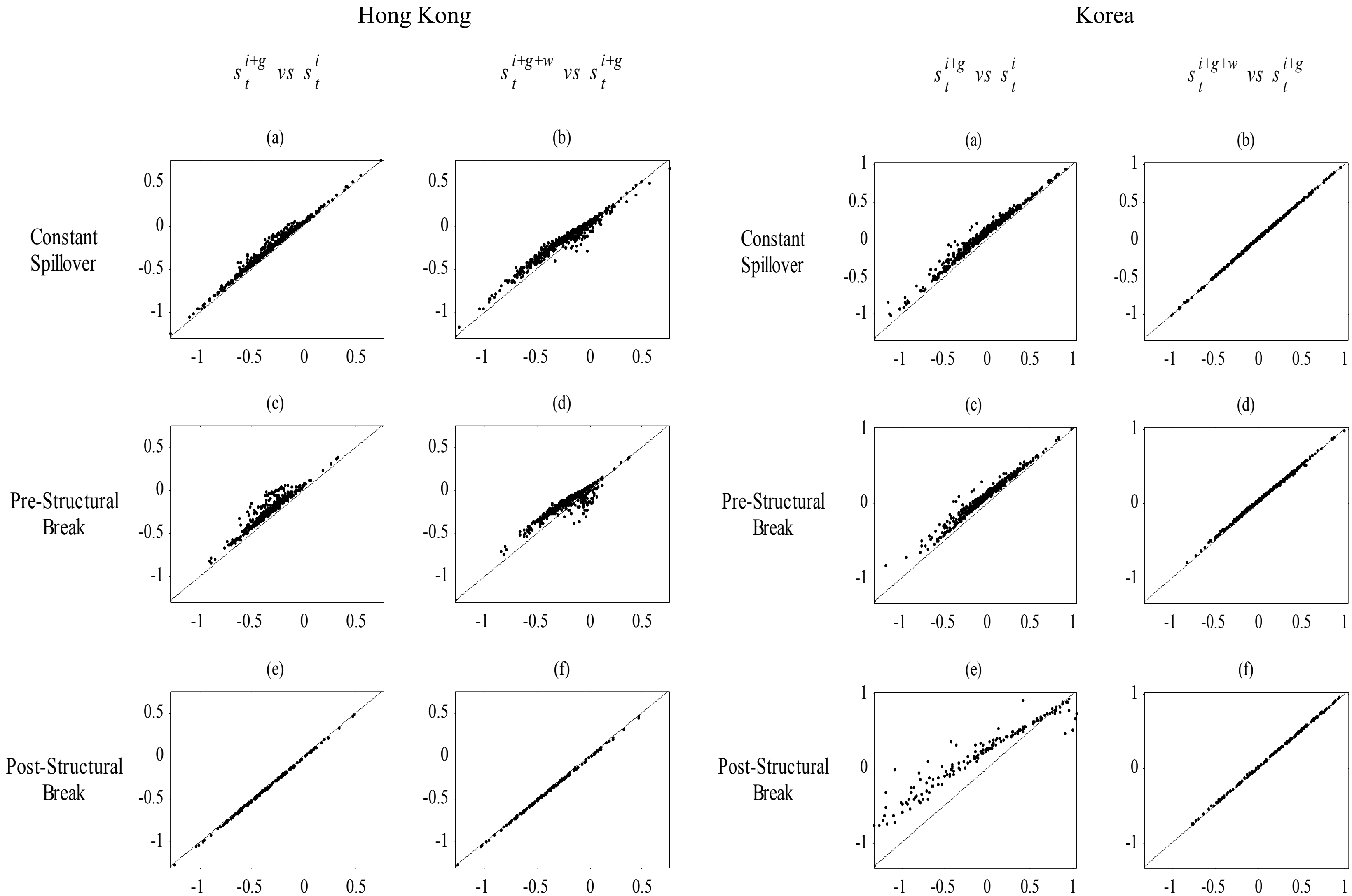


Figure 3 Scatterplots of Skewness Coefficients (continued)

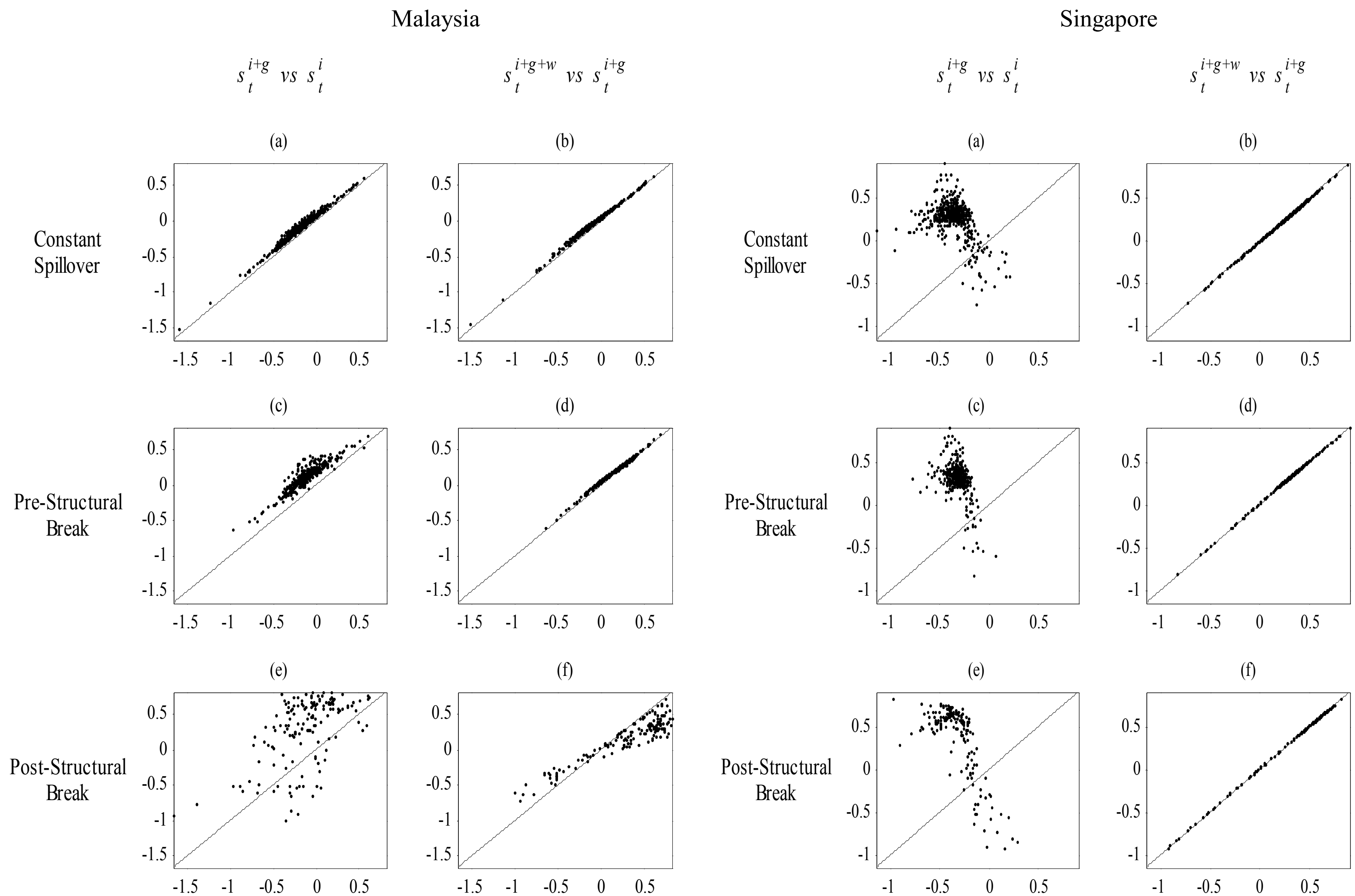


Figure 3 Scatterplots of Skewness Coefficients (continued)

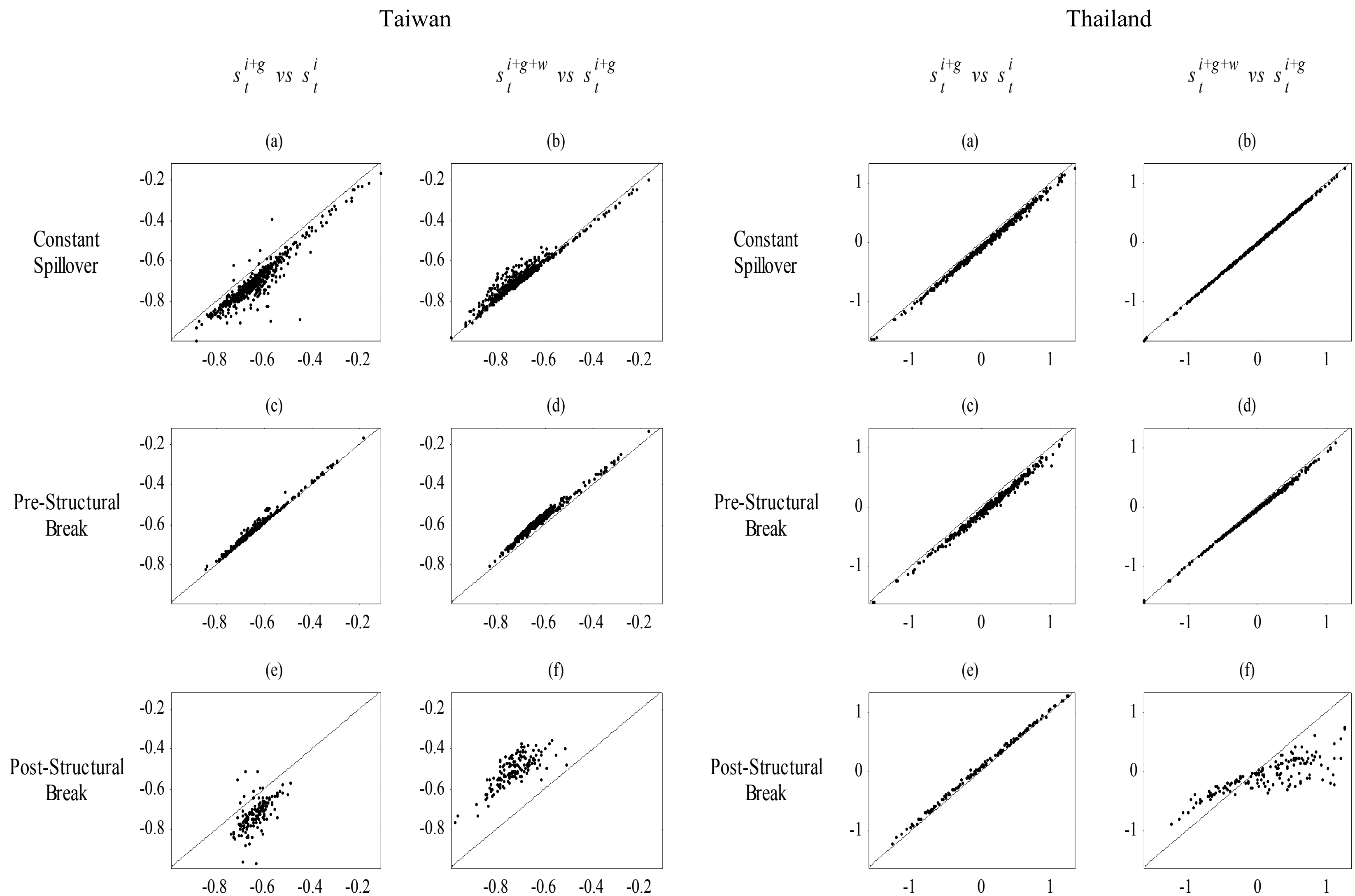


Figure 4 Scatterplots of Skewness Coefficients (Time Varying Skewness Model with News)

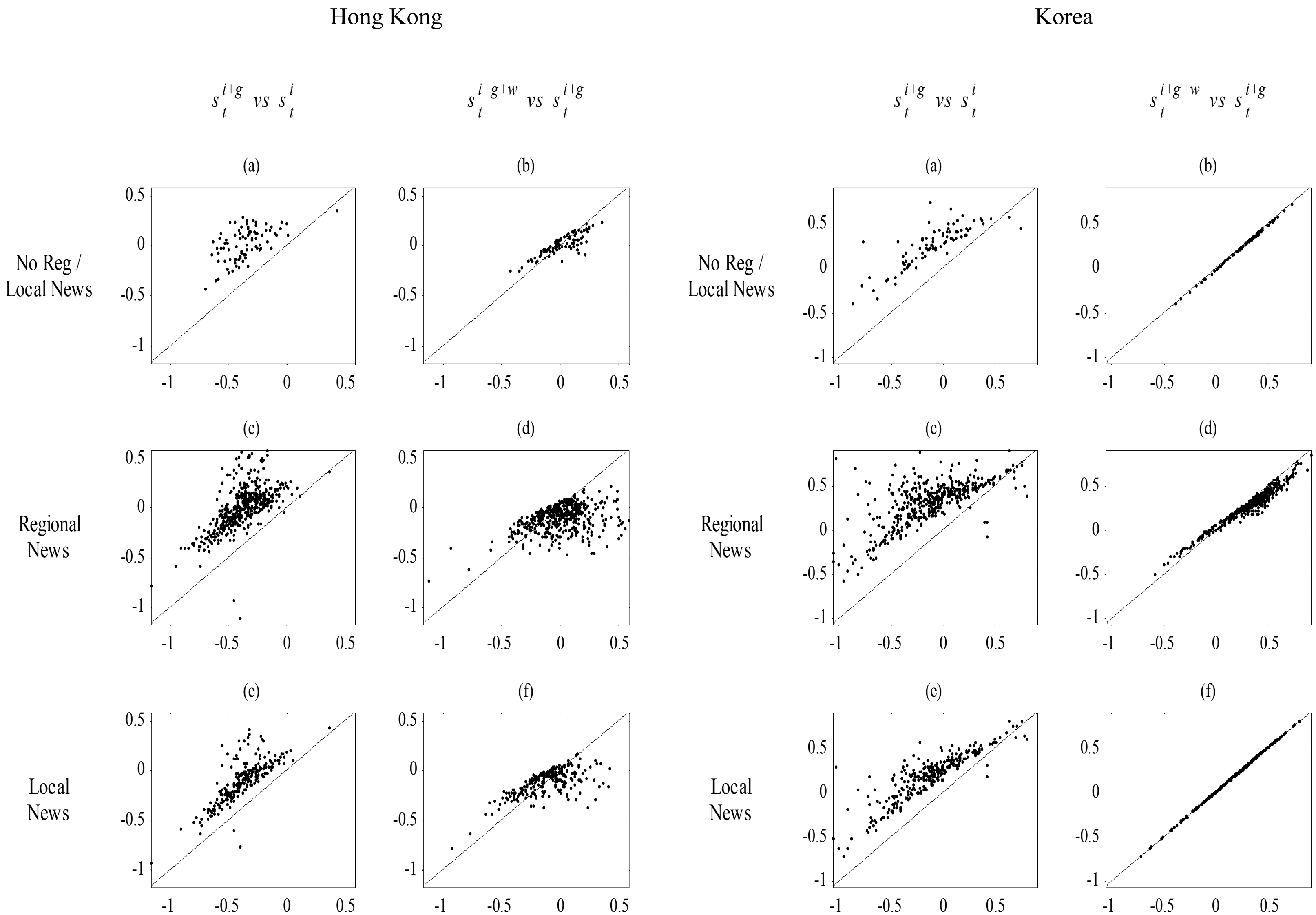


Figure 4 (continued) Scatterplots of Skewness Coefficients (Time Varying Skewness Model with News)

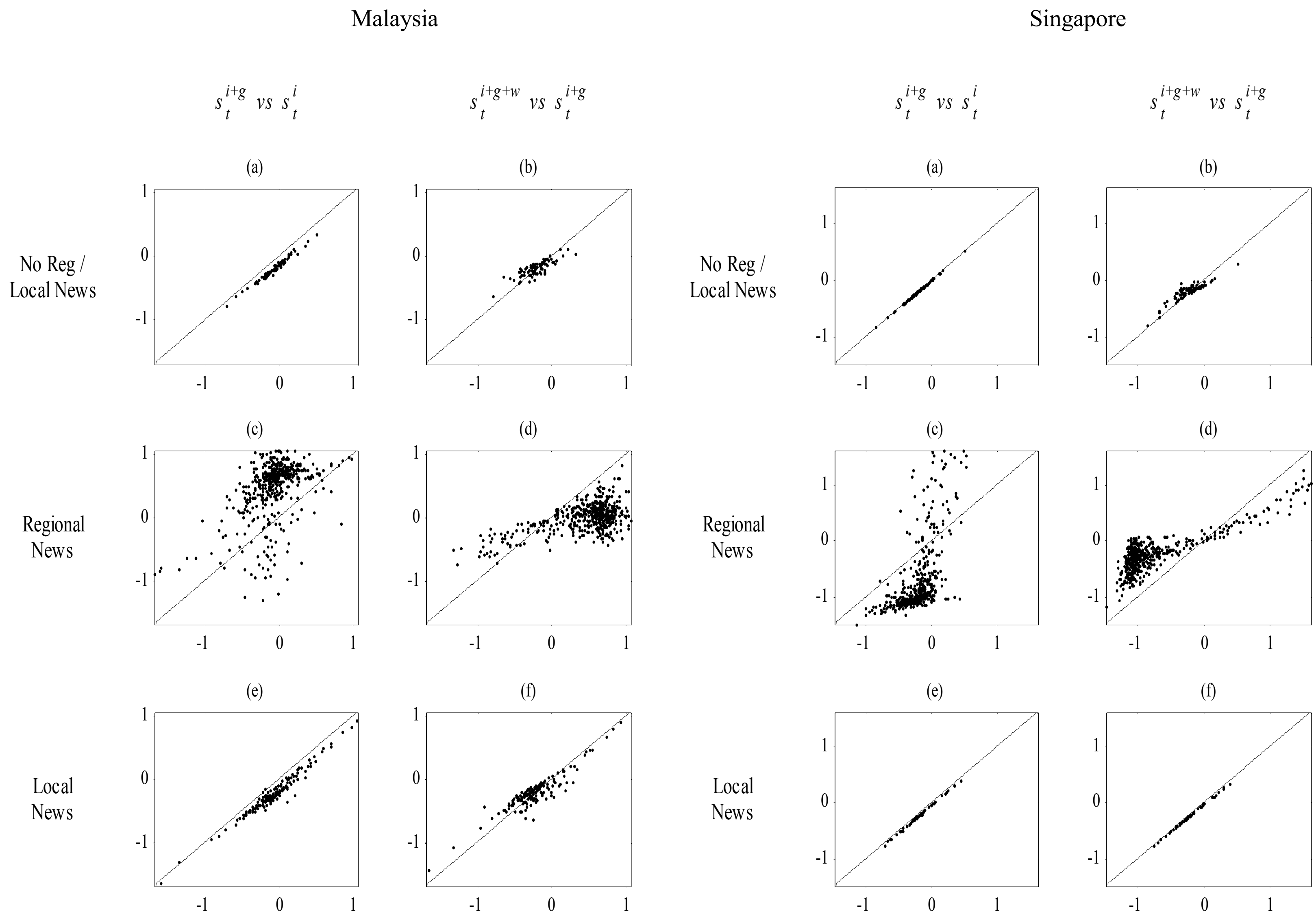


Figure 4 (continued) Scatterplots of Skewness Coefficients (Time Varying Skewness Model with News)

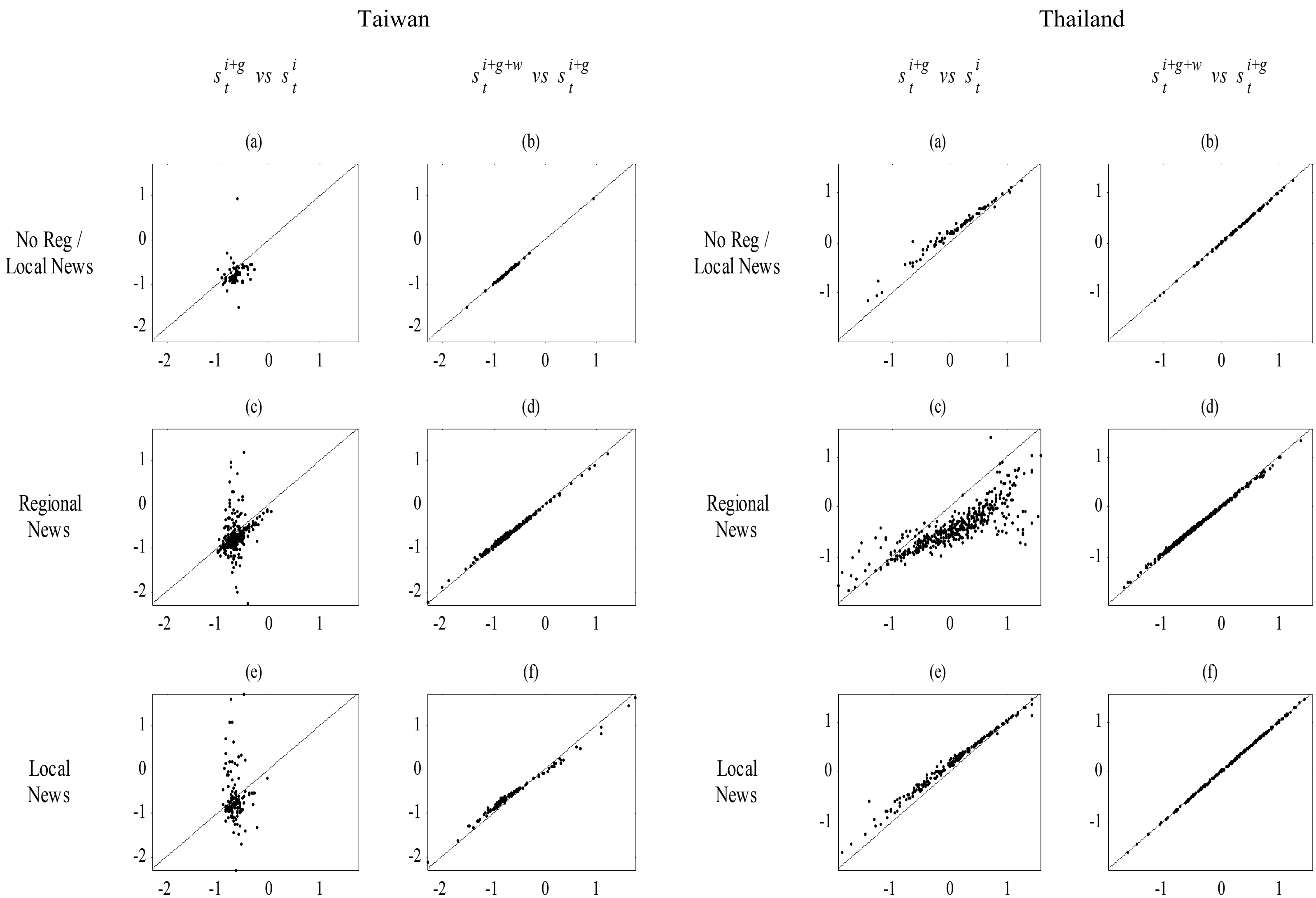


Table 1a Summary Statistics for Weekly Stock Returns[a]

	World	Region $_{HK}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Mean	0.131	–0.072	0.287	–0.103	0.030	0.082	–0.124	–0.213
Median	0.260	0.019	0.336	–0.145	–0.005	0.153	0.276	–0.381
Std. Dev.	1.825	3.085	4.206	4.775	4.261	3.556	4.714	4.917
Skewness	–0.556***	–0.092	–0.724***	0.068	0.333***	–0.295***	–0.647***	0.435***
Kurtosis	5.216***	5.100***	9.531***	4.837***	9.641***	7.435***	6.041***	6.053***
Jarque–Bera	144.7***	104.3***	1058.0***	79.53***	1053.0***	472.4***	257.5***	237.5***
$\widehat{\rho}1(1)$	–0.069*	0.012	–0.085**	–0.075*	–0.031	–0.063	0.042	0.042
Q1(10)	12.99	22.02**	23.05**	11.80	17.47*	16.23*	21.13**	10.44
$\widehat{\rho}2(1)$	0.064	0.187***	0.314***	0.202***	0.340***	0.317***	0.195***	0.064
Q2(10)	89.62***	98.17***	114.8***	179.1***	190.0***	135.52***	240.0***	47.43***
$\widehat{\rho}3(1)$	–0.047	–0.022	–0.124***	–0.009	–0.243***	–0.236***	–0.026	0.010
Q3(10)	40.73***	12.81	11.93	10.77	40.42***	59.88***	34.12***	15.42
$\widehat{\rho}4(1)$	0.004	0.096**	0.103**	0.068	0.259***	0.248***	0.084**	–0.000
Q4(10)	34.02***	13.01	6.558	68.08***	42.69***	65.18***	37.55***	9.931

[a]There are 573 observations in each series. *, **, and *** denote statistical significance at 10, 5, and 1% respectively. $\widehat{\rho}\,j(1)$ is the 1st order autocorrelation of the returns to the *j*th power. Q*j*(10) is the Ljung-Box Q statistic at lag 10 for the returns raised to the *j*th power. Region $_{HK}$ refers to the weighted index of the country returns excluding Hong Kong.

Table 1b Correlations[a]

	World	Region $_j$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Hong Kong	0.556	0.607	1.000	0.363	0.510	0.714	0.289	0.517
Korea	0.312	0.392	–	1.000	0.267	0.405	0.226	0.344
Malaysia	0.419	0.540	–	–	1.000	0.608	0.267	0.482
Singapore	0.546	0.729	–	–	–	1.000	0.319	0.585
Taiwan	0.263	0.352	–	–	–	–	1.000	0.228
Thailand	0.384	0.545	–	–	–	–	–	1.000

[a] Region $_j$ refers to the weighted index of the country returns, excluding the market under consideration. For instance, the (unconditional correlation between Hong Kong returns and the regional index return (excluding Hong Kong) is 0.607; the correlation between Korean returns and the regional index return (excluding Korea) is 0.392. The correlation between the world index and the various regional indexes range from 0.492 to 0.592.

Table 2 Univariate Model with Time–Varying Conditional Skewness[a]

	World	Region $_{HK}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Mean Equation								
$\alpha_{i,0}$	0.143**	0.069	0.393***	–0.190	0.093	0.112	–0.078	–0.068
	(0.069)	(0.100)	(0.151)	(0.155)	(0.126)	(0.117)	(0.170)	(0.171)
$\alpha_{i,1}$	–0.064*	0.062	0.007	–0.073	0.041	0.014	0.027	0.093**
	(0.036)	(0.051)	(0.048)	(0.049)	(0.043)	(0.049)	(0.050)	(0.041)
Variance Equation								
$\beta_{i,0}$	0.039	0.236*	0.642**	0.070	0.471**	0.547*	1.409***	0.586
	(0.026)	(0.126)	(0.318)	(0.056)	(0.226)	(0.327)	(0.503)	(0.386)
$\beta_{i,1}$	0.953***	0.829***	0.818***	0.971***	0.836***	0.816***	0.789***	0.874***
	(0.016)	(0.043)	(0.037)	(0.022)	(0.042)	(0.070)	(0.056)	(0.049)
$\beta_{i,2}$	0.071**	0.199***	0.185***	0.070***	0.234***	0.217**	0.159***	0.158**
	(0.030)	(0.065)	(0.051)	(0.021)	(0.068)	(0.087)	(0.051)	(0.073)
$\beta_{i,3}$	–0.076*	–0.096	–0.085	–0.080***	–0.177***	–0.155**	–0.042	–0.096*
	(0.044)	(0.065)	(0.065)	(0.017)	(0.063)	(0.075)	(0.056)	(0.058)
Skewness Equation								
$\gamma_{i,0}$	–0.235	–0.220*	–0.168	0.023	0.041	–0.063	–0.105*	0.249**
	(0.148)	(0.127)	(0.111)	(0.096)	(0.063)	(0.113)	(0.056)	(0.125)
$\gamma_{i,1}$	0.183**	–0.001	0.058**	0.048**	0.011	0.038	–0.013	0.074***
	(0.085)	(0.048)	(0.024)	(0.019)	(0.019)	(0.031)	(0.012)	(0.026)
$\gamma_{i,2}$	0.352*	0.084	0.330	0.186	0.435**	0.033	0.801***	0.029
	(0.183)	(0.122)	(0.209)	(0.265)	(0.221)	(0.382)	(0.094)	(0.180)
$\gamma_{i,3}$	–0.079**	0.040**	–	–	–	–	–	–
	(0.032)	(0.017)	–	–	–	–	–	–
Degrees of Freedom								
η	9.988**	8.506***	12.686**	14.786*	5.461***	7.446***	12.699**	6.476***
	(4.044)	(2.826)	(5.558)	(8.288)	(1.230)	(2.556)	(6.145)	(1.684)

Table 2 continued

		World	Region $_{HK}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Wald		8.719**	8.566**	3.340	0.496	13.872***	4.828*	17.293***	9.106**
K–S		0.017	0.027	0.033	0.024	0.023	0.023	0.025	0.026
$(q_t - \overline{q})$	$\widehat{\rho 1}(1)$	0.027	–0.018	0.020	0.064	0.029	0.023	0.032	0.014
	Q1(10)	6.365	18.201	3.601	6.174	16.483	8.104	18.998	6.773
$(q_t - \overline{q})^2$	$\widehat{\rho 2}(1)$	–0.022	–0.047	–0.077*	0.068	–0.058	0.029	–0.016	–0.043
	Q2(10)	5.191	15.759	15.274*	5.420	6.068	10.070	3.808	7.260
$(q_t - \overline{q})^3$	$\widehat{\rho 3}(1)$	–0.009	–0.036	–0.004	0.026	0.013	0.013	0.016	–0.016
	Q3(10)	5.363	16.974	5.496	5.803	15.460	14.079	11.004	4.933
$(q_t - \overline{q})^4$	$\widehat{\rho 4}(1)$	–0.027	–0.061	–0.049	0.099**	–0.045	0.022	–0.000	–0.020
	Q4(10)	3.344	16.723	11.038	9.970**	6.042	11.785	2.116	6.461

[a]The estimated model is

$$r_{i,t} = \alpha_{i,0} + \alpha_{i,1} r_{i,t-1} + \varepsilon_{i,t}, \ \varepsilon_{i,t} = \sigma_{i,t} z_{i,t},$$

$$\sigma^2_{i,t} = \beta_{i,0} + \beta_{i,1}\sigma^2_{i,t-1} + \beta_{i,2}\varepsilon^2_{i,t-1} + \beta_{i,3}\left[\max(0, \varepsilon_{i,t-1})\right]^2$$

$$\lambda'_{i,t} = \gamma_{i,0} + \gamma_{i,1}\lambda'_{i,t-1} + \gamma_{i,2}\varepsilon_{i,t-1} + \gamma_{i,3}\max(0, \varepsilon_{i,t-1}) \ .$$

where $z_{i,t} \sim g\left(z_{i,t} \middle| \eta, \lambda_t\right)$ is the distribution as specified in equation (2.4) of the text. Standard errors are in parentheses, and *, **, and *** denote statistical significance at 10, 5, and 1% respectively. 'Wald' refers to the Wald test statistic for the restriction $\gamma_{i,1} = \gamma_{i,2} (= \gamma_{i,3}) = 0$. $q_t = \int_{-\infty}^{y_t} g(u_t)\, du_t$. K-S is the Kolmogorov-Smirnov test for uniformity. $\widehat{\rho}\, j(1)$ is the 1st order autocorrelation of $(q_t - \overline{q})$ raised to the *j*th power. Q*j*(10) is the Ljung-Box Q statistic at lag 10 for the returns raised to the *j*th power. Region $_{HK}$ refers to the weighted index of the country returns excluding Hong Kong.

Table 3 Estimated $\lambda_{\bullet,t}$ from the Univariate Models [a]

	World	Reg $_{HK}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
mean	-0.254	-0.041	-0.126	0.016	0.035	-0.033	-0.251	0.118
max	-0.103	0.988	0.326	0.440	0.147	0.247	-0.015	0.812
min	-0.848	-0.118	-0.816	-0.398	-0.082	-0.371	-0.400	-0.512

[a] Mean, maximum and minimum values of the estimated asymmetry parameters obtained from the univariate models with time-varying conditional skewness (see note to Table 2).

Table 4a Correlation between $\lambda_{w,t}$ and $\sigma^2_{w,t}$, $\lambda_{g,t}$ and $\sigma^2_{g,t}$, and $\lambda_{i,t}$ and $\sigma^2_{i,t}$ [a]

	World	Region $_{HK}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
	–0.525	0.342	–0.156	–0.049	–0.135	–0.148	0.438	–0.132

Table 4b Correlation between $\lambda_{w,t}$, $\lambda_{g,t}$ and $\lambda_{i,t}$ [b]

	World	Region $_{j}$	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Hong Kong	0.294	0.406	1.000	0.376	0.482	0.686	–0.217	0.496
Korea	0.105	0.401	–	1.000	0.276	0.403	–0.180	0.330
Malaysia	0.195	0.395	–	–	1.000	0.564	–0.263	0.448
Singapore	0.244	0.591	–	–	–	1.000	–0.207	0.579
Taiwan	–0.222	–0.233	–	–	–	–	1.000	–0.111
Thailand	0.185	0.473	–	–	–	–	–	1.000

[a, b] $\lambda_{w,t}$ and $\sigma^2_{w,t}$, $\lambda_{g,t}$ and $\sigma^2_{g,t}$, and $\lambda_{i,t}$ and $\sigma^2_{i,t}$ are the estimated asymmetry parameters and conditional variances obtained from the univariate models with time-varying conditional skewness (see note to Table 2). The subscripts *w* and *g* refer to the world and regional indexes respectively while $i = 1, \ldots, 6$ refers to the six individual markets. Region $_{HK}$ refers to the weighted index of the country returns, excluding Hong Kong. Region $_{j}$ refers to the weighted index of the country returns, excluding the market under consideration.

Table 5 Constant Spillover Model with Time–Varying Conditional Skewness

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Mean Equation						
$\alpha_{i,0}$	0.425***	–0.194	0.071	0.057	–0.124	–0.110
	(0.142)	(0.175)	(0.128)	(0.116)	(0.168)	(0.173)
$\alpha_{i,1}$	0.079	0.191	0.218**	0.258***	0.177*	0.264*
	(0.123)	(0.197)	(0.106)	(0.086)	(0.104)	(0.137)
$\alpha_{i,2}$	–0.010	0.036	0.034	0.038	–0.076	–0.218***
	(0.057)	(0.063)	(0.059)	(0.059)	(0.057)	(0.079)
$\alpha_{i,3}$	–0.035	–0.061	–0.033	–0.088	0.036	0.137***
	(0.062)	(0.084)	(0.048)	(0.059)	(0.050)	(0.046)
Factor Equation						
$\phi_{i,1}$	0.931	0.159	0.555	–0.163	–0.568	–0.184
	(0.647)	(1.478)	(1.062)	(0.797)	(0.635)	(0.654)
$\phi_{i,2}$	–0.128	–0.251	–0.161	–0.960	0.181	0.201
	(0.228)	(0.341)	(0.497)	(0.641)	(0.241)	(0.284)
Variance Equation						
$\beta_{i,0}$	0.573**	0.500	0.456	0.652**	1.377**	0.541
	(0.243)	(0.927)	(0.281)	(0.307)	(0.580)	(0.375)
$\beta_{i,1}$	0.822***	0.843***	0.838***	0.787***	0.789***	0.875***
	(0.040)	(0.196)	(0.057)	(0.067)	(0.070)	(0.048)
$\beta_{i,2}$	0.213***	0.177	0.227***	0.072	0.163***	0.180**
	(0.059)	(0.191)	(0.086)	(0.058)	(0.057)	(0.080)
$\beta_{i,3}$	–0.071	–0.100	–0.158*	–0.050	–0.060	–0.114*
	(0.066)	(0.090)	(0.095)	(0.044)	(0.059)	(0.067)
Skewness Equation						
$\gamma_{i,0}$	–0.099	0.057	0.091	–0.127	–0.105**	0.228
	(0.079)	(0.096)	(0.185)	(0.109)	(0.051)	(0.144)
$\gamma_{i,1}$	0.488*	0.294*	–0.647***	0.180	0.805***	0.051
	(0.261)	(0.152)	(0.146)	(0.313)	(0.088)	(0.190)
$\gamma_{i,2}$	0.072***	0.072	–0.020	0.018	–0.013	0.082***
	(0.026)	(0.046)	(0.020)	(0.021)	(0.011)	(0.027)
Degree of Freedom						
η	12.632**	11.072**	5.200***	7.635***	11.192**	6.435***
	(5.676)	(5.008)	(1.138)	(2.612)	(5.148)	(1.685)

[a]The estimated equations are:

$$r_{i,t} = \alpha_{i,0} + \alpha_{i,1} r_{w,t-1} + \alpha_{i,2} r_{g,t-1} + \alpha_{i,3} r_{i,t-1} + \varepsilon_{i,t} ,$$

$$\varepsilon_{i,t} = \phi_{i,1} \varepsilon_{w,t} + \phi_{i,2} e_{g,t} + e_{i,t} , \; e_{i,t} = \sigma_{i,t} z_{i,t}$$

$$\sigma^2_{i,t} = \beta_{i,0} + \beta_{i,1} \sigma^2_{i,t-1} + \beta_{i,2} e^2_{i,t-1} + \beta_{i,3} \left[\max(0, e_{i,t-1}) \right]^2$$

$$\lambda'_{i,t} = \gamma_{i,0} + \gamma_{i,1} \lambda'_{i,t-1} + \gamma_{i,2} \varepsilon_{i,t-1}$$

where $z_{i,t} \sim g\left(z_{i,t} \middle| \eta, \lambda_t\right)$ is the distribution as specified in equation (2.4) of the text. Standard errors are in parentheses, and *, **, and *** denote statistical significance at 10, 5, and 1% respectively. The subscripts w and g refer to the world and regional indexes respectively while i = 1, …, 6 refers to the six individual markets.

Table 6 Spillover Model with Crisis Dummy and Time Varying Conditional Skewness

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
$\alpha_{i,1}$	–0.023	0.110	0.241**	0.189*	0.237*	0.208
	(0.117)	(0.152)	(0.106)	(0.097)	(0.142)	(0.163)
$\alpha_{i,2}$	0.364	0.422	–0.212	0.242	–0.054	0.167
	(0.398)	(0.477)	(0.215)	(0.262)	(0.246)	(0.382)
$\alpha_{i,3}$	0.017	0.036	0.001	0.044	–0.112	–0.190*
	(0.064)	(0.069)	(0.062)	(0.060)	(0.086)	(0.097)
$\alpha_{i,4}$	–0.148	0.085	0.201	–0.078	0.024	–0.143
	(0.173)	(0.329)	(0.162)	(0.180)	(0.121)	(0.205)
$\phi_{i,1}$	1.082**	0.448	0.557	0.292	0.339	–0.508
	(0.442)	(1.020)	(0.864)	(0.796)	(1.233)	(0.938)
$\phi_{i,2}$	–1.213	–0.017	1.539	0.103	0.846	2.799*
	(2.468)	(5.104)	(1.177)	(2.003)	(1.187)	(1.460)
$\phi_{i,3}$	–0.201	–0.255	–0.428	–0.945	–0.039	0.267
	(0.250)	(0.281)	(0.340)	(0.648)	(0.263)	(0.332)
$\phi_{i,4}$	0.236	–0.714	–0.803*	–0.584	0.264	–0.447
	(1.154)	(2.130)	(0.418)	(0.829)	(0.304)	(1.173)

[a] Estimated parameters from the spillover model with mean equation

$$r_{i,t} = \alpha_{i,0} + (\alpha_{i,1} + \alpha_{i,2} d_c) r_{w,t-1} + (\alpha_{i,3} + \alpha_{i,4} d_c) r_{g,t-1} + \alpha_{i,5}\, r_{i,t-1} + \varepsilon_{i,t}$$

and factor equation

$$\varepsilon_{i,t} = (\phi_{i,1} + \phi_{i,2} d_c)\varepsilon_{w,t} + (\phi_{i,3} + \phi_{i,4} d_c) e_{g,t} + e_{i,t} \quad .$$

*, **, and *** denote statistical significance at 10, 5, and 1% respectively. The subscripts w and g refer to the world and regional indexes respectively while i = 1, …, 6 refers to the six individual markets. d_c represents the post-crisis dummy variable.

Table 7 Average Variance Ratios[a]

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Spillover Model with Time Varying Conditional Skewness						
World	0.180	0.005	0.080	0.005	0.057	0.005
Regional	0.009	0.036	0.018	0.439	0.022	0.017
Spillover Model with Time Varying Conditional Skewness and Crisis Dummy						
<u>Pre-Structural Break</u>						
World	0.235	0.043	0.075	0.018	0.017	0.037
Regional	0.022	0.045	0.115	0.439	0.001	0.029
<u>Post-Structural Break</u>						
World	0.004	0.015	0.310	0.015	0.284	0.426
Regional	0.001	0.196	0.326	0.634	0.042	0.008

[a] Average values of the ratio of variance explained by the world and regional factor, computed using equation (3.12) for various models.

Table 8 Probability of Unexpected Return ≤ -2 Times Standard Deviation[a]

		Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Spillover Model with Time Varying Conditional Skewness							
p_t^i	Mean	0.029	0.023	0.023	0.029	0.034	0.020
$p_t^{i+g} - p_t^i$	Max	0.002	0.002	0.002	0.013	0.004	0.006
	Min	–0.007	–0.012	–0.005	–0.020	–0.006	–0.004
$p_t^{i+g+w} - p_t^{i+g}$	Max	0.012	0.004	0.005	0.004	0.005	0.003
	Min	–0.004	–0.005	–0.003	–0.004	–0.005	–0.003

		Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Spillover Model with Time Varying Conditional Skewness and post – Crisis dummy							
Pre – July 1997							
p_t^i	Mean	0.029	0.022	0.023	0.027	0.034	0.020
$p_t^{i+g} - p_t^i$	Max	0.002	0.002	0.005	0.014	0.001	0.007
	Min	–0.011	–0.012	–0.013	–0.020	–0.002	–0.003
$p_t^{i+g+w} - p_t^{i+g}$	Max	0.010	0.006	0.008	0.005	0.002	0.004
	Min	–0.007	–0.006	–0.003	–0.004	–0.003	–0.003
Post – July 1997							
p_t^i	Mean	0.030	0.022	0.023	0.028	0.034	0.020
$p_t^{i+g} - p_t^i$	Max	0.002	0.018	0.016	0.022	0.003	0.002
	Min	–0.001	–0.019	–0.018	–0.022	–0.005	–0.005
$p_t^{i+g+w} - p_t^{i+g}$	Max	0.003	0.005	0.014	0.003	0.008	0.026
	Min	–0.003	–0.004	–0.007	–0.004	–0.001	–0.003

[a]Based on 1000 random draws from $e_{i,t}$, $\phi_{i,2}e_{g,t} + e_{i,t}$, $\phi_{i,1}\varepsilon_{w,t} + \phi_{i,2}e_{g,t} + e_{i,t}$, $(\phi_{i,2} + \phi_{i,4})e_{g,t} + e_{i,t}$ and $(\phi_{i,1} + \phi_{i,3})\varepsilon_{w,t} + (\phi_{i,2} + \phi_{i,4})e_{g,t} + e_{i,t}$ at each period t, with parameter estimates from the various models. 'Mean' reports the average frequency with which a draw that is less than 2 standard deviations is obtained. The superscripts *w* and *g* refer to the world and regional indexes respectively while i = 1, …, 6 refers to the six individual markets.

Table 9a Mean Spillover with Crisis Dummy (Alternative Models)[a]

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Constant Conditional Skewness						
$\alpha_{i,1}$	–0.027	0.156	0.234**	0.188*	0.215	0.223
	(0.114)	(0.116)	(0.104)	(0.096)	(0.163)	(0.147)
$\alpha_{i,2}$	0.164	0.260	–0.232	0.248	–0.038	0.174
	(0.334)	(0.351)	(0.214)	(0.259)	(0.228)	(0.309)
$\alpha_{i,3}$	0.031	0.031	0.002	0.043	–0.100	–0.162*
	(0.064)	(0.056)	(0.061)	(0.061)	(0.111)	(0.097)
$\alpha_{i,4}$	–0.081	–0.090	0.223	–0.091	0.023	–0.205
	(0.180)	(0.248)	(0.159)	(0.170)	(0.132)	(0.192)
Conditional Symmetry						
$\alpha_{i,1}$	–0.002	0.161	0.233**	0.172*	0.236	0.250*
	(0.114)	(0.115)	(0.104)	(0.093)	(0.168)	(0.142)
$\alpha_{i,2}$	0.314	0.299	–0.212	0.274	–0.079	0.198
	(0.282)	(0.337)	(0.212)	(0.249)	(0.235)	(0.331)
$\alpha_{i,3}$	0.020	0.026	0.003	0.043	–0.093	–0.156*
	(0.061)	(0.055)	(0.061)	(0.059)	(0.085)	(0.093)
$\alpha_{i,4}$	–0.163	–0.120	0.219	–0.096	0.014	–0.207
	(0.175)	(0.238)	(0.164)	(0.171)	(0.115)	(0.209)

[a] Estimated parameters from the spillover model with mean equation

$$r_{i,t} = \alpha_{i,0} + (\alpha_{i,1} + \alpha_{i,2} d_c) r_{w,t-1} + (\alpha_{i,3} + \alpha_{i,4} d_c) r_{g,t-1} + \alpha_{i,5}\, r_{i,t-1} + \varepsilon_{i,t}$$

and factor equation

$$\varepsilon_{i,t} = (\phi_{i,1} + \phi_{i,2} d_c)\varepsilon_{w,t} + (\phi_{i,3} + \phi_{i,4} d_c) e_{g,t} + e_{i,t} \quad .$$

The subscripts w and g refer to the world and regional indexes respectively while i = 1, …, 6 refers to the six individual markets.

Table 9b Average Variance Ratios (Alternative Models)[a]

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
Spillover Model with Constant Conditional Skewness and Post-Crisis Dummy						
Pre-Structural Break						
World	0.211	0.000	0.090	0.019	0.002	0.131
Regional	0.020	0.281	0.110	0.477	0.000	0.031
Post-Structural Break						
World	0.164	0.418	0.301	0.022	0.114	0.463
Regional	0.229	0.463	0.308	0.665	0.140	0.095
Spillover Model with Conditional Symmetry and Post-Crisis Dummy						
Pre-Structural Break						
World	0.212	0.004	0.096	0.009	0.059	0.131
Regional	0.015	0.288	0.135	0.460	0.001	0.036
Post-Structural Break						
World	0.002	0.396	0.254	0.033	0.059	0.465
Regional	0.002	0.486	0.332	0.672	0.116	0.098

[a] Average values of the ratio of variance explained by the world and regional factor, computed using equation (3.12) for various models.

Table 10a Mean Spillover (TimeVarying Conditional Skewness with News)[a]

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
No Regional/Local News						
$\alpha_{i,1}$	0.033	0.256	0.003	0.338**	0.345	0.057
	(0.222)	(0.276)	(0.200)	(0.152)	(0.318)	(0.291)
$\alpha_{i,4}$	0.185	0.188	0.128	0.018	–0.111	–0.253
	(0.144)	(0.141)	(0.139)	(0.165)	(0.153)	(0.192)
Change in Mean Spillover due to Regional News						
$\alpha_{i,2}$	0.057	0.115	0.305	–0.041	–0.148	0.119
	(0.224)	(0.309)	(0.250)	(0.193)	(0.335)	(0.311)
$\alpha_{i,5}$	–0.016	–0.127	–0.108	–0.036	0.015	–0.011
	(0.125)	(0.165)	(0.157)	(0.170)	(0.159)	(0.209)
Change in Mean Spillover due to Local News						
$\alpha_{i,3}$	–0.041	–0.202	–0.038	–0.165	–0.121	0.165
	(0.195)	(0.233)	(0.280)	(0.210)	(0.284)	(0.306)
$\alpha_{i,6}$	–0.248**	–0.114	–0.118	0.143	0.049	0.202
	(0.114)	(0.137)	(0.153)	(0.131)	(0.114)	(0.171)

[a] Estimated parameters from the spillover model with mean equation

$$r_{i,t} = \alpha_{i,0} + (\alpha_{i,1} + \alpha_{i,2} d_g + \alpha_{i,3} d_i) r_{w,t-1}$$
$$+ (\alpha_{i,4} + \alpha_{i,5} d_g + \alpha_{i,6} d_i) r_{g,t-1} + \alpha_{i,7} r_{i,t-1} + \varepsilon_{i,t}$$

and factor equation

$$\varepsilon_{i,t} = (\phi_{i,1} + \phi_{i,2} d_g + \phi_{i,3} d_i)\varepsilon_{w,t} + (\phi_{i,4} + \phi_{i,5} d_g + \phi_{i,6} d_i) e_{g,t} + e_{i,t}\,.$$

The subscripts w and g refer to the world and regional indexes respectively while i = 1, …, 6 refers to the six individual markets. d_i and d_g refers to the local and regional news dummies respectively.

Table 10b Average Variance Ratios (TimeVarying Conditional Skewness with News)[a]

	Hong Kong	Korea	Malaysia	Singapore	Taiwan	Thailand
No Regional/Local News						
World	0.308	0.006	0.411	0.266	0.000	0.001
Region	0.078	0.142	0.011	0.000	0.112	0.040
Change in Variance Spillover due to Regional News						
World	0.421	0.005	0.405	0.024	0.147	0.000
Region	0.032	0.088	0.014	0.003	0.144	0.026
Change in Variance Spillover due to Local News						
World	0.546	0.211	0.709	0.685	0.061	0.068
Region	0.046	0.126	0.081	0.234	0.059	0.177

[a] Average values of the ratio of variance explained by the world and regional factor, computed using equation (3.12) for various models.