1-1-2004

Volatility clustering, leverage effects, and jumps dynamics in emerging asian equity markets

Elton Daal
University of New Orleans

Atsuyuki Naka
University of New Orleans

Jung-Suk Yu
University of New Orleans

Volatility Clustering, Leverage Effects, and Jumps Dynamics in Emerging Asian Equity Markets

Elton Daal
Department of Economics and Finance
University of New Orleans, 2000 Lakeshore Drive
New Orleans, LA 70148
e-mail: edaal@uno.edu, tel: (504) 280-6270

Atsuyuki Naka
Department of Economics and Finance
University of New Orleans, 2000 Lakeshore Drive
New Orleans, LA 70148
e-mail: anaka@uno.edu, tel: (504) 280-6896

Jung-Suk Yu
Department of Economics and Finance
University of New Orleans, 2000 Lakeshore Drive
New Orleans, LA 70148
jsyu@uno.edu

September 30, 2004

We thank Oscar Varela, Gerald Whitney, and Dilip Madan for their comments and suggestions.

Abstract

This paper proposes a mixed GARCH-Jump model that is tailored to the specific circumstances arising in emerging equity markets. Our model accommodates lagged currency returns as a local information variable in the autoregressive jump intensity function, incorporates jumps in the returns and volatility, and allows volatility to respond asymmetrically to both normal innovations and jump shocks. The model captures the distinguishing features of the Asian index returns and significantly improves the fit for those markets that were affected by the 1997 Asian crisis. Our proposed model yields higher levels of conditional kurtosis and superior forecasts of the expected arrival rate of jumps.

1 Introduction

Mixed GARCH-Jump modeling has recently emerged as a powerful tool to describe the dynamics of asset returns in developed markets. Duan, Ritchken and Sun (2004) develop a NGARCH-Jump model that allows for correlated jumps in the returns and volatilities. In the limit, their discrete-time model can converge to continuous-time jump-diffusion processes with jumps in the stochastic volatility. They find that the NGARCH-Jump model provides a better fit for the time-series of S&P 500 index returns relative to the normal NGARCH specification. Maheu and McCurdy (2004) develop a mixed GARCH-Jump model that admits time-variation and clustering in the jump intensity. When applied to individual stocks and indices in the US, their model outperforms the constant intensity GARCH-Jump model. They also provide evidence supporting the presence of leverage effects, volatility clustering, and leptokurtosis in the time-series of asset returns.

As documented in the literature, stock index returns from emerging markets exhibit different characteristics compared to those from developed markets. For example, Harvey (1995) and Bekaert and Harvey (2002) argue that emerging market returns have higher volatility, fatter tails, and greater predictability. In contrast to the mature markets, Bekaert and Harvey (1997) show that volatilities in emerging markets are primarily determined by local information variables. Aggarwal, Inclan and Leal (1999) find that the volatilities in emerging markets exhibit large and sudden shifts. They find that these jump-like changes in the emerging markets' volatility are primarily associated with important local events. Aggarwal *et al.* also find that most emerging markets' returns show positive skewness, which is in contrast to the negative skewness in developed markets. The question arises whether a mixed GARCH-Jump model can capture the distinguishing features in the emerging markets.

In this paper, we propose a mixed GARCH-Jump model that is tailored to the specific circumstances arising in emerging markets. Our model extends existing GARCH-Jump models by allowing for greater predictability in the jump process. In addition to being autoregressive, the time-varying jump intensity is also a function of the lagged exchange-rate changes. We incorporate the absolute value of lagged currency returns as an information variable in the jump structure because it captures the macro-economic conditions and is an important determinant of the emerging markets' volatility. As shown in Maroney, Naka and Wansi (2004), the foreign exchange markets contain information that can result in large movements in both the dollar and local returns in the emerging equity markets. The inclusion of the lagged exchange-rate changes in the GARCH-jump model can therefore help explain or predict the arrival of jumps in these markets. The proposed jump structure is sufficiently flexible to allow for both clustering and reversals in the jump likelihood. In addition, it induces more time-variation and state-dependency in the tail behavior, which can lead to greater kurtosis in the return distribution.

As in Duan *et al.* (2004) and Maheu and McCurdy (2004), our mixed GARCH-Jump model incorporates jumps in the returns and volatilities. The inclusion of jumps in the volatility can potentially account for the large, but persistent movements in the emerging market volatility. The model allows conditional volatility to respond asymmetrically to both normal innovations and jump shocks. It can therefore accommodate both positive and negative correlations between the asset returns and volatilities. Our model specification seems therefore well-equipped to capture the main time-series properties of the stock index returns in the emerging markets.

We apply the proposed model to daily Asian index returns. We select a diversified group of emerging Asian markets (EAM), ranging from countries that were severely affected by the 1997 Asian financial crisis to those that were relatively unaffected. We consider a sample period from July 5, 1995 through August 7, 2002, which allows us to examine the dynamics of the Asian index returns before, during, and after the crisis. To evaluate the contribution of each model's component, we estimate and test six special cases of the model. The main results can be summarized as follows:

First, the mixed GARCH-Jump model captures several stylized features of the volatilities of returns in EAM. As expected, the results indicate higher volatilities for EAM relative to the US. For most EAM, the relatively high volatility is accompanied by negative mean returns during and after the Asian crisis. On aggregate, there is also more volatility persistence in EAM than in the US equity market. In most cases, we obtain less leverage effect in the EAM volatilities as compared to the US. We note that the volatilities in the EAM and the US exhibit large, abrupt movements that indicate the presence of jumps in returns and volatilities. In addition, we find that the EAM volatilities respond asymmetrically to jump shocks.

Second, jumps play a more critical role and induce quite different tail behavior in the EAM as compared to the US. In particular, in the absence of GARCH effects, the decomposition of the quadratic variation shows that the dominance of the jump component over the diffusion component is greater in most EAM relative to the US. The dominant role of the jump component in the EAM is primarily due to the relatively high variability of the jump size. In contrast, the dominance of jumps in the US equity market is primarily driven by the frequency of jumps. The introduction of GARCH effects significantly reduce to role of jumps, indicating that jumps mimic the high volatility regimes in the constant volatility models. With respect to the tail distribution, we observe that the model-implied skewness is positive for most EAM and negative for the US, and the implied kurtosis is substantially higher in the EAM than in the US.

Third, in all cases, allowing for time-varying jump intensity significantly improve the overall performance of the GARCH-Jump model. This improvement is accompanied by higher levels of tail thickness in most markets. The time-varying jumps exhibit significant clustering for all index returns, but are more predictable for the EAM index returns. In this respect, the inclusion of lagged exchange-rate changes as a local information variable in the jump dynamics significantly improves the fit of the GARCH-Jump model for most

EAM returns and provides further evidence of the predictability of jumps in these markets. Specifically, we find that the lagged exchange-rate changes have substantial predictive power in those EAM that were affected by the crisis.

The remainder of the paper is structured as follows. In Section 2, we specify our mixed GARCH-Jump model with state-dependent jump intensities and six nested models. Section 3 presents the data and econometric methodology. The results are discussed in Section 4 and Section 5 provides the conclusion of the paper.

2 Model Specifications

In this section, we present a general model that can capture the main stylized features in the time-series of equity returns in emerging markets. This general specification accommodates leverage effects, volatility clustering, leptokurtosis, and state-dependent jumps that affect both the index returns and volatility. It extends the existing mixed GARCH-jump models by allowing the time-varying jump intensity to be a function of the lagged exchange-rate changes. To examine the role and significancy of each component of the general model, we also consider a hierarchy of six special cases.

2.1 The General Model

The general specification is a discrete-time jump-diffusion model with state-dependent jump intensity and asymmetric power-GARCH effects. We denote this model henceforth as the JDSI-PG model. Under this model, the dynamics of the index returns, r_t, is given by

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right) = \mu + \varepsilon_t, \tag{1}$$

where

$$
\begin{aligned}
\varepsilon_t &= \varepsilon_{1,t} + \varepsilon_{2,t} \\
\varepsilon_{1,t} &= \sqrt{h_t} z_t \\
\varepsilon_{2,t} &= \sum_{i=1}^{N_t} J_{i,t} - \phi \lambda_t \\
z_t | I_{t-1} &\sim NID\left(0,1\right) \\
J_{i,t} &\sim NID\left(\phi, \delta^2\right) \text{ for } i = 1, 2, ...,
\end{aligned}
$$

S_t is the daily closing price of the stock index (including accumulated interest or dividends), N_t is a Poisson random variable with conditional jump intensity λ_t, $J_{i,t}$ is the random jump size, ϕ is the mean jump size, δ^2 is the jump variability, and I_{t-1} is the information set available at the beginning of time t. The Poisson-distributed variable, N_t, and the random jump size, $J_{i,t}$, are contemporaneously uncorrelated with each other and with z_t. The aggregate stochastic innovation ε_t consists of a normal "diffusion" component, $\varepsilon_{1,t}$, and a jump component, $\varepsilon_{2,t}$.

The parameter μ in Equation (1) represents the mean return. Following Das and Sundaram (1999), we find that the model-implied conditional variance, skewness, and kurtosis of the returns are given by

$$
\mathrm{Var}\left(r_t | I_{t-1}\right) = h_t + \left(\phi^2 + \delta^2\right) \lambda_t \tag{2}
$$

$$
\mathrm{Sk}\left(r_t | I_{t-1}\right) = \frac{\lambda_t \left(\phi^3 + 3\phi\delta^2\right)}{\left(h_t + \lambda_t \delta^2 + \lambda_t \phi^2\right)^{1.5}} \tag{3}
$$

$$
\mathrm{Ku}\left(r_t | I_{t-1}\right) = 3 + \frac{\lambda_t \left(\phi^4 + 6\phi^2\delta^2 + 3\delta^4\right)}{\left(h_t + \lambda_t \delta^2 + \lambda_t \phi^2\right)^2}. \tag{4}
$$

As can be inferred from equations (2), (3), and (4), all higher moments are time-varying in the general specification. In Equation (2), the total variation of the returns can be decomposed into smooth, diffusion-driven variation, h_t, and jump-induced variation. The conditional variance, h_t, affects the conditional skewness and excess kurtosis only when $\lambda_t \neq 0$. Hence, only jumps can induce non-normalities in the distribution of the index returns.

The conditional variance, h_t, of the diffusion component follows an asymmetric power GARCH(1,1) process,

$$h_t = \alpha_0 + \alpha_1 \left(|\varepsilon_{t-1}| + \theta\varepsilon_{t-1}\right)^2 + \beta h_{t-1}, \tag{5}$$

where θ is the leverage parameter and β captures the volatility clustering. The conditional variance in Equation (5) is quite similar to the power-GARCH and NGARCH models used respectively in Heston and Nandi (2000) and Duan *et al.* (2004). To ensure positive h_t, nonnegative constraints are imposed on the parameters α_0, α_1, and β. In addition, for stationarity, the parameter β is restricted to be smaller than unity. As shown in Heston and Nandi, the parameter α_1 controls for the kurtosis in the return distribution and the stochastic nature of the volatility. For example, when $\alpha_1 = 0$, the volatility changes deterministically over time.

The specifications in equations (1) and (5) incorporate jumps in both the returns and volatilities. Several recent studies find that accommodating for jumps in the return and volatility process considerably improves the model's fit for the return data of developed equity markets.[1] We expect similar, or even greater improvements for the emerging equity markets. As documented in Aggarwal *et al.* (1999), the emerging markets are characterized by high volatilities and exhibit large, sudden changes in the variance. The inclusion of jumps in the volatility can account for these large, but persistent movements in the emerging markets' volatility. In the JDSI-PG model, the jump innovation of the previous period, $\varepsilon_{2,t-1}$, affects the conditional volatility, h_t. Thus, while the current jump events are incorporated immediately in the *current* prices, they have an impact on the *future* expected volatility.

The parameter, θ, in Equation (5) allows for asymmetric shock effects in the conditional

[1] See, for example, Eraker (2004), Eraker et al. (2003), Duan et al. (2004), Maheu and McCurdy (2004).

variance. For $\theta < 0$, an aggregate negative shock ($\varepsilon_{t-1} < 0$) on the returns increases the variance more than an aggregate positive shock ($\varepsilon_{t-1} > 0$). This asymmetry implies a negative correlation between the index returns and the conditional volatility, and is loosely refer to as leverage effect. Bekaert and Wu (2000) and Wu (2001) find that both leverage effect and volatility feedback can be important explanations for asymmetric volatility. The leverage effect entails that bad news ($\varepsilon_{t-1} < 0$) reduces the value of the stock, which in turn increases financial leverage, making the stock riskier and, hence, its volatility higher. The volatility feedback assumes that volatility is priced and that its increase causes an increase in the expected return, resulting in a drop in the current stock price. In the JDSI-PG model, as in Maheu and McCurdy (2004) and Duan *et al.* (2004), the conditional volatility can respond asymmetrically to both normal innovations ($\varepsilon_{1,t-1}$) and jump shocks ($\varepsilon_{2,t-1}$).

For the specification of stochastic jump intensity, we build on the autoregressive conditional jump intensity model presented in Maheu and McCurdy (2004). In this model, the probability of jumps is allowed to change over time. The conditional jump intensity, λ_t, depends on the last period's conditional intensity, λ_{t-1}, and an intensity residual, ξ_{t-1}, which is given by

$$\xi_{t-1} = E\left[N_{t-1}|I_{t-1}\right] - \lambda_{t-1}, \tag{6}$$

where $E\left[N_{t-1}|I_{t-1}\right]$ is the ex post probability of jumps and λ_{t-1} represents the ex ante probability. In Appendix I, we present the explicit expression for the ex post probability. The jump structure of the autoregressive jump intensity model allows for clustering in the jump likelihood. Maheu and McCurdy present evidence supporting the presence of jump clustering in the US stock returns and find that their model outperforms the constant jump intensity specification.

We extend the autoregressive jump intensity model for the EAM by allowing the conditional jump intensity to also be a function of the lagged changes in the exchange rate vis à vis the US dollar,

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma_1\xi_{t-1} + \gamma_2 |x_{t-1}|, \tag{7}$$

where x_{t-1} is the lagged rate of change in the dollar value of the each Asian currency. Our motivation for incorporating lagged currency returns as an information variable in the jump structure in Equation (7) is twofold:

First, exchange rate realignments capture macro-economic conditions in the emerging markets and play therefore an important role during periods of major distress in these markets. Recent examples include the Mexican Peso (1994), the Thai Bhat (1997), the Malaysian Ringgit (1997), the Russian GKO's (1998), and the Brazilian Real (1999). In the case of the Asian crisis, Kaminsky and Schmukler (1999) note that the devaluations resulted in sharp decreases in both the dollar and local stock returns. Maroney *et al.* (2004) attribute this reduction in the average returns to the fact that the Asian firms were heavily leveraged in the foreign currency.

Second, the absolute value of the currency returns is, at least partially, a measure of the volatility of the dollar return of the stock index. Maroney *et al.* show that in the post-crash period, half of the volatility of dollar returns in most EAM is due to exchange rate movements. Recent work by Bates (2000), Duffie *et al.* (1998), and Pan (1999) points to the importance of incorporating volatility in the random jump intensity. They show that a high volatility before and during a market crash can increase the probability of jumps. However, as noted in Chernov *et al.* (2003), a jump intensity that is an affine function of the volatility may not be suitable to accommodate the jump behavior observed in the equity markets. We see that volatility tends to remain high after a market crash, while the arrival of jumps drops considerably after a crash. In our JDSI-PG model, the inclusion of the absolute value of the currency returns allows the jump intensity to be a non-affine function of the volatility. It can therefore allow for both clustering and reversals in the jump likelihood. The latter implies that high (low) jump probability can be followed by low (high) intensity.

The general model is therefore well-equipped and tailored to capture several stylized features of the stock index returns in the emerging equity markets. Whether these features play an important role in time-series of index returns in the EAM remain an open question that can be addressed by examining each feature separately.

2.2 The Nested Models

We use six special cases of the JDSI-PG model to obtain more insights in each specific characteristic of the equity returns in the EAM. The simplest case is the discrete version of the geometric Brownian motion (GBM). In the GBM, there are only two free parameters to be estimated, namely, μ and $\sigma = \sqrt{\alpha_0}$. Next, we augment the GBM with symmetric GARCH effects. This GBM-G model is obtained from the general model by setting $\lambda_t = \lambda = 0$ and $\theta = 0$. To gauge the importance of asymmetry in the volatility structure, we relax the restriction on the leverage parameter, θ, but maintain $\lambda_t = \lambda = 0$. This case is labeled the GBM-PG model.

To isolate the impact of jumps, we start with the Merton (1976) jump-diffusion (JD) model. This nested model allows for jumps in the returns, but ignores time-variation in the volatility and jump intensity. We next consider the case with stochastic volatility, but constant jump intensity, $\lambda_t = \lambda$. We refer to this specification as the JD-PG model. The final special case allows for time-varying jump intensity, but excludes the lagged currency returns by letting $\gamma_2 = 0$. This case with autoregressive jump structure is denoted as JDAI-PG model.

3 The Data and Estimation Methodology

The data used in this study consist of daily closing prices for stock indexes from the US and eight emerging Asian markets (EAM). For the US, we use the time series data on the S&P

500 obtained from the Center for Research in Security Prices (CRSP) data base. The eight EAM are China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, and Thailand. The EAM affected by the 1997 Asian financial crisis are Indonesia, Korea, Thailand, Malaysia and Philippines (henceforth, EAM-5), where Indonesia, Korea, and Thailand were hit the hardest. China, India, and Taiwan were relatively unaffected. The data for the EAM are obtained from the International Finance Corporation's Emerging Markets Data Base (EMDB). All stock indexes are expressed in the US dollar terms. The sample covers the period from July 5, 1995 through August 7, 2002. We filter out all zero returns, since those are returns that the EMDB conventionally report for the trading holidays. For most EAM, the zero returns constitute less than two percent of the full sample.

[Insert Table 1 here]

We divide the data into three subsamples. The first subsample covers the pre-crisis period, starting from July 1995 to right before the official crisis date of each country. As indicated in Table 1, the crisis dates vary across countries.[2] The second subsample refers to the crisis years, spanning the crisis-date in July through December 1999. The remainder of the sample, that is, January 2000 through August 2002, is considered the post-crisis period. Although the selection of the subsamples is ad hoc in nature, each period gives roughly equal number of observations.

Panel A of Table 1 presents the summary statistics for the daily index returns. Except for China, the average daily returns on the stock indexes are negative for all EAM during the full sample period. The index returns in China display a higher average than the S&P 500, and the Thailand index records the lowest average in our sample. We notice that the

[2] Maroney, Naka and Wansi (2004) estimate the dates of the structural changes during the crisis periods and provide the confidence intervals for six Asian countries. According to their estimates, the structural changes occur much later (three to five months) than the official dates.

index returns in most EAM exhibit large extremes. The maximum daily return observed in the EAM (Korea) and the US is respectively 26.79 and 5.57 percent, and the minimum is respectively −40.85 (Indonesia) and −7.11 percent. These extreme returns are detected primarily during the crisis period in Panel C and are concentrated in those EAM that were most affected by the Asian crisis.

[Insert Figure 1 and 2 here]

The time series plots of the index level and returns in Figure 1 and 2 provide further illustration of the extreme movements in the EAM. In Table 1, the standard deviation of the daily returns in all EAM is higher than in the US. It ranges from 1.65 percent for India to 3.68 percent for Indonesia. We also note that the non-normality of the returns, as measured by the skewness and kurtosis, is substantially larger for the EAM-5 countries relative to the US. For example, the sample kurtosis of the index returns in the EAM-5 countries ranges from 8.18 for Thailand to 24.25 for Malaysia. In Panel E, we observe that the exchange rates of all the EAM, excluding China, have depreciated vis-à-vis the US dollar. On average, Indonesia has the largest depreciation and shows the largest standard deviation. We also note that the standard deviation for China is very small due to the tight foreign exchange rate policy conducted in this country.

We use the maximum likelihood estimation (MLE) for all model specifications. For each model, the estimation involves maximizing the conditional log-likelihood function with respect to the parameter vector of that model. The conditional probability density function for the general JDSI-PG model is presented in the Appendix. As in Jorion (1988) and Maheu and McCurdy (2004), we find that truncation of the infinite sum in the likelihood at 10 captures all the tail probabilities and gleans sufficient precision in the estimation procedure. We use the Likelihood Ratio (LR) to test the nested models and to examine the importance of each component of the JDSI-PG model.

4 Results

4.1 Mean return and volatility level

Panel A of Table 2 presents the results for the GBM model. The estimates for the mean and the volatility in Table 2 are almost similar to the sample moments in Table 1.[3] As expected, the full-sample parameter estimates for the volatility, σ, are higher for all stock index returns in the EAM relative to the S&P 500. The daily volatility in the EAM ranges from 1.65 percent in India to 3.68 percent in Indonesia, as compared to 1.20 percent in the US. The relatively high volatilities in the EAM, except China, are accompanied by negative mean returns. This can be primarily attributed to the Asian crisis in 1997. As pointed out in Maroney *et al.* (2004), it is the high leverage linked to exchange rate resulting in higher risk and lower mean returns when the Asian crisis began.

[Insert Table 2 here]

The subsample results for the GBM model indicate large shifts in the volatility of the EAM. Specifically, for most EAM, the volatilities during the crisis period are substantially higher than the volatilities before and after the crisis. For example, the pre-crisis volatility for Indonesia increases from 1.60 to 5.85 percent during the crisis, and then drops to 2.24 percent in the post-crisis period. We also note that across all subperiods the volatility of the index returns is higher for EAM as compared to the US. These findings are consistent with the summary statistics in Table 1.

4.2 Volatility clustering and leverage effects

In Panel A of Table 3, the log-likelihoods of the GBM-PG model indicate that allowing for time-variations and leverage effects in the volatility of the index returns of both EAM and

[3] We note, however, that they do differ at the fifth decimal.

the US significantly improves the performance relative to the GBM model. For all EAM and the US, the LR tests strongly reject the GBM in favor of the GBM-PG at the conventional 5 percent significance level. The parameter estimates for the GBM-PG model provide further evidence that the volatility in the EAM is stochastic, persistent, and asymmetric. The estimates for the parameter α_1 are significant and show that the volatility is changing stochastically over time. The fact that all the estimates for β are positive and statistically significant implies volatility clustering in EAM and the US. The aggregate autoregressive coefficient in the volatility process is very close to one for the EAM-5 group, resulting in a persistence effect that is stronger than in the US.[4]

[Insert Table 3 here]

For all EAM and the US, Panel A shows negative values for the leverage parameter, θ.[5] With an estimated value of -0.99 for θ, the volatility of the US index returns is substantially more asymmetric than that of the EAM. A possible explanation is that volatility is more systematic in the US as compared to the EAM. As noted in Harvey (1995) and Bekaert and Campbell (1997), the volatility in the emerging markets is primarily driven by local factors. These country-specific factors are either not priced or have a low correlation with the world market. In this respect, we notice that the EAM that is less integrated with the world market, namely China, has (in absolute value) the lowest parameter estimate for the asymmetry, $\theta = -0.0466$. In contrast, with $\theta = -0.3363$, the well-integrated Taiwanese market exhibit the highest asymmetry among the EAM.

Panel B, C, and D of Table 3 present the subsample results for the GBM-PG model. During the crisis-period in Panel C, the aggregate persistence effect in the EAM, except India, is stronger than in the US. We note that the volatility clustering in most EAM-5

[4] We use $\beta + \alpha_1$ as a proxy for the aggregate autoregressive coefficient.

[5] To separately examine the impact of leverage effect on the overall fit of the model, we also perform LR tests of the symmetric GBM-G. For all EAM and the US, the LR tests reject the GBM-G in favor of the GBM-PG. To limit the size of the paper, we do not report these results.

(except Korea) dropped substantially after the crisis period. The subsample results show that the Asian crisis also brought about changes in the volatility asymmetry of most EAM. The post-crisis leverage effect is higher as compared to the pre-crisis for all markets, except Thailand. For Korea, the estimate of the post-crisis leverage parameter is -1.0003, which is substantially higher in absolute value than the pre-crisis estimate of -0.2805. For China and India, we observe a change from no leverage effect before the crisis to relatively high leverage effects after the crisis.

[Insert Figure 3 here]

Figure 3 graphs the time-series of the conditional volatility generated by the GBM-PG model. It shows that the volatility process in both the crisis and post-crisis period exhibits more fluctuations as compared to the pre-crisis process. Figure 3 also illustrates the presence of extreme large, abrupt movements in the volatility process. These characteristics in the emerging markets are also documented by Aggarwal *et al.* (1994).

4.3 Jumps, skewness, and excess kurtosis

The results for the JD model are reported in Table 4. For all EAM and the US, the log likelihoods in the last rows of Table 2 and 4 reject the GBM in favor of the JD at the 5 percent significance level. They show that index returns in the EAM and US exhibit large, infrequent moves that cannot be captured by a diffusion process. In addition, the results also suggest that the return distributions of the indexes in these markets deviate significantly from the normal distribution.

[Insert Table 4 here]

Substituting the relevant parameter estimates from Panel A of Table 4 in equations (2), (3), and (4), we get the total variation and its decomposition, skewness, and kurtosis of the index returns implied by the JD model. These results are reported in Table 5. Consistent with the GBM, we find that the total variation of the index returns is higher in the EAM as compared to the US. We also note that the total variation in EAM and US is predominantly due to the jump component. Specifically, jumps account for more than 70 percent of the total variation of the index returns in the EAM (except Taiwan) and 68.49 percent in the US. The source of the high contribution of the jump volatility in the EAM is primarily the relatively high variability of the jump size, δ. All the estimated values for δ in the EAM are higher than the 1.15 percent in the US. The dominance of the jump component in the US is driven by the high value of 0.7205 for the arrival rate of jumps, λ.

[Insert Table 5 here]

Except for India, the implied skewness is positive for all EAM and negative for the US. With an implied skewness of -0.3364, the index returns are more skewed in the Indonesia equity markets relative to the other EAM and the US. In most cases, the sign of implied skewness is consistent with that of the sample skewness in Table 1. However, in terms of magnitude, the JD model cannot generate the sample skewness for the EAM. We also note that the estimates for the skewness parameter, ϕ, should be interpreted with some caution since they are statistically insignificant in most cases.

Using the moments in equations (2), (3) and (4), we find that the implied kurtosis is higher for the EAM as compared to the US. Although the JD model can capture the stylized feature of fatter tails in the EAM, it cannot reproduce the extreme high statistical kurtosis in the EAM-5. For example, the model implied kurtosis for Malaysia is 7.94, which is significantly lower than the value of 24.25 for the sample kurtosis. Such a mismatch can be attributed to the Gaussian distribution of the jump sizes and the i.i.d. arrival rate of jumps in the JD model. In this respect, using an alternative distribution for the jump size or permitting the tail thickness to change over time may improve the model's performance for the EAM.

The subsample estimates in Panel B, C, and D of Table 5 indicate that the arrival rate of jumps and, therefore, the tail behavior in the EAM differ substantially across the subperiods. Quintos *et al.* (2001) provide evidence that supports structural changes in the tail behavior of the Asian asset returns. In addition, we find that jumps dominate across all the subperiods. Except for China and India, this dominance is greater for the EAM as compared to the US and is more pronounced during the crisis. For Indonesia, the jump component accounts for 83.38 percent of the total variation, making the diffusion component almost absent during this period.

4.4 Jumps and asymmetric GARCH effects

The results of the JD-PG model are presented in Table 6. For all countries, the log likelihoods in the last rows of Table 3, 4, and 6 reject the GBM-PG and JD in favor of the JD-PG model at the 5 percent significance level. This result indicates that both stochastic volatility and jumps are important characteristics of the asset returns. On the one hand, jump discontinuities in the equity index returns play a significant role even in the presence of time-varying volatilities. On the other hand, introducing jumps in the returns without accommodating for time-variation in the volatility can only account for some of the stylized facts in the EAM and the US.

[Insert Table 6 here]

The parameter estimates of the JD-PG model in Panel A of Table 6 show that allowing for time-varying volatility substantially reduces the burden on the jump component. In comparison to the JD model, the values for the estimates of the arrival rate of jumps, λ, in the JD-PG model are dramatically lower for all the cases. For example, in case of the US and India, the estimated value for λ fell respectively from 0.7205 and 0.8826 in the JD model to 0.1564 and 0.0737 in the JD-PG model. This indicates that the jump component in the JD model appears to mimic the high volatility persistence in the returns. Put differently, under the JD model, the contribution of jumps is extremely high because it also incorporates the high volatility regimes of the returns. However, in the presence of asymmetric power-GARCH effects, the role of jumps is drastically reduced in all the markets. In addition, we note that for most EAM the jumps in the return and volatility lead to an increase in the estimate of the leverage effect parameter, θ. For China, the absolute value of the leverage effect parameter increased from 0.0466 (Table 3) to 0.1431 (Table 6). This increase can be an indication that the conditional volatility responds asymmetrically to both normal and jump shocks in these EAM.

At first glance, the subsample estimates for the arrival rate of jumps, λ, in Panel B, C, and D of Table 6 are quite puzzling. In contrast to the JD results, we observe for most countries that the arrival rate of jumps drops considerably during and after the crisis. A possible explanation for this seemingly conflicting result is the fact that for the JD model the high and volatile volatility during these two subperiods has to be captured by the jump component, while under the JD-PG model it is captured by the GARCH component. Hence, in the presence of GARCH effects, the jump component is released of the extra burden of capturing the high volatility regimes and only has to describe the extreme rare movements in the returns. In this respect, we observe that in most cases the absolute value of the mean jump size, $|\phi|$, in the JD-PG model increases during the last two subperiods.

4.5 The impact of autoregressive jump intensity

Table 7 presents the results for the JDAI-PG model. For all cases, the LR tests reject the null hypothesis of constant arrival rate (JD-PG) in favor of the autoregressive jump intensity of the JDAI-PG model. Thus, the autoregressive specification proposed by Maheu and McCurdy (2004) is flexible enough to capture the jump dynamics in both developed and emerging equity markets. Surprisingly, with a log likelihood of 5607.45 compared to 5591.62, the improvement in the statistical fit is more pronounced for the US, followed by China and Korea. This result suggests that autoregressive jump intensity can be critical in both mature and emerging markets, and does not necessarily depend on the occurrence of market crashes.

[Insert Table 7 here]

The estimated parameters for ρ and γ_1 provide further evidence supporting time-variation in the jump intensity. For most EAM and the US, the estimated values for ρ are high and statistically significant, indicating clustering in the jump process. The result for the US is broadly agreeable with the findings in Maheu and McCurdy (2004) for the US index returns. We note that the jump clustering is higher for China and Thailand. In addition, the estimates for γ_1 show that the jumps in most EAM are more predictable than in the US. Specifically, with a higher estimated value of 0.4196 for the parameter γ_1, the revisions in the conditional forecasts of N_{t-1} play a more important role for the US as compared to most EAM.

Panel B of Table 7 shows that accommodating time-varying jump intensity significantly impacts the tail distribution of the index returns. For almost all EAM, the average implied kurtosis of the JDAI-PG model is notably higher than that of the JD and JD-PG model. Thus, the JDAI-PG can capture the stylized feature of fatter tails in the EAM better than the constant jump intensity models. We note, however, that the JDAI-PG model cannot match the extreme high statistical kurtosis of the EAM-5. For example, for Malaysia, we observe that the average implied kurtosis of 10.59 for the JDAI-PG model is significantly lower than the statistical kurtosis of 24.24 in Table 1.

[Insert Figure 4 here]

Figure 4 displays the time-series of the conditional jump intensity for the EAM and the US. In all nine countries, the arrival rate of jumps exhibit significant changes over time. We observe, however, that the arrival rates follow notably different paths among the EAM. For example, for the EAM-5 group, there is a substantial increase in the time-variation of the jump likelihood when the crisis began. In contrast, for China, India, and Taiwan, the peaks in the arrival rate of jumps do not appear to be related to the Asian crisis.

4.6 The predictive power of exchange-rate changes

Table 8 reports the likelihoods and parameter estimates for the full-fledged JDSI-PG model. Except for China and Taiwan, the LR tests show that the inclusion of the lagged exchange-rate changes in the jump structure significantly improves the fit relative to the nested JDAI-PG model. With an increase of the log likelihood from 4239.27 to 4255.22 and one degree of freedom, we observe that the greatest improvement is recorded for Indonesia. It appears that the predictive power of this information variable depends on the prevailing exchange rate regime in the emerging market. In the case of China, we see that the lagged currency returns do not contribute significantly due to the non-convertibility and fixed exchange rate policy. Most EAM maintain a managed exchange rate regime before the crisis. During the midst of the Asian crisis, all EAM-5 replaced the managed-floating exchange rate regime by a free-floating exchange rate arrangement, which may explain the predictive power of the lagged currency returns in this group of EAM.

[Insert Table 8 here]

The parameter estimates for γ_2 are positive and statistically significant at the one percent level for all EAM-5 countries. Hence, the greater the absolute value of the exchange rates changes, the higher the expected jump likelihood in these EAM. In contrast, we see that γ_2 is statistically insignificant for China, India, and Taiwan, indicating that the lagged currency returns have no predictive power in those Asian markets that were not affected by the crisis. The predictive power of the lagged currency returns varies considerably across the EAM-5 countries. With an estimated value of 0.0737 for γ_2, the lagged exchange-rate changes in

Malaysia is a stronger predictor than in the other EAM-5 countries. The inclusion of lagged currency returns leads to lower parameter estimates for γ_1 in all EAM-5, which indicates that the importance of the forecast revisions is reduced in the presence of this information variable. Furthermore, we detect that the parameter values for ρ are still quite large, indicating jump clustering across all EAM. Thus, for most EAM, the presence of lagged currency returns does not diminish, but rather complements the role of the autoregressive jump intensity.

[Insert Figure 5 here]

Panel B of Table 8 indicates that in most cases the lagged currency returns in the intensity function reduce the role of the jump component in total variation of the index returns. For example, when comparing the JDAI-PG with the JDSI-PG, we observe that the jump portion of the total variation for Indonesia drops noticeably from 49.30 to 39.82 percent. For the EAM-5 results of both models, the jump component of the total variation is the highest for Indonesia and the lowest for Korea. Since the absolute value of the lagged currency return is a measure of the currency returns' volatility, its inclusion in the jump intensity function can result in a greater role for the time-varying volatility.

In this respect, Figure 5 illustrates the total variation and its components for both the JDAI-PG and JDSI-PG model. To save space, we only plot the graphs for Indonesia and Korea. Figure 5 shows how the conditional volatility affects the pattern of the jump intensity under the JDSI-PG model. In particular, we observe for Indonesia and Korea that high volatility increases the probability of jumps when lagged currency returns are incorporated in the jump structure. In contrast, under the JDAI-PG model, we note that the jumps capture only a small fraction of the total variation during the high volatility periods and the jump likelihood is not affected by the volatility.

We also notice that adding the local information variable has an impact on the tail probabilities of the index returns. In most cases, the average implied skewness and kurtosis of the JDSI-PG model are slightly higher than those of the JDAI-PG model. However, for the EAM-5 countries, the average conditional kurtosis implied by the JDSI-PG model is still not high enough to match the sample kurtosis.

[Insert Table 9 here]

The findings in Table 9 show that the λ_t are unbiased forecasts for $E[N_t|I_t]$ for both the JDAI-PG and JDSI-PG model. We note, however, that on average the forecast errors are lower for the JDSI-PG model. For most EAM-5 countries, the incorporation of lagged currency returns increases the arrival rate of jumps and improves the forecast ability of λ_t. This result indicates that the local information variable can help explain or predict the number of jumps in distressed equity markets. For China, India, and Taiwan, the forecast ability of λ_t remained (on average) the same after the inclusion of the currency returns in the intensity function. The jump process in these EAM is most probably influenced by other local information variables.

5 Conclusion

In this paper, we have proposed a mixed GARCH-Jump model with state-dependent jump intensities to examine the stylized features of the index returns in emerging Asian markets. Our mixed GARCH-Jump (JDSI-PG) model allows the jump intensity to be autoregressive and dependent on the lagged exchange-rate changes. It accommodates jumps in the returns and volatility. In the GARCH component of the model, conditional volatility can respond asymmetrically to both normal and jump returns shocks. We investigate whether this model can capture the essential features in the emerging Asian equity markets, covering the periods before, during and after the Asian crisis. To examine the significancy of each model's component we have also estimated six nested models.

We find that the mixed GARCH-Jump model can capture several distinguishing features of the emerging Asian equity markets. As expected, the volatility is higher in these markets as compared to the US. The high volatilities are accompanied by negative returns even long after the Asian crisis. The volatility is highly persistent and exhibits large, abrupt changes in the presence of the Asian crisis. The leverage effect of normal return shocks in the Asian markets is less than in the US, but the asymmetric response of the volatility to jump-like shocks is greater in the Asian markets.

Although jumps plays a significant role in both the emerging Asian markets and the US, we note that its contribution is greater in those markets that were affected by the crisis. This jump contribution in the Asian markets is primarily induced by the high jump variability, whereas in the US it is driven by the higher arrival rate of jumps. In comparison to the US returns, the tails of the Asian returns are notably fatter before, during, and after the crisis. The constant jump intensity fails to capture these extreme tail distributions in the emerging markets and is strongly rejected by the time-varying jump intensity.

The autoregressive jump intensity generates higher levels of conditional kurtosis and improves the model's performance more for the emerging Asian markets as compared to the US. We find that jumps affect volatility and are highly clustered in both types of markets. We also observe that the jump dynamics exhibit different patterns among the Asian markets, indicating the importance of local information variables in the jump structure. Adding lagged exchange-rate changes as an information variable in the autoregressive jump intensity function significantly improves the fit of the mixed GARCH-Jump model for those Asian markets that were affected by the crisis. It offers higher levels of conditional kurtosis and superior forecasts of the expected arrival rate of jumps in these countries.

Our mixed GARCH-Jump model and the nested models are not able to reproduce the sample skewness in a satisfactory manner. This can be due to sampling error or model misspecification. In the Poisson-based jump models considered, the skewness parameter is also the parameter for the average jump size. In addition, the jump size is assumed to be normally distributed. An avenue for future research of emerging market returns is to consider alternative distributions of the random jump size and to examine the impact of other local information variables.

Appendix

The ex-post probability of jumps, $E\left[N_t|I_t\right]$, is defined by Maheu and McCurdy (2004) as

$$E\left[N_t|I_t\right] = \sum_{j=0}^{\infty} jP\left(N_t = j|I_t\right), \tag{A.1}$$

where $P\left(N_t = j|I_t\right)$ is the ex post inference on N_t given the time t information,

$$P\left(N_t = j|I_t\right) = \frac{f\left(r_t|N_t = j, I_{t-1}\right) P\left(N_t = j|I_{t-1}\right)}{f\left(r_t|I_{t-1}\right)}, \tag{A.2}$$

r_t is the lagged index return, $f\left(r_t|N_t = j, I_{t-1}\right)$ is the probability density function conditional on j jumps and information set I_{t-1},

$$f\left(r_t|N_t = j, I_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(h_t + j\delta^2\right)}} \exp\left(-\frac{\left(r_t - \mu + \lambda_t\phi - j\phi\right)^2}{2\left(h_t + j\delta^2\right)}\right), \tag{A.3}$$

and $f\left(r_t|I_{t-1}\right)$ is the likelihood function conditional on the information set I_{t-1},

$$f\left(r_t|I_{t-1}\right) = \sum_{j=0}^{\infty} f\left(r_t|N_t = j, I_{t-1}\right) P\left(N_t = j|I_{t-1}\right).$$

References

Aggarwal, R., C. Inclan, and R. Leal, 1999, Volatility in Emerging Stock Markets, *Journal of Financial and Quantitative Analysis*, 34, 33-55.

Bekaert, G. and C.R. Harvey, 1997, Emerging Equity Market Volatility, *Journal of Financial Economics* 43, 29-77.

Bekaert, G. and C.R. Harvey, 2002, Research in emerging markets finance: looking to the future, *Emerging Markets Review* 3, 429-448.

Bekaert, G. and G. Wu, 2000, Asymmetric Volatility and Risk in Equity Markets, *The Review of Financial Studies* 13, 1-42.

Das, S.R., and R. K. Sundaram, 1999, Of Smiles and Smirks: A Term Structure Perspective, *Journal of Financial and Quantitative Analysis* 34, 211-239.

Duan, J., P. Ritchken, and Z. Sun, 2004, Jump Starting GARCH: Pricing and Hedging Options with Jumps in Returns and Volatilities, *Forthcoming Journal of Finance.*

Eraker, B., 2004, Do Stock Prices and Volatility Jump? Reconciling Evidence from Spot and Option Prices, *Journal of Finance* 59, 1367-1403.

Eraker, B., M.S. Johannes, and N.G. Polson, 2003, The Impact of Jumps in Returns and Volatility, *Journal of Finance* 53, 1269-1300.

Harvey, C.R., 1995, Predictable Risk and Returns in Emerging Markets, *The Review of Financial Studies* 8, 773-816.

Heston, S.L., and S. Nandi, 2000, A Closed-Form GARCH Option Valuation Model, *Review of Financial Studies* 13, 585-625.

Jorion, P., 1988, On Jump Processes in the Foreign Exchange and Stock Markets, *Review of Financial Studies* 1, 427-445.

Kaminsky, G., and S. Schmukler, 1999, What Triggers Market Jitters? A Chronicle of the Asian Crisis, *Journal of International Money and Finance* 18, 537-560.

Maheu J.M., and T.H. McCurdy, 2004, News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns, *Journal of Finance* 59, 755-793.

Maroney N., A. Naka, and T. Wansi, 2004, Changing Risk, Return, and Leverage: The 1997 Asian Financial Crisis, *Journal of Financial and Quantitative Analysis* 39, 143-166.

Merton, R.C., 1976, Option Pricing When Underlying Stock Returns are Discontinuous, *Journal of Financial Economics* 3, 125-144.

Quintos, C., S. Fan, and P.C. Philips, 2001, Structural Change Tests in Tail Behaviour and the Asian Crisis, *Review of Economic Studies* 68, 633-663.

Wu, G., 2001, The Determinants of Asymmetric Volatility, *The Review of Financial Studies* 14, 837-859.

Table 1

Summary Statistics of Equity Returns and Foreign Currency Returns

Panel A: Whole Period

	US	CH	IN	ID	KR	MY	PH	TW	TH
Obs	1788	1804	1801	1815	1784	1781	1810	1788	1823
Mean	0.0003	0.0005	-0.0002	-0.0008	-0.0002	-0.0004	-0.0009	-0.0002	-0.0010
Min	-0.0711	-0.1019	-0.0787	-0.4085	-0.2156	-0.2382	-0.0971	-0.1108	-0.1505
Max	0.0557	0.0870	0.0922	0.2543	0.2679	0.2295	0.2026	0.0754	0.1658
Std	0.0120	0.0173	0.0165	0.0368	0.0307	0.0230	0.0187	0.0195	0.0259
Skewness	-0.1745	-0.2802	0.0106	-0.8631	0.3049	0.7105	1.0928	0.0415	0.5885
Kurtosis	6.1418	7.3847	5.4622	22.1726	11.6586	24.2447	17.6643	4.7962	8.1800

Panel B: 1st sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
Obs	507	510	509	546	587	524	516	574	515
Mean	0.0010	0.0018	0.0002	0.0000	-0.0015	-0.0001	-0.0004	0.0004	-0.0020
Min	-0.0313	-0.1019	-0.0787	-0.0768	-0.0881	-0.0347	-0.0583	-0.0703	-0.0776
Max	0.0269	0.0802	0.0629	0.0392	0.0765	0.0276	0.0468	0.0652	0.0649
Std	0.0076	0.0224	0.0138	0.0120	0.0168	0.0090	0.0108	0.0154	0.0169
Skewness	-0.4198	-0.5832	0.2878	-0.9225	-0.1850	-0.1985	-0.4010	-0.1097	-0.0968
Kurtosis	4.5688	6.0953	6.8692	8.4281	7.5724	4.3320	6.3687	5.4800	6.0809

Panel C: 2nd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
Obs	630	635	629	599	540	623	632	533	637
Mean	0.0008	0.0000	0.0004	-0.0014	0.0014	-0.0010	-0.0007	0.0003	-0.0006
Min	-0.0711	-0.0828	-0.0672	-0.4085	-0.2156	-0.2382	-0.0971	-0.0705	-0.1505
Max	0.0499	0.0599	0.0922	0.2543	0.2679	0.2295	0.1275	0.0686	0.1658
Std	0.0123	0.0155	0.0173	0.0585	0.0431	0.0355	0.0244	0.0192	0.0358
Skewness	-0.4406	-0.2191	0.2522	-0.5963	0.3830	0.6193	0.0335	0.1776	0.6525
Kurtosis	7.0671	6.8022	5.2634	10.4326	8.6351	12.0711	5.6447	4.5864	5.7357

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
Obs	651	659	663	670	657	634	662	661	671
Mean	-0.0008	-0.0001	-0.0009	-0.0009	-0.0005	-0.0001	-0.0014	-0.0010	-0.0007
Min	-0.0601	-0.0612	-0.0698	-0.0897	-0.1268	-0.0690	-0.0788	-0.1108	-0.0815
Max	0.0557	0.0870	0.0716	0.1058	0.0932	0.0562	0.2026	0.0754	0.0690
Std	0.0142	0.0140	0.0175	0.0224	0.0278	0.0134	0.0172	0.0228	0.0198
Skewness	0.1515	0.3661	-0.3031	-0.3118	-0.3043	-0.3517	3.8325	0.0602	-0.1781
Kurtosis	4.4706	6.8050	4.7388	5.0481	4.7539	6.3817	45.1850	4.1049	4.6369

Table 1 (continued)

Summary Statistics of Equity Returns and Foreign Currency Returns

Panel E: Currency Returns

	CH	IN	ID	KR	MY	PH	TW	TH
Obs	1804	1801	1815	1784	1781	1810	1788	1823
Mean	0.0000	-0.00024	-0.00077	-0.00026	-0.00025	-0.00039	-0.00015	-0.00030
Min	-0.0050	-0.06151	-0.23936	-0.13645	-0.06773	-0.12632	-0.04747	-0.11905
Max	0.0050	0.04705	0.20416	0.19795	0.07309	0.11096	0.02621	0.06245
Std	0.0002	0.00331	0.02330	0.01186	0.00704	0.00764	0.00307	0.00842
Skewness	-0.0433	-2.97400	-1.22321	0.68159	0.30790	-1.22480	-2.99751	-1.58348
Kurtosis	621.5013	107.7060	31.6921	83.5571	33.0356	76.4616	52.3823	40.9150

This table presents summary statistics for returns on the S&P 500 index (US), eight emerging Asian stock market indices, and eight Asian currencies. The Asian markets are China (CH), India (IN), Indonesia (IN), Korea (KR), Malaysia (MY), Philippines (PH), Taiwan (TW), and Thailand (TH). All returns are denominated in US dollar terms. The exchange rates are defined as the value of one unit of each Asian currency in terms of the U.S. dollar. Excluded are holidays (zero returns) for the US and Asian markets. The sample covers the period from 7/5/95 through 8/7/02. The sample period for each country is divided into three sub-periods:

- 1st sub-period: US, CH, IN, TH 7/5/95-7/2/97; ID 7/5/95-8/14/97; KR 7/5/95-11/7/97; MY 7/5/95-7/14/97; PH 7/5/95-7/11/97; TW 7/5/95-10/17/97
- 2nd sub-period: US 7/3/97-12/31/99; CH, IN, TH 7/3/97-12/30/99; ID 8/15/97-12/30/99; KR 11/10/97-12/30/99; MY 7/15/97-12/30/99; PH 7/14/97-12/29/99; TW 10/17/97-12/30/99
- 3rd sub-period: 1/3/00-8/7/02 (except ID 1/4/00-8/7/02)

Table 2

Parameter Estimates for the GBM Model

Panel A: Whole Period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0003	0.0005	-0.0002	-0.0008	-0.0002	-0.0004	-0.0009	-0.0002	-0.0011
	(0.2863)	(0.1181)	(0.3072)	(0.1692)	(0.3680)	(0.2178)	(0.0231)	(0.4457)	(0.0401)
σ	0.0120	0.0173	0.0165	0.0368	0.0307	0.0230	0.0187	0.0195	0.0259
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	5375.90	4758.53	4837.59	3414.83	3683.80	4189.34	4634.36	4499.83	4070.12

Panel B: 1st sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0010	0.0025	0.0002	0.0002	-0.0014	-0.0001	-0.0003	0.0004	-0.0015
	(0.0013)	(0.0192)	(0.4024)	(0.3625)	(0.0215)	(0.4269)	(0.2488)	(0.2539)	(0.0465)
σ	0.0073	0.0276	0.0138	0.0160	0.0165	0.0090	0.0104	0.0153	0.0187
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1755.51	1192.55	1454.71	1610.64	1573.19	1727.95	1618.30	1582.39	1364.12

Panel C: 2nd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0008	0.0000	0.0004	-0.0015	0.0014	-0.0011	-0.0008	0.0002	-0.0006
	(0.0537)	(0.4770)	(0.2970)	(0.2667)	(0.4272)	(0.2329)	(0.2199)	(0.3825)	(0.3273)
σ	0.0124	0.0155	0.0174	0.0585	0.0431	0.0355	0.0244	0.0192	0.0358
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1874.71	1742.89	1557.11	849.33	930.21	1193.18	1447.98	1399.35	1215.99

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	-0.0008	-0.0001	-0.0010	-0.0010	-0.0005	-0.0001	-0.0014	-0.0014	-0.0007
	(0.0668)	(0.4436)	(0.0794)	(0.1332)	(0.3231)	(0.4507)	(0.0195)	(0.0652)	(0.1929)
σ	0.0141	0.0140	0.0172	0.0224	0.0278	0.0134	0.0172	0.0228	0.0198
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1845.61	1874.24	1733.21	1591.43	1419.71	1832.85	1748.10	1510.51	1676.96

This table presents estimation results of the GBM model for the S&P 500 index (US) and eight emerging Asian stock market indices denominated in US dollar terms. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 3

Parameter Estimates for the GBM-PG Model

Panel A: Whole Period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0003	0.0002	0.0001	0.0000	-0.0006	0.0000	-0.0006	-0.0002	-0.0010
	(0.1077)	(0.3120)	(0.3367)	(0.4697)	(0.1307)	(0.4965)	(0.0160)	(0.2979)	(0.0162)
α_0	0.0018	0.0053	0.0062	0.0023	0.0018	0.0017	0.0022	0.0038	0.0030
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0487	0.1703	0.1419	0.1216	0.0751	0.1145	0.1490	0.0758	0.1025
	(0.0027)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.8823	0.7407	0.7078	0.8836	0.9248	0.8821	0.8499	0.8818	0.8874
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.9980	-0.0466	-0.3053	-0.1546	-0.1579	-0.1843	-0.2685	-0.3363	-0.1197
	(0.0018)	(0.1561)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0004)
$\ln L$	5576.73	4925.14	4936.01	4153.05	4072.38	4903.56	5011.69	4603.79	4384.46

Panel B: 1st sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0009	0.0019	-0.0002	0.0005	-0.0013	-0.0001	-0.0002	0.0005	-0.0015
	(0.0023)	(0.0146)	(0.3868)	(0.1298)	(0.0155)	(0.4148)	(0.3100)	(0.1867)	(0.0069)
α_0	0.0009	0.0098	0.0037	0.0061	0.0029	0.0018	0.0021	0.0075	0.0010
	(0.0011)	(0.0000)	(0.0108)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0153)
α_1	0.0544	0.2004	0.0753	0.2701	0.0960	0.0795	0.1152	0.1386	0.0722
	(0.0010)	(0.0000)	(0.0242)	(0.0008)	(0.0002)	(0.0007)	(0.0047)	(0.0012)	(0.0000)
β	0.9285	0.6055	0.8558	0.4752	0.8711	0.8804	0.8383	0.6177	0.9329
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.2541	0.1230	0.0651	-0.3314	-0.2805	-0.2118	-0.3502	-0.3132	-0.2595
	(0.0703)	(0.1109)	(0.3113)	(0.0013)	(0.0040)	(0.0303)	(0.0030)	(0.0009)	(0.0013)
$\ln L$	1776.39	1247.59	1467.73	1673.20	1638.14	1748.82	1667.40	1597.76	1428.17

Panel C: 2nd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0007	-0.0001	0.0006	-0.0003	0.0013	0.0005	-0.0003	0.0000	-0.0002
	(0.0380)	(0.3924)	(0.1791)	(0.4302)	(0.1741)	(0.2904)	(0.3429)	(0.4954)	(0.4001)
α_0	0.0033	0.0047	0.0076	0.0094	0.0084	0.0033	0.0034	0.0045	0.0049
	(0.0000)	(0.0064)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0720	0.1755	0.0514	0.1207	0.1026	0.1459	0.1812	0.0309	0.0324
	(0.0016)	(0.0119)	(0.2151)	(0.0015)	(0.0031)	(0.0000)	(0.0000)	(0.0012)	(0.0310)
β	0.7901	0.7260	0.7096	0.8464	0.8467	0.8542	0.8093	0.8834	0.8742
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-1.0013	-0.2719	-0.9999	-0.3594	-0.1671	-0.2383	-0.1070	-1.0175	-0.9524
	(0.0000)	(0.0002)	(0.1835)	(0.0003)	(0.0543)	(0.0000)	(0.0289)	(0.0000)	(0.0003)
$\ln L$	1926.85	1806.00	1576.61	954.02	1139.93	1321.40	1538.89	1426.54	1641.60

Table 3 (continued)

Parameter Estimates for the GBM-PG Model

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	-0.0013	-0.0003	-0.0003	-0.0007	-0.0005	0.0000	-0.0012	-0.0015	-0.0007
	(0.0026)	(0.2922)	(0.2774)	(0.2265)	(0.2847)	(0.4992)	(0.0100)	(0.0372)	(0.1648)
α_0	0.0023	0.0021	0.0055	0.0127	0.0033	0.0070	0.0033	0.0036	0.0073
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0004)	(0.0000)
α_1	0.0557	0.0377	0.1537	0.0686	0.0093	0.1453	0.0696	0.0585	0.1653
	(0.0024)	(0.0000)	(0.0004)	(0.0910)	(0.0623)	(0.0004)	(0.0042)	(0.0136)	(0.0000)
β	0.8757	0.9135	0.7121	0.5956	0.9660	0.5596	0.8700	0.9078	0.6944
	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.9999	-0.8886	-0.3494	-0.4047	-1.0003	-0.2339	-0.8455	-0.5296	-0.1425
	(0.0003)	(0.0000)	(0.0027)	(0.1074)	(0.0318)	(0.0206)	(0.0001)	(0.0031)	(0.0528)
$\ln L$	1899.36	1914.57	1813.09	1599.05	1435.63	1865.19	1832.47	1592.69	1715.30

This table presents estimation results of the GBM-PG model for the S&P 500 index (US) and eight emerging Asian stock market indices denominated in US dollar terms. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 4

Parameter Estimates for the JD Model

Panel A: Whole Period

	US	**CH**	**IN**	**ID**	**KR**	**MY**	**PH**	**TW**	**TH**
μ	0.0003	0.0005	0.0003	-0.0010	-0.0003	-0.0006	-0.0011	-0.0006	-0.0010
	(0.1771)	(0.0861)	(0.2732)	(0.1166)	(0.3269)	(0.0840)	(0.0010)	(0.0854)	(0.0267)
σ	0.0067	0.0086	0.0082	0.0148	0.0149	0.0083	0.0081	0.0124	0.0105
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.7205	0.5039	0.8826	0.3658	0.4259	0.4050	0.5003	0.5421	0.7091
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ	-0.0011	0.0002	-0.0002	-0.0049	-0.0004	0.0004	-0.0003	0.0032	0.0013
	(0.0320)	(0.3706)	(0.3860)	(0.0001)	(0.3777)	(0.2890)	(0.3150)	(0.0001)	(0.0896)
δ	0.0115	0.0206	0.0149	0.0548	0.0389	0.0274	0.0214	0.0193	0.0274
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	5464.81	4939.83	4921.54	3960.57	3930.68	4670.06	4949.67	4567.57	4280.33

Panel B: 1st sub-period

	US	**CH**	**IN**	**ID**	**KR**	**MY**	**PH**	**TW**	**TH**
μ	0.0010	0.0019	0.0002	0.0000	-0.0013	-0.0001	-0.0004	0.0004	-0.0020
	(0.0002)	(0.0231)	(0.3660)	(0.4688)	(0.0249)	(0.3923)	(0.1910)	(0.2827)	(0.0021)
σ	0.0056	0.0077	0.0100	0.0082	0.0127	0.0049	0.0061	0.0077	0.0062
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.3144	0.8616	0.1854	0.2798	0.2041	0.8553	0.4924	0.6510	0.9258
	(0.0263)	(0.0000)	(0.0075)	(0.0000)	(0.0778)	(0.0038)	(0.0534)	(0.0007)	(0.0000)
ϕ	-0.0018	-0.0016	0.0062	-0.0024	0.0004	-0.0005	-0.0004	0.0001	0.0007
	(0.0143)	(0.1604)	(0.0159)	(0.1201)	(0.3949)	(0.2774)	(0.3432)	(0.4558)	(0.2685)
δ	0.0092	0.0225	0.0213	0.0161	0.0210	0.0080	0.0122	0.0165	0.0160
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1773.62	1264.90	1492.49	1680.31	1604.39	1742.02	1642.60	1620.37	1415.93

Panel C: 2nd sub-period

	US	**CH**	**IN**	**ID**	**KR**	**MY**	**PH**	**TW**	**TH**
μ	0.0010	0.0000	0.0006	-0.0009	0.0015	-0.0015	-0.0009	0.0003	-0.0005
	(0.0561)	(0.4815)	(0.2222)	(0.3886)	(0.2061)	(0.1198)	(0.2047)	(0.3143)	(0.3564)
σ	0.0073	0.0088	0.0135	0.0298	0.0241	0.0198	0.0124	0.0097	0.0209
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.8325	0.4496	0.2734	0.3153	0.3232	0.3295	0.5762	0.8846	0.3892
	(0.0000)	(0.0201)	(0.0026)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0091)	(0.0000)
ϕ	-0.0006	0.0007	0.0011	0.0007	0.0044	0.0072	-0.0024	0.0026	0.0121
	(0.2915)	(0.2758)	(0.3337)	(0.4650)	(0.2364)	(0.0040)	(0.0990)	(0.0368)	(0.0166)
δ	0.0105	0.0187	0.0213	0.0891	0.0618	0.0467	0.0288	0.0174	0.0431
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1904.28	1794.63	1579.13	950.58	996.58	1286.47	1491.19	1424.06	1262.52

Table 4 (continued)

Parameter Estimates for the JD Model

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	-0.0008	-0.0001	-0.0008	-0.0010	-0.0004	-0.0003	-0.0014	-0.0012	-0.0006
	(0.0842)	(0.4080)	(0.1590)	(0.1252)	(0.3352)	(0.3289)	(0.0128)	(0.1260)	(0.2000)
σ	0.0091	0.0089	0.0115	0.0155	0.0097	0.0066	0.0096	0.0169	0.0098
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0019)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.7867	0.3503	0.3746	0.3108	1.2989	0.8272	0.1681	0.3698	0.7930
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
ϕ	0.0005	0.0010	-0.0055	-0.0086	-0.0012	0.0011	0.0014	0.0053	-0.0004
	(0.3541)	(0.2952)	(0.0124)	(0.0004)	(0.2193)	(0.1626)	(0.0837)	(0.0046)	(0.4088)
δ	0.0123	0.0176	0.0205	0.0277	0.0228	0.0126	0.0275	0.0274	0.0193
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1862.44	1918.52	1772.95	1621.54	1446.98	1873.50	1920.83	1571.72	1709.31

This table presents estimation results of the JD model for the S&P 500 index (US) and eight emerging Asian stock market indices denominated in US dollar terms. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 5

Variance Decomposition and Higher Moments of the Index Returns

Panel A: Whole Period

	US	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0001	0.0003	0.0003	0.0013	0.0009	0.0004	0.0003	0.0004	0.0006
JV/TV	0.6849	0.7418	0.7430	0.8338	0.7441	0.8163	0.7756	0.5765	0.8303
DV/TV	0.3151	0.2582	0.2570	0.1662	0.2559	0.1837	0.2244	0.4235	0.1697
skewness	-0.1848	0.0284	-0.0290	-0.3364	-0.0271	0.0525	-0.0421	0.2826	0.1285
kurtosis	4.9532	6.2760	4.8766	8.7003	6.9000	7.9359	6.6076	4.8386	5.9166

Panel B: 1st sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0001	0.0005	0.0002	0.0001	0.0003	0.0001	0.0001	0.0002	0.0003
JV/TV	0.4682	0.8803	0.4799	0.6862	0.3557	0.6896	0.6635	0.7484	0.8615
DV/TV	0.5318	0.1197	0.5201	0.3138	0.6443	0.3104	0.3365	0.2516	0.1385
skewness	-0.3182	-0.1867	0.6163	-0.2563	0.0250	-0.1057	-0.0686	0.0191	0.1063
kurtosis	5.0896	5.6985	6.7127	4.9742	4.8589	4.6680	5.6822	5.5811	5.4048

Panel C: 2nd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0001	0.0002	0.0003	0.0034	0.0018	0.0011	0.0006	0.0004	0.0012
JV/TV	0.6341	0.6643	0.4068	0.7378	0.6819	0.6524	0.7567	0.7459	0.6403
DV/TV	0.3659	0.3357	0.5932	0.2622	0.3181	0.3476	0.2433	0.2541	0.3597
skewness	-0.0894	0.1673	0.0792	0.0267	0.2115	0.4155	-0.2131	0.2980	0.6342
kurtosis	4.4491	6.9876	4.8159	8.1806	7.3156	6.8741	5.9813	4.8862	6.1496

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0002	0.0002	0.0003	0.0005	0.0008	0.0002	0.0002	0.0006	0.0004
JV/TV	0.5887	0.5810	0.5589	0.5207	0.8773	0.7547	0.5780	0.5023	0.7554
DV/TV	0.4113	0.4190	0.4411	0.4793	0.1227	0.2453	0.4220	0.4977	0.2446
skewness	0.0562	0.1253	-0.5100	-0.5647	-0.1127	0.1898	0.1669	0.3273	-0.0421
kurtosis	4.3216	5.8910	5.4934	5.6035	4.7776	5.0659	8.9603	5.0448	5.1584

This table reports the sample averages of the total conditional variation (TV) and its decomposition (JV/TV, DV/TV) computed from equation (2), the conditional skewness, and the conditional kurtosis of the index returns implied by the JD model. JV/TV and DV/TV are respectively the sample averages of the variance of the jump component and the diffusion variance, each divided by the total variance. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 6

Parameter Estimates for the JD-PG Model

Panel A: Whole Period

	US	**CH**	**IN**	**ID**	**KR**	**MY**	**PH**	**TW**	**TH**
μ	0.0004	-0.0002	0.0000	-0.0004	-0.0006	-0.0001	-0.0006	0.0000	-0.0006
	(0.0332)	(0.2926)	(0.4895)	(0.1972)	(0.1192)	(0.3452)	(0.0368)	(0.4710)	(0.0937)
α_0	0.0001	0.0022	0.0028	0.0028	0.0028	0.0015	0.0025	0.0010	0.0006
	(0.2059)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0108)
α_1	0.0591	0.1311	0.0727	0.1255	0.0859	0.1232	0.1637	0.0256	0.0844
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.9157	0.7917	0.8619	0.8196	0.8791	0.8375	0.7526	0.9486	0.8694
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.5291	-0.1431	-0.2386	-0.1668	-0.3087	-0.1642	-0.1703	-0.6238	-0.2146
	(0.0000)	(0.0041)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
λ	0.1564	0.1505	0.0737	0.0956	0.0919	0.1106	0.1052	0.1653	0.2142
	(0.0012)	(0.0000)	(0.0071)	(0.0000)	(0.0001)	(0.0000)	(0.0003)	(0.0000)	(0.0000)
ϕ	-0.0056	-0.0018	0.0018	-0.0053	0.0030	-0.0015	0.0003	0.0051	0.0047
	(0.0000)	(0.0271)	(0.0428)	(0.0000)	(0.0136)	(0.0159)	(0.3710)	(0.0000)	(0.0049)
δ	0.0095	0.0241	0.0273	0.0504	0.0341	0.0198	0.0243	0.0251	0.0291
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	5591.62	5026.72	4985.12	4233.40	4092.89	4950.42	5113.07	4633.73	4445.80

Panel B: 1st sub-period

	US	**CH**	**IN**	**ID**	**KR**	**MY**	**PH**	**TW**	**TH**
μ	0.0008	0.0016	0.0006	0.0000	-0.0011	0.0000	-0.0003	0.0004	-0.0017
	(0.0030)	(0.0307)	(0.1453)	(0.4961)	(0.0281)	(0.4391)	(0.2197)	(0.2432)	(0.0007)
α_0	0.0011	0.0001	0.0017	0.0061	0.0007	0.0010	0.0003	0.0016	0.0002
	(0.0001)	(0.4126)	(0.0020)	(0.0000)	(0.0434)	(0.0000)	(0.1132)	(0.0004)	(0.2898)
α_1	0.0591	0.1392	0.0282	0.7362	0.0984	0.0461	0.1136	0.0326	0.0774
	(0.0004)	(0.0000)	(0.0728)	(0.0000)	(0.0003)	(0.0008)	(0.0000)	(0.0015)	(0.0001)
β	0.8946	0.7411	0.9229	0.1979	0.8952	0.9244	0.8692	0.9129	0.8667
	(0.0000)	(0.0000)	(0.0000)	(0.0026)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.1814	-0.0946	-0.2997	-0.1179	-0.2492	-0.3366	-0.3181	-0.2618	-0.5067
	(0.0494)	(0.1549)	(0.0015)	(0.0817)	(0.0002)	(0.0039)	(0.0000)	(0.0310)	(0.0000)
λ	0.1134	0.3346	0.1327	0.0310	0.2038	0.0696	0.2552	0.2293	0.2649
	(0.0241)	(0.0000)	(0.0095)	(0.0373)	(0.0084)	(0.0511)	(0.0002)	(0.0000)	(0.0000)
ϕ	-0.0065	0.0009	0.0042	-0.0151	0.0087	-0.0030	0.0030	0.0013	0.0041
	(0.0000)	(0.3140)	(0.0081)	(0.0000)	(0.0000)	(0.0731)	(0.0158)	(0.1802)	(0.0049)
δ	0.0082	0.0263	0.0218	0.0218	0.0067	0.0150	0.0078	0.0220	0.0172
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1787.02	1284.96	1489.63	1682.60	1637.33	1758.43	1664.8743	1625.35	1447.90

Table 6 (continued)

Parameter Estimates for the JD-PG Model

Panel C: 2nd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0004	-0.0002	0.0005	-0.0015	0.0025	0.0001	-0.0012	-0.0001	0.0000
	(0.1474)	(0.3626)	(0.2063)	(0.1809)	(0.0524)	(0.4731)	(0.1170)	(0.4559)	(0.4925)
α_0	0.0031	0.0027	0.0047	0.0051	0.0040	0.0007	0.0009	0.0032	0.0043
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0053)	(0.1767)	(0.0226)	(0.0000)	(0.0019)
α_1	0.0645	0.1021	0.0679	0.0515	0.0636	0.1213	0.1133	0.0347	0.0749
	(0.0001)	(0.0017)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0003)	(0.0051)	(0.0000)
β	0.7997	0.8255	0.8124	0.8755	0.9027	0.8495	0.8582	0.8938	0.8770
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.8142	-0.1739	-0.5032	-0.3618	-0.2904	-0.1320	-0.0684	-0.6613	-0.2426
	(0.0000)	(0.0032)	(0.0001)	(0.0001)	(0.0009)	(0.0322)	(0.1900)	(0.0000)	(0.0001)
λ	0.0609	0.0797	0.0525	0.1829	0.1220	0.2080	0.2088	0.1791	0.1059
	(0.0020)	(0.0321)	(0.1273)	(0.0001)	(0.0910)	(0.0007)	(0.0003)	(0.0084)	(0.0333)
ϕ	-0.0172	-0.0033	0.0053	0.0030	0.0117	0.0020	-0.0022	0.0020	0.0245
	(0.0000)	(0.0241)	(0.0141)	(0.1807)	(0.0180)	(0.2299)	(0.2367)	(0.2086)	(0.0000)
δ	0.0049	0.0233	0.0294	0.0821	0.0405	0.0300	0.0214	0.0231	0.0450
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	1931.75	1824.26	1589.72	992.83	1035.01	1327.95	1541.17	1433.06	1297.89

Panel D: 3rd sub-period

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	-0.0009	-0.0004	-0.0006	-0.0002	-0.0007	-0.0003	-0.0011	-0.0015	-0.0008
	(0.0243)	(0.2158)	(0.1358)	(0.4112)	(0.2361)	(0.2856)	(0.0061)	(0.0307)	(0.1382)
α_0	0.0015	0.0010	0.0041	0.0010	0.0025	0.0039	0.0028	0.0025	0.0016
	(0.0001)	(0.0077)	(0.0001)	(0.0963)	(0.0399)	(0.0000)	(0.0000)	(0.0089)	(0.0004)
α_1	0.0453	0.0217	0.1404	0.0494	0.0100	0.1012	0.1745	0.0405	0.0983
	(0.0004)	(0.0533)	(0.0001)	(0.0000)	(0.1279)	(0.0108)	(0.0000)	(0.0786)	(0.0132)
β	0.9054	0.9315	0.7536	0.8998	0.9598	0.7330	0.6644	0.9262	0.8265
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.9940	-0.9817	-0.2898	-0.1293	-0.9818	-0.2281	-0.3380	-0.7244	-0.1223
	(0.0000)	(0.0019)	(0.0001)	(0.1005)	(0.0026)	(0.0011)	(0.0000)	(0.0072)	(0.0409)
λ	0.0226	0.1201	0.0665	0.3220	0.1426	0.0733	0.1650	0.1079	0.2414
	(0.2951)	(0.0025)	(0.0992)	(0.0000)	(0.0046)	(0.0107)	(0.0000)	(0.0880)	(0.0000)
ϕ	0.0139	-0.0023	-0.0149	-0.0042	-0.0133	-0.0015	0.0038	0.0061	0.0001
	(0.0000)	(0.1745)	(0.0004)	(0.0645)	(0.0091)	(0.1292)	(0.0005)	(0.1420)	(0.4763)
δ	0.0017	0.0221	0.0206	0.0273	0.0355	0.0248	0.0298	0.0209	0.0253
	(0.1449)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
$\ln L$	1898.07	1943.72	1822.09	1618.22	1455.22	1896.99	1928.02	1594.24	1731.51

This table presents estimation results of the JD-PG model. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 7

Parameter Estimates for the JDAI-PG Model

Panel A: Parameters Estimates

	US	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0002	0.0000	-0.0001	-0.0009	-0.0006	-0.0001	-0.0010	-0.0001	-0.0008
	(0.1553)	(0.4399)	(0.4391)	(0.0578)	(0.0990)	(0.4259)	(0.0003)	(0.4281)	(0.0400)
α_0	0.0013	0.0050	0.0035	0.0022	0.0022	0.0015	0.0020	0.0016	0.0026
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0002)
α_1	0.0358	0.1355	0.0871	0.0639	0.0593	0.1222	0.0576	0.0369	0.1061
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0228)	(0.0000)
β	0.9092	0.5962	0.8096	0.8934	0.9222	0.8508	0.8861	0.9216	0.8241
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.9345	-0.3111	-0.3143	-0.1894	-0.2400	-0.1581	-0.3711	-0.6784	-0.2128
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0015)	(0.0000)
λ_0	0.0329	0.0037	0.0939	0.0697	0.0177	0.0224	0.0306	0.0328	0.0008
	(0.0000)	(0.0323)	(0.0743)	(0.0000)	(0.0147)	(0.0000)	(0.0000)	(0.0017)	(0.0369)
ρ	0.5835	0.9812	0.2371	0.3442	0.5165	0.2595	0.7353	0.8342	0.9969
	(0.0000)	(0.0000)	(0.3154)	(0.0022)	(0.0001)	(0.0069)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.4196	0.1180	0.2259	0.3453	0.5888	0.3827	0.4478	0.1252	0.0200
	(0.0044)	(0.0007)	(0.0772)	(0.0006)	(0.0000)	(0.0000)	(0.0025)	(0.1062)	(0.0720)
ϕ	-0.0136	-0.0010	0.0011	-0.0113	0.0015	-0.0031	-0.0027	0.0036	0.0054
	(0.0000)	(0.2985)	(0.3342)	(0.0106)	(0.4223)	(0.2625)	(0.2203)	(0.0305)	(0.0190)
δ	0.0081	0.0258	0.0237	0.0601	0.0480	0.0361	0.0314	0.0218	0.0307
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	5607.94	5042.07	4990.54	4239.27	4106.21	4954.95	5117.12	4639.29	4453.16

Panel B: Variance Decomposition and Higher Moments of the Index Returns

	US	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0001	0.0003	0.0003	0.0013	0.0009	0.0005	0.0003	0.0004	0.0006
JV/TV	0.1674	0.4428	0.2939	0.4930	0.1708	0.2571	0.3820	0.3073	0.3938
DV/TV	0.8326	0.5572	0.7061	0.5070	0.8292	0.7429	0.6180	0.6927	0.6062
skewness	-0.3742	-0.0852	0.0668	-0.6726	0.0373	-0.1979	-0.2186	0.1981	0.3193
kurtosis	4.0165	7.0471	5.3958	12.9736	5.8979	10.5933	9.1939	4.7176	6.2976

The Panel A of this table presents estimation results of the JDAI-PG model for the S&P 500 index (US) and eight emerging Asian stock market indices denominated in US dollar terms. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. The Panel B of this table reports the sample averages of the total conditional variation (TV) and its decomposition (JV/TV, DV/TV) computed from equation (2), the conditional skewness, and the conditional kurtosis of the index returns implied by the JDAI-PG model. JV/TV and DV/TV are respectively the sample averages of the variance of the jump component and the diffusion variance, each divided by the total variance. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 8

Parameter Estimates for the JDSI-PG Model

Panel A: Parameters Estimates

	CH	IN	ID	KR	MY	PH	TW	TH
μ	0.0000	0.0000	-0.0001	-0.0006	0.0001	-0.0007	-0.0001	-0.0007
	(0.4766)	(0.4717)	(0.3688)	(0.0926)	(0.3565)	(0.0161)	(0.4361)	(0.0751)
α_0	0.0050	0.0035	0.0027	0.0021	0.0020	0.0021	0.0015	0.0027
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.1357	0.0891	0.0653	0.0613	0.1347	0.0459	0.0355	0.1064
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.6024	0.8082	0.8823	0.9207	0.8253	0.8929	0.9252	0.8224
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
θ	-0.3063	-0.2984	-0.2082	-0.2395	-0.1363	-0.4704	-0.6610	-0.2265
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)
λ_0	0.0015	0.0758	0.0129	0.0002	0.0218	0.0084	0.0327	0.0008
	(0.2052)	(0.0135)	(0.0037)	(0.4687)	(0.0000)	(0.1827)	(0.0001)	(0.0176)
ρ	0.9835	0.1906	0.4498	0.4372	0.4265	0.8426	0.8201	0.9892
	(0.0000)	(0.0833)	(0.0004)	(0.0079)	(0.0053)	(0.0000)	(0.0000)	(0.0000)
γ_1	0.0994	0.1906	0.1439	0.4930	0.0273	0.2897	0.1267	0.0000
	(0.0037)	(0.0822)	(0.0424)	(0.0001)	(0.3093)	(0.0076)	(0.0975)	(0.4998)
γ_2	0.4088	0.1172	0.0458	0.0542	0.0737	0.0287	0.0222	0.0034
	(0.1106)	(0.1121)	(0.0000)	(0.0000)	(0.0058)	(0.0150)	(0.2359)	(0.0089)
ϕ	-0.0014	0.0018	-0.0056	0.0032	0.0047	-0.0019	0.0033	0.0082
	(0.2363)	(0.2584)	(0.2251)	(0.3734)	(0.1574)	(0.2333)	(0.2011)	(0.0136)
δ	0.0260	0.0244	0.0595	0.0521	0.0376	0.0321	0.0219	0.0315
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\ln L$	5042.73	4991.55	4255.22	4111.60	4961.33	5121.34	4639.43	4457.35

Panel B: Variance Decomposition and Higher Moments of the Index Returns

	CH	IN	ID	KR	MY	PH	TW	TH
TV	0.0003	0.0003	0.0013	0.0010	0.0005	0.0003	0.0004	0.0007
JV/TV	0.4343	0.2810	0.3982	0.1332	0.3243	0.3567	0.3094	0.3875
DV/TV	0.5657	0.7190	0.6018	0.8669	0.6757	0.6433	0.6906	0.6125
skewness	-0.1155	0.1007	-0.3038	0.0540	0.3404	-0.1401	0.1846	0.4710
kurtosis	6.9810	5.4305	13.3543	5.2228	11.4265	8.9834	4.7373	6.5573

The Panel A of this table presents estimation results of the JDSI-PG model for the S&P 500 index (US) and eight emerging Asian stock market indices denominated in US dollar terms. The *p*-values are reported in parentheses. $\ln L$ is the log likelihood. The Panel B of this table reports the sample averages of the total conditional variation (TV) and its decomposition (JV/TV, DV/TV) computed from equation (2), the conditional skewness, and the conditional kurtosis of the index returns implied by the JDSI-PG model. JV/TV and DV/TV are respectively the sample averages of the variance of the jump component and the diffusion variance, each divided by the total variance. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Table 9

Jump Predictions for Emerging Asian Stock Markets

	JDAI-PG Model		JDSI-PG Model	
Country	Ex Ante Jump Prob.	Ex Post Jump Prob.	Ex Ante Jump Prob.	Ex Post Jump Prob.
CH	0.1918	0.1914	0.1877	0.1871
IN	0.1232	0.1233	0.1127	0.1128
ID	0.1033	0.0971	0.1115	0.1128
KR	0.0513	0.0509	0.0552	0.0550
MY	0.0461	0.0471	0.0683	0.0664
PH	0.1102	0.1070	0.1152	0.1147
TW	0.1980	0.1985	0.1999	0.2005
TH	0.2014	0.1997	0.1932	0.1917

This table reports ex-ante and ex-post probability of jumps for the JDAI-PG and JDSI-PG model. The ex-post probability of jumps, $E\left[N_t \middle| I_t\right]$ is defined as $E\left[N_t \middle| I_t\right] = \sum_{j=0}^{\infty} j \cdot P\left(N_t = j \middle| I_t\right)$, where $P\left(N_t = j \middle| I_t\right)$ is the ex-post inference on N_t given the time t information. (CH-China, IN-India, ID-Indonesia, KR-Korea, MY-Malaysia, PH-Philippines, TW-Taiwan, TH-Thailand)

Figure 1

Time Series Plots of the Daily Index Level

The following graphs illustrate the time series plots of the daily index level for the US and eight emerging Asian stock markets from 7/5/95 to 8/7/02.

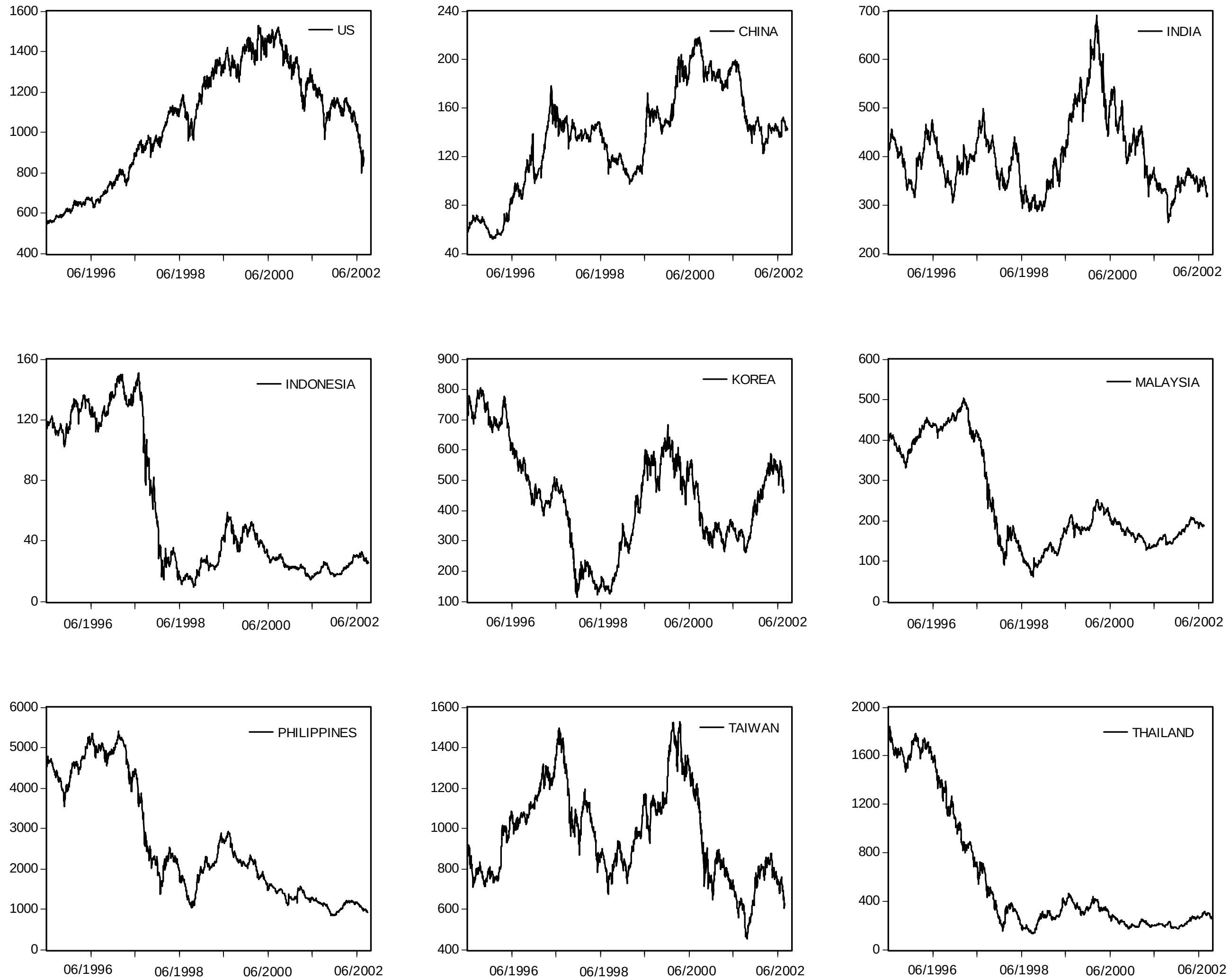


Figure 2

Time Series Plots of Daily Returns

The following graphs illustrate the time series plots of the daily returns for the US and eight emerging Asian stock markets from 7/5/95 to 8/7/02.

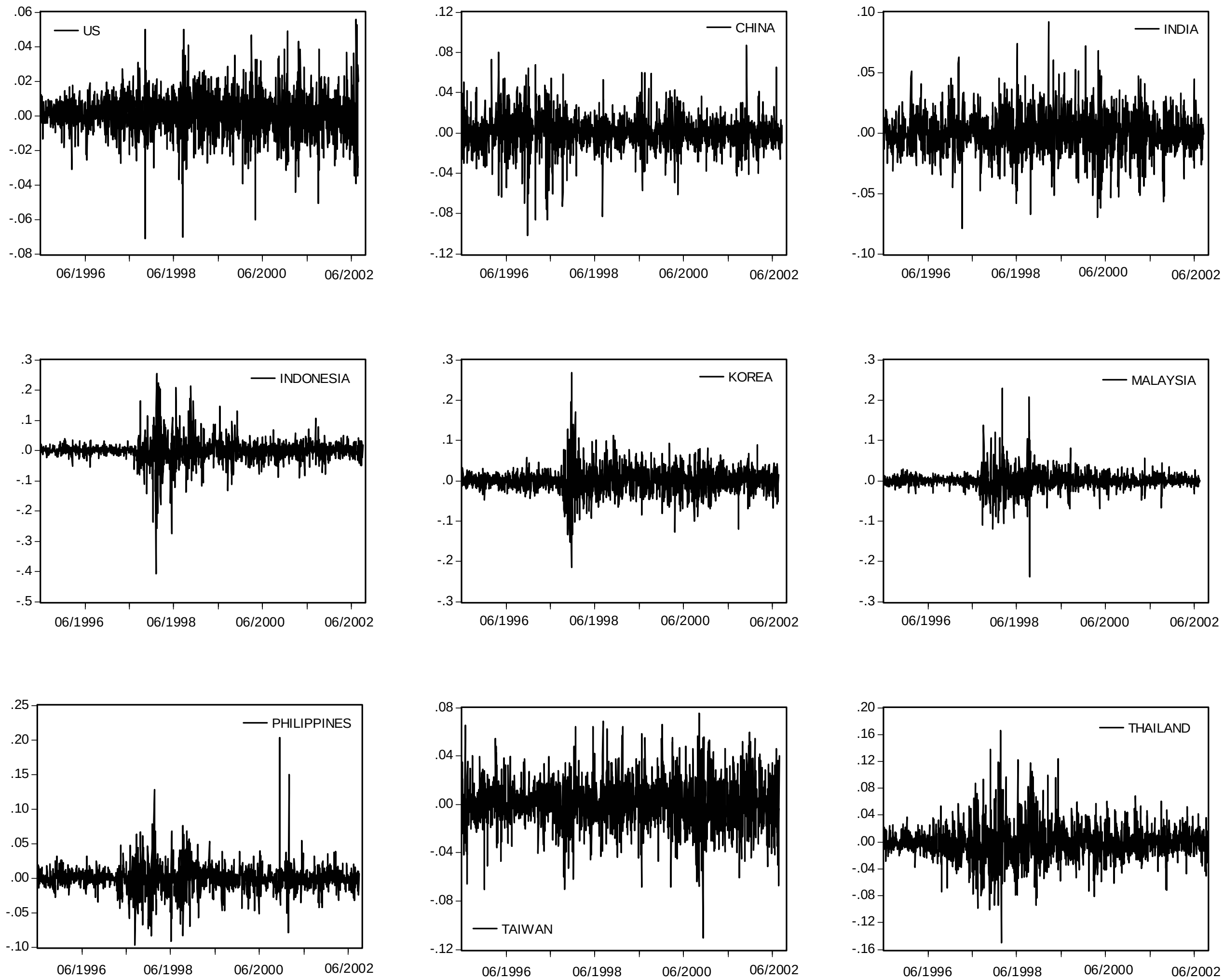


Figure 3

Time Series Plots of Conditional Volatility (GBM-PG Model)

The following graphs illustrate the time series plots of conditional volatilities computed from the GBM-PG model for the US and eight emerging Asian stock markets from 7/5/95 to 8/7/02.

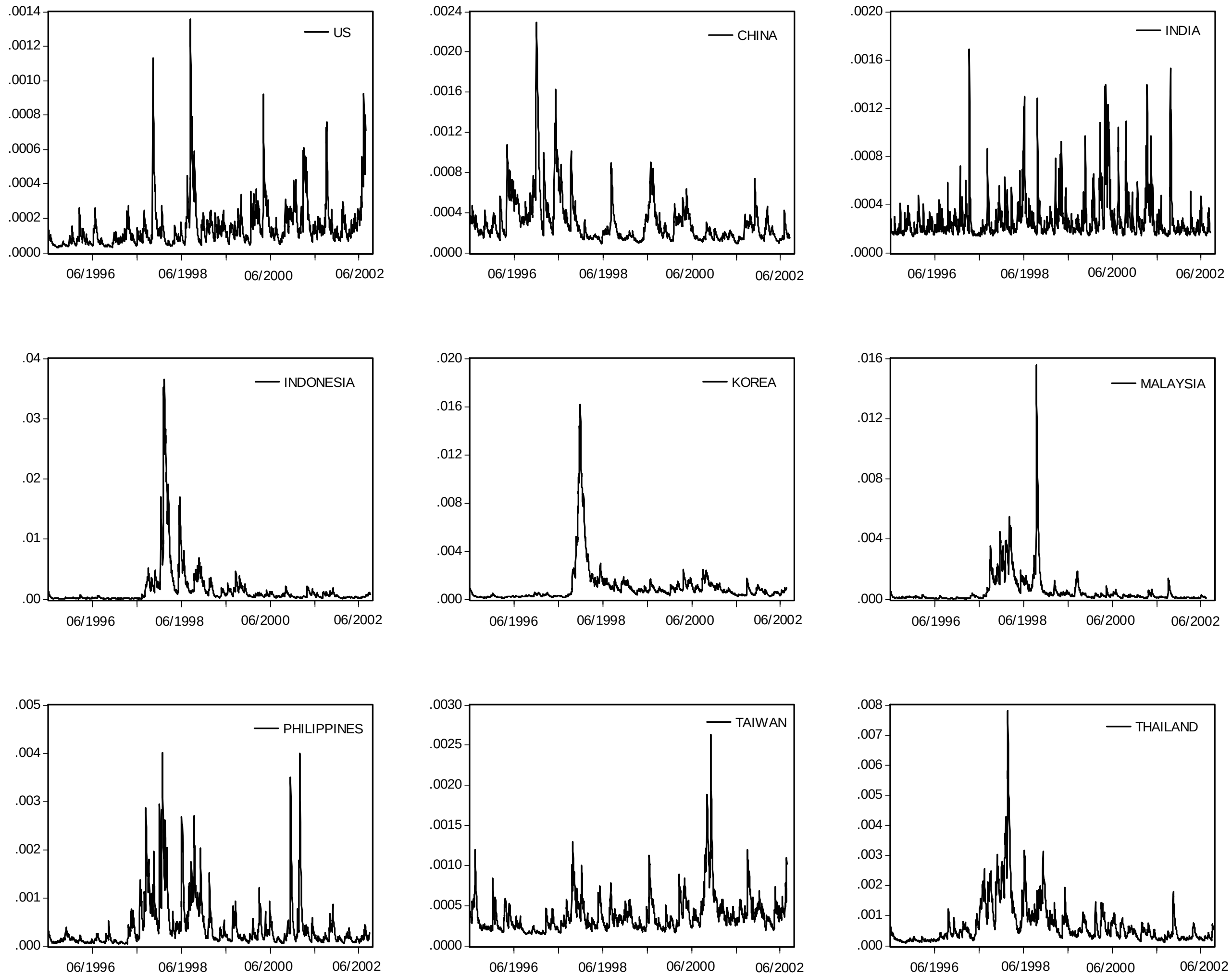


Figure 4

Time Series Plots of Conditional Jump Intensity (JDAI-PG Model)

The following graphs illustrate the time series plots of conditional jump intensities computed from the JDAI-PG model for the US and eight emerging Asian stock markets from 7/5/95 to 8/7/02.

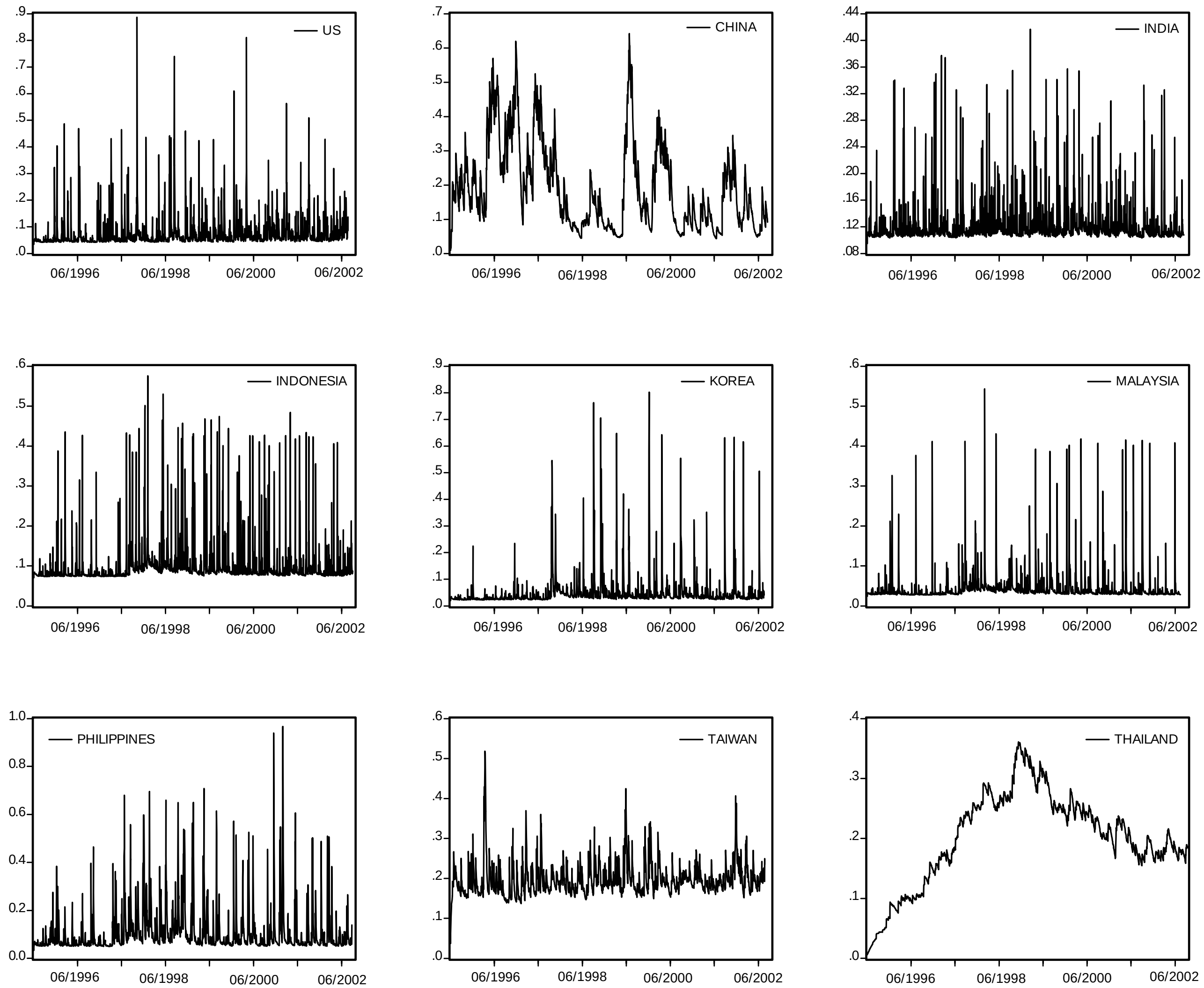
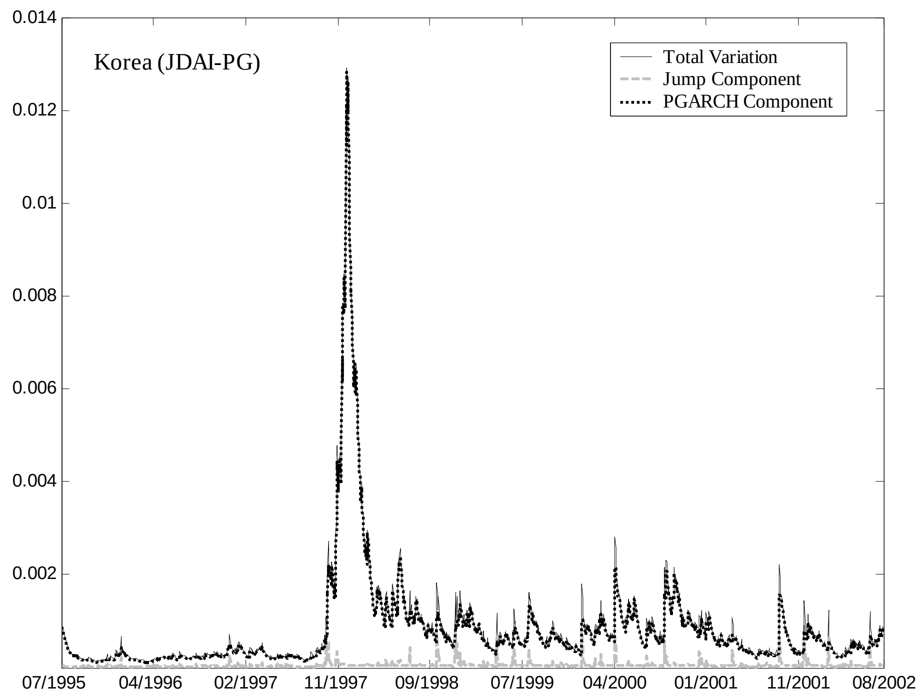
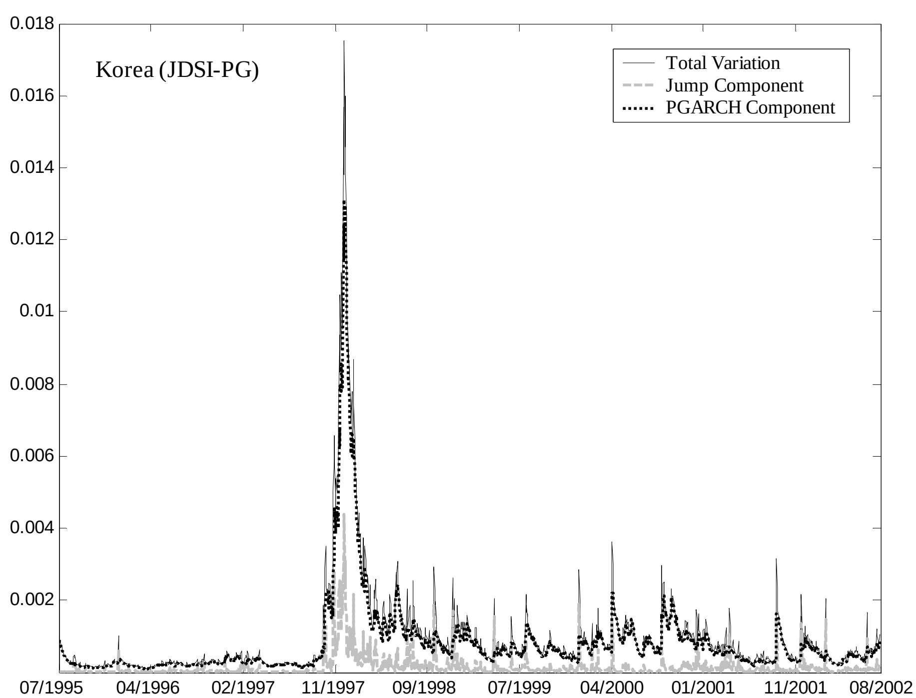


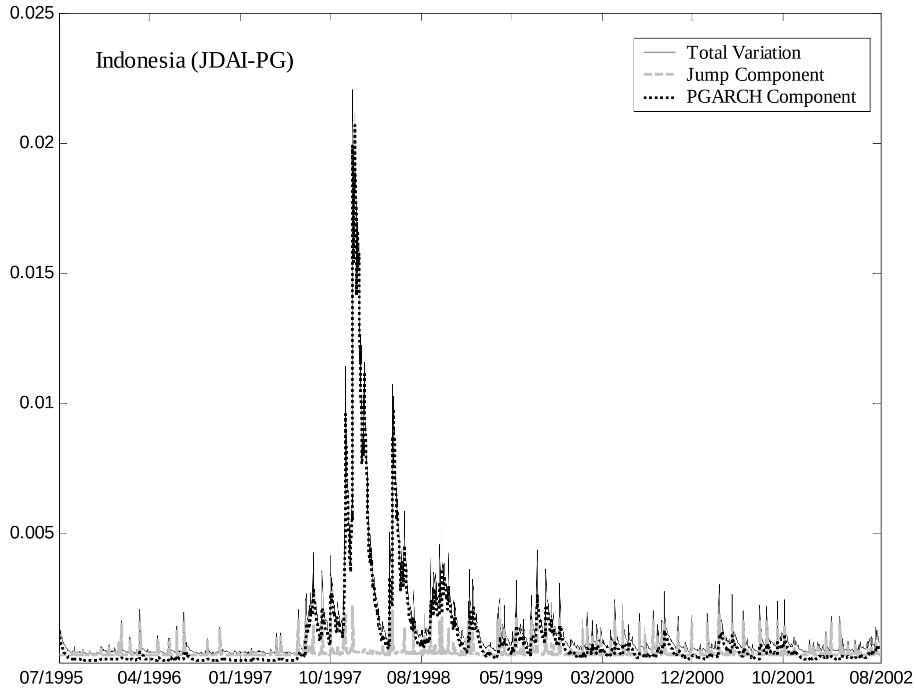
Figure 5

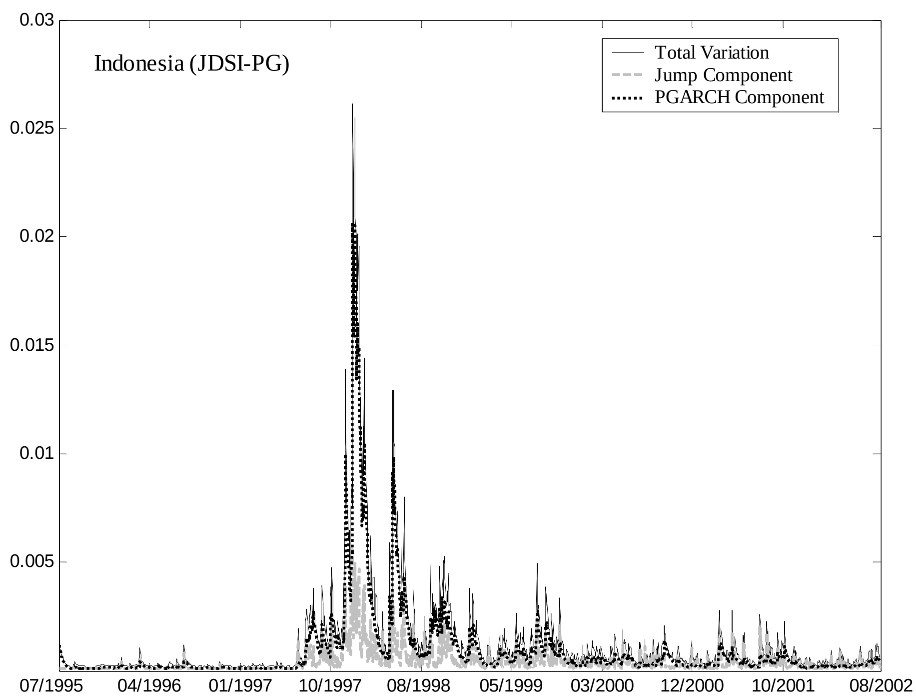
Time Series Plots of Variance Components

The following graphs illustrate the distinction of time series plots of the total variance implied by the JDAI-PG and the JDSI-PG model and the variance components for two (Korea and Indonesia) of five emerging Asian markets affected by the 1997 Asian financial crisis from 7/5/95 to 8/7/02.






Indonesia (JDAI-PG)
Total Variation
Jump Component
PGARCH Component
0.025
0.02
0.015
0.01
0.005
07/1995
04/1996
01/1997
10/1997
08/1998
05/1999
03/2000
12/2000
10/2001
08/2002


Indonesia (JDSI-PG)
Total Variation
Jump Component
PGARCH Component
0.03
0.025
0.02
0.015
0.01
0.005
07/1995
04/1996
01/1997
10/1997
08/1998
05/1999
03/2000
12/2000
10/2001
08/2002