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GARCH, jumps and permanent and transitory components of volatility: the case of the Taiwan exchange rate

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Abstract

This paper investigates whether there are three distinctive features in financial asset prices, that is, time-varying conditional volatility, jumps and the component factors of volatility. It adopts a component-GARCH-Jump, which can efficiently capture the three features simultaneously. Our results demonstrate that the three features exist in the Taiwan exchange rate. Besides time-varying conditional volatility, our model identifies 172 jumps between 5 January 1988 and 21 March 2003. The empirical evidence shows that the permanent component of the conditional variance is a relatively smooth movement except for a fairly sharp shift which began in 1997. This means that the effect of the Asian crisis shock might very well have exerted not only a transitory jump effect, but also a permanent effect on Taiwan's exchange rate.

JEL classification: G12

Keywords: Component model in volatiltiy; GARCH; Jump

1. Introduction

The specification of a statistical distribution which accurately models the behavior of asset prices continues to be a salient issue in financial studies. Option pricing, for example, requires a precise description of the stochastic process that is followed by an underlying asset. Two distinctive features of the stochastic process which are often mentioned in the literature are time-varying volatility and occasional jumps. The

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first of these suggests that the unconditional distribution of an asset price exhibits a "fat tail and high peak", though the price is conditionally normal. The most well-known models which characterize this feature are the autoregressive conditional heteroscedasticity (ARCH) model by Engle [5] and the more generalized version of it by Bollerslev [2]. The stochastic volatility models of Taylor [18] and Jacquier et al. [10] are also designed to capture the effect.

While the GARCH-type models reflect time-varying volatility, they do not describe jump behavior, i.e., the second distinctive feature of financial assets. Ignoring this feature may indeed distort hedging or pricing strategies. To explain, if jumps are present but ignored, models may severely overestimate the effectiveness of short-term hedging strategies which are based on dynamic portfolio adjustments. Similarly, the prices of out-of-the-money options that are close to maturity will also be underestimated if jumps are present but again not taken into account. Thus, the Merton [13] option pricing model explicitly admits jumps in the underlying assets. Jorion [11], Nieuwland et al. [16] and Vlaar and Palm [19] present a "GARCH-Jump" model, which addresses the issues of testing for jumps, the estimations of frequency and the size of jumps within models that also allow for conditional heteroskedasticity. Ball and Torous [1] provided empirical evidence of Poisson-distributed jumps in 30 daily common stock returns listed on the New York Stock Exchange.

Engle and Lee [6] later claimed that there is a third feature of the stochastic process, i.e., permanent and/or transitory components in volatiltiy. Typically, permanent and transitory components exist in nonstationary volatility. Thus, finding a unit root in volatility is indirect evidence of this feature. To cite some examples, Nelson [15], French et al. [9] and other reported that stock volatility is best described as an ARIMA (0,1,3), which is indicative of a stochastic trend, a permanent trend in the volatility. While component feature may exist, not much empirical evidence have been reported to directly demonstrate its existence,[2] Furthermore, few studies have explored their dynamic characteristics and how they are related with the first two features. For these reasons, Engle and Lee [6] proposed a "component-GARCH" model to decompose time-varying volatility into a permanent (long-run) and a transitory (short-run) component. Their specifications describe the behaviors of these two components and the ARCH effect.

While the GARCH-Jump and component-GARCH models are both successful in integrating any two of the three features of financial assets, neither takes all three of the distinctive features into account simultaneously. It is, therefore, reasonable to adopt a component-GARCH-Jump model to consider the concurrence of the above three features. This new model is ideal as far as applying it to all Taiwan exchange rate since we have strong reason to believe that the Taiwan exchange rate encompasses three features. To illustrate this, regarding the jump feature, during the Asian crisis, Taiwan's authority initially defeated all speculative attacks by providing unlimited US dollars. As a consequence, the exchange rate remained at US$ 28.5 NTD in the early period. Once Taiwan had lost 7 billion US dollars in foreign reserves, which almost depleted the vault foreign reserves, the authority halted all intervening abruptly announcing at 5:00 p.m., 16 October 1997 a "respect the market" policy. The exchange rate immediately devalued (jumped) to 29.5 NTD the next morning, which obviously created a sharp jump in the market.

Aside from the jump just referred to, jumps have also frequently appeared in other periods. The Fig. 1 plots the daily raw data of the Taiwan exchange rate. Where several big jumps are evident. The Fig. 2 is the daily returns of the Taiwan exchange rate, and many spikes are observed in the return plots, and these

[2] This is probably because the technique to decompose it is not an easy one, or alternatively the effect may be elusive.

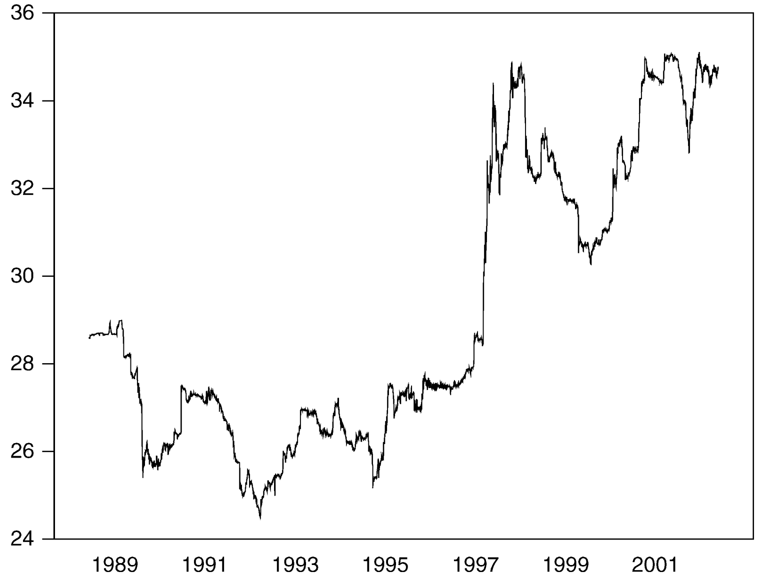

Fig. 1. Taiwan exchange rate.

correspond closely to the jumps shown in the upper panel. The Fig. 3 displays the absolute value of the daily returns for the exchange rate, which may suggest not only the presence of conditional time-varying volatility but also long-term trend components.

This paper investigates how to extract these three features using the Taiwan exchange rate. Because the component-GARCH-Jump model nests the GARCH-Jump, component-Jump and component-GARCH,

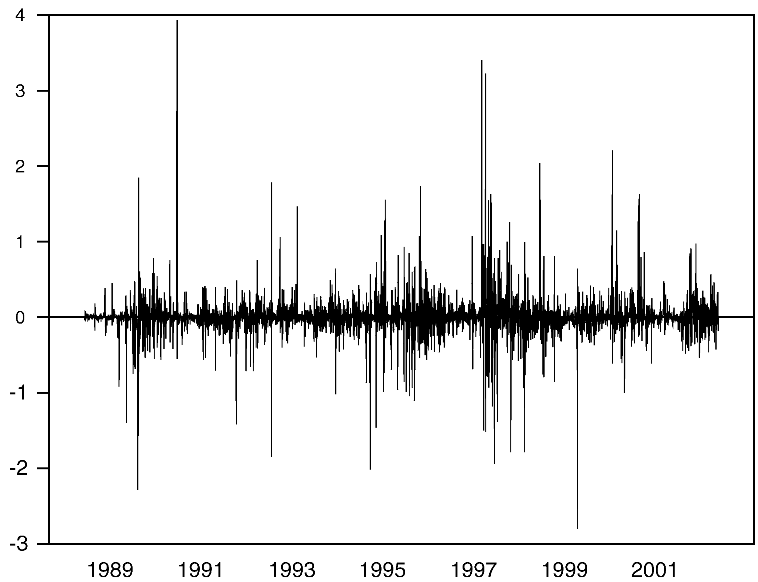

Fig. 2. Daily returns.

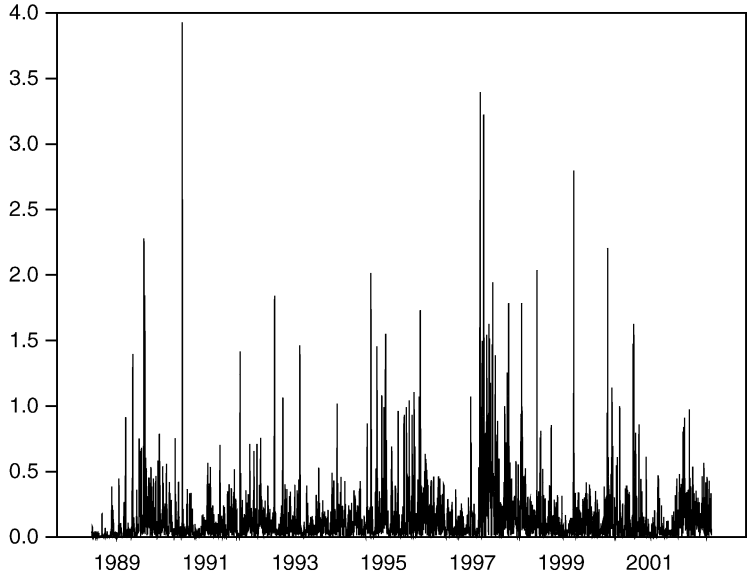

Fig. 3. Absolute value of daily returns.

we can test the validity of taking only two features into account. Another question which arises is how the three features evolve over time if they do in fact exist? Finally, this model explores the common belief that the Asian crisis has only had a temporary effect on volatility.

Our results are fruitful. First, our model rejects others which only consider two features. Thus, we demonstrate that pricing or hedging strategies we should be careful with since the three features may also exist in other financial assets. Also, our results are helpful when it comes to volatility forecasting. We also note that the permanent component of the conditional variance is relatively smoothed except for the sharp shift which began in 1997 and coincided with the Asian crisis. This means that the effect of the Asian crisis shock could have exerted not only a transitory jump effect, but also a permanent effect on Taiwan's exchange rate. Third, for the most of part, the jumps are short and only have a temporary effect on exchange rate volatility, 172 jumps are identified from 5 January 1988 to 21 March 2003. The year with the highest numbers of jumps is 1989, with a total of 26.

The organization of the paper is as follows: Section 2 briefly presents a review of the history of Taiwan's exchange rate market. Section 3 describes the setup of empirical models, including that of the component-GARCH model and of the component-GARCH-Jump model. Section 4 presents the data and empirical results. Section 5 concludes the paper.

2. Taiwan exchange market

It is well known that dramatic market shocks and/or such non-market changes as political events may contribute to observed high volatility in an exchange rate. Taiwan is no exception. In addition, jumps in exchange rates may well be generated by discontinuities in the arrival of "news", which Mussa [14] and Frenkle [8] argued should be the predominant cause of exchange rate movements. Jumps may also be caused by changes in monetary policies directed at affecting the external value of a currency, which Flood and Hodrick [7] labeled “process switching”. The component behavior, however, is less discussed in the literature, and not easy to describe ex ante.

Exchange rates in many countries are often not floated but are managed floating or pegged to one or some key currencies.[3] The Taiwan monetary authority adopts a managed floating exchange rate system. It pegs the US dollar but also allows the exchange rate to adjust when the rate is considered to have deviated from the fundamental rate or when there is a so-called non-market shock. Besides the jumps during the Asian crisis of 1997 mentioned in Section 1, other examples include the two China missile tests in the Taiwan Straits in 1995 and 1996. During those periods, the Central Bank actively intervened in the market protecting the NTD from devaluation and successfully stabilizing the exchange rate, which is indicative of suggesting a “flat” exchange rate with no jump.

Shen and Chen [17] claim that the Taiwan exchange rate displays a unique phenomenon of “fast devaluation, slow appreciation”. That is, the exchange rates persist for an extended period during the appreciation stage but that they are short-lived during the depreciation stage. Such an asymmetric swing depicts a long swing in appreciation and a short swing in depreciation,[4] the latter representing the phenomenon of jumps.

3. Component-GARCH-Jump model

We first discuss the models in light of only the two features, that is the GARCH-Jump and component-GARCH models. We then address the component-GARCH-Jump model in light of all three features.

3.1. The component-GARCH model

Define $y_t = \ln(S_t/S_{t-1})$ as exchange rate, expressed in the rate of return, where S_t is the exchange rate per US dollar. The component-GARCH model, first proposed by Engle and Lee [6], is employed here as a benchmark as follows:

$$y_t = \delta + \varepsilon_t, \tag{1}$$

$$\varepsilon_t|\Psi^{t-1} = \sigma_t \xi_t \sim N(0, \sigma_t^2), \quad \xi_t \sim N(0, 1), \tag{2}$$

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_t^2 - q_{t-1}), \tag{3}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2), \tag{4}$$

where term δ is the mean of the process, and q_t a permanent, or trend, component in the conditional variance that captures the idea of time-varying long-term volatility with the speed of mean reversion determined by ρ. Term Ψ^{t-1} denotes the information set. Typically ρ is between 0.9 and 1, so the q_t approach it unconditional variance very slowly. For $\rho = 1$, the long-term volatility process is integrated. The forecasting error term $(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$ is the zero-mean and serial uncorrelated, which drives the evolution of the permanent component. The difference between σ_t^2 and q_t represents the transitory component of

[3] See the IMF’s country report for different exchange rate systems.

[4] They applied Engle and Hamilton’s [4] two-state Markov Switching model to examine long swings in Taiwan’s exchange rate, and they attribute such asymmetric swings to the Central Bank’s asymmetric preferences, where a long swing in appreciation is a result of a “slowdown” policy, and a short swing is the “let-it-go” policy.

the conditional variance that dies out with time; thus the long-run movement of asset return volatility is dominated by the current expectation of the permanent trend given $\alpha + \beta$ is less than one. Note that the GARCH (2,2) process represents the underlying data-generating process for the conditional variance in the component model as shown in Engle and Lee [6].

3.2. The GARCH-Jump model

The GARCH-Jump model is an extension of the GARCH model and allows the jump variable J_t, which is an indicator of jumps which account for the spikes. The complete GARCH-Jump model can be represented as follows:

$$y_t = \delta + \varepsilon_t + \sum_{j=0}^{J_t} \upsilon_j, \tag{5}$$

$$\varepsilon_t | \Psi^{t-1} = \sigma_t \xi_t \sim N(0, \sigma_t^2), \quad \xi_t \sim N(0, 1), \tag{6}$$

$$J_t \sim \frac{\mathrm{e}^{-\lambda}\lambda^j}{j!}, \quad \upsilon_j \sim N(\mu, \nu^2), \tag{7}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{8}$$

where J_t is assumed to be a Poisson random variable with parameter λ. It is assumed that each Poisson event causes a discrete jump of size $\exp(\upsilon_j)$, $j = 1, 2, \ldots, J_t$. Hence, jumps are assumed to be independently lognormally distributed random variables, which are independent of ξ_t, while υ_j is assumed to be an identical independent, and normally distributed random variable with mean μ and variance ν^2.

3.3. The component-GARCH-Jump model

The component-GARCH-Jump model is an extension of the component-GARCH model and allows the jump variable J_t, which is an indicator of jumps. The complete component-GARCH-Jump model can be represented as follows:

$$y_t = \delta + \varepsilon_t + \sum_{j=0}^{J_t} \upsilon_j, \tag{9}$$

$$\varepsilon_t | \Psi^{t-1} = \sigma_t \xi_t \sim N(0, \sigma_t^2), \quad \xi_t \sim N(0, 1), \tag{10}$$

$$J_t \sim \frac{\mathrm{e}^{-\lambda}\lambda^j}{j!}, \quad \upsilon_j \sim N(\mu, \nu^2), \tag{11}$$

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_t^2 - q_{t-1}), \tag{12}$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2). \tag{13}$$

where the definition of the term J_t is the same as that in the last section. This model has also been used, for example, by Yoo and Kim [20], Chang and Kim [3], and Kim and Mei [12] who have respectively studied seven EMS exchange rates, Hong Kong exchange rate volatility behavior, and the Korean financial crisis.

3.4. State-space representation of the model

If the maximum number of jumps is $J_t = 5$, then the component-GARCH-Jump model (with $(j) = 5$) can be represented as a state-space form as follows:

$$\begin{bmatrix} y_t \\ y_t \\ y_t \\ y_t \\ y_t \\ y_t \end{bmatrix} = \begin{bmatrix} \delta \\ \delta+\mu \\ \delta+2\mu \\ \delta+3\mu \\ \delta+4\mu \\ \delta+5\mu \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \upsilon_{1t}-\mu \\ \upsilon_{2t}-\mu \\ \upsilon_{3t}-\mu \\ \upsilon_{4t}-\mu \\ \upsilon_{5t}-\mu \end{bmatrix} \quad (14)$$

$$\begin{bmatrix} \varepsilon_t \\ \upsilon_{1t}-\mu \\ \upsilon_{2t}-\mu \\ \upsilon_{3t}-\mu \\ \upsilon_{4t}-\mu \\ \upsilon_{5t}-\mu \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{t-1} \\ \upsilon_{1t-1}-\mu \\ \upsilon_{2t-1}-\mu \\ \upsilon_{3t-1}-\mu \\ \upsilon_{4t-1}-\mu \\ \upsilon_{5t-1}-\mu \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \upsilon_{1t}-\mu \\ \upsilon_{2t}-\mu \\ \upsilon_{3t}-\mu \\ \upsilon_{4t}-\mu \\ \upsilon_{5t}-\mu \end{bmatrix} \quad (15)$$

Alternatively, Eqs. (14) and (15) can be written in a more compact form:

$$Y_t = \Delta^{(j)} + G_t^{(j)}\zeta_t, \quad (16)$$

$$\zeta_t = T_t\zeta_{t-1} + R\varpi_t, \quad (17)$$

where $E(R\varpi\varpi'R') = Q = \text{diag}\{\sigma_t^2, \nu^2, \nu^2, \nu^2, \nu^2, \nu^2\}$. The maximum likelihood method is employed to estimate the unknown parameters. A numerical estimation of the unknown parameters is performed using the OPTMUM module of GAUSS 3.2 with a combination of the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. Readers are referred to the appendix of Chang and Kim [3] for details.

4. Data and results

4.1. Data analysis

Our daily data starts from 5 January 1988 to 21 March 2003, which totals 3642 observations. The data are taken from the *Pacific Exchange Rate Service*. Table 1 summarizes the sample statistics for the daily return data. The positive skewness of 1.41 implies that a devaluation in size may dominate the data.[5] The kurtosis is 36.73 which suggests the market is highly non-normally distributed. The LM-ARCH

[5] Our skewness and kurtosis are, in fact, the excess skewness and excess kurtosis, which deviate from their respective means.

Table 1
Sample statistics of the log difference in the exchange rate

Statistics	Estimate
Mean	0.005316
Median	0.000000
Maximum	3.930653
Minimum	−2.797611
Standard deviation	0.283756
Skewness	1.412817
Kurtosis	36.73748
Jarque–Bera normality test	173888.3
Probability	(0.000000)
LM-ARCH test	21.69170
Probability	(0.000000)
Ljung–Box autocorrelation test	81.07000
Probability	(0.000000)

Jarque–Bera normality test: $T*(\text{Kur}^2/24+\text{SK}^2/6) \sim \chi_2^2$, where T: sample size; Kur: kurtosis; SK: skewness. LM-ARCH test: $y_t^2 = a_0 + \sum_i^4 a_i y_{t-i}^2$, TR^2, where R^2 is the coefficient of determination. Ljung–Box: $T(T+2)\sum_{i=1}^{24}(T-i)^{-1}r_i^2 \sim \chi_{24}^2$, where r_i^2 is the autocorrelation function.

test equals to 21.69, rejects the null hypothesis of no relation between the squared return and its lagged squared returns. The Ljung–Box is equal to 81, rejecting the null of no autocorrelation among returns.

4.2. *Empirical results*

Table 2 presents the parameter estimates of the GARCH (1,1) and component-GARCH and GARCH-Jump models, respectively.[6] With regard to the GARCH (1,1) model, the volatility persistence rate is estimated to be $\alpha + \beta = 0.987$, which approximates unity. Thus, a nonstationary variance may exist. While the diagnostic tests using LM-ARCH show the ARCH effect is removed, a strong autocorrelation remains in the residuals. The high skewnesss and kurtosis, 2.69 and 68, respectively, causes the normality assumption to be rejected.

Turning to the case of the component-GARCH model in Table 2, the estimated $\alpha+\beta$ is similar to that of the GARCH model. The decay rate of the permanent component, ρ, is estimated as 0.985, implying that approximately 73.9% ((=0.985)^{20}) of a shock remains even after 20 trading days. Diagnostic checking shows similar results to those using only the GARCH effect. Because the GARCH is nested in the component GARCH, we can apply the log-likelihood ratio to examine the validity of the GARCH model. The log-likelihood ratio test, which is $-2 \times (\log L_1 - \log L_2) = 14.626$, shows that the null of no components is rejected at the 5% significant level. The possible reason for the rejection of the GARCH

[6] Since most empirical implementations of the GARCH(p, q) models adopt low orders for the lag lengths p and q and such a small number of parameters seem sufficient to model variance over very long sample periods, we set $p = q = 1$ for the GARCH model.

Table 2
Parameter estimates from the GARCH-type model

Parameter	GARCH (1,1)		Component-GARCH		GARCH-Jump	
	Estimate	$\|t\|$-stat.	Estimate	$\|t\|$-stat.	Estimate	$\|t\|$-stat.
ω	0.124	15.108	0.863	1.964	0.131	2.217
α	0.531	21.699	0.527	20.731	0.417	19.493
β	0.456	19.906	0.458	18.948	0.576	27.451
δ	−0.010	3.307	−0.010	3.289	−0.001	1.156
λ					0.143	12.447
μ					0.018	0.805
ν					0.521	18.290
ρ			0.985	18.067		
ϕ			0.001	0.119		
$\log L$	228.576		235.889		1339.759	
H_0: no component		LR	14.636			
H_0: no jump		LR			2222.366	
Diagnosis check of residuals						
Mean	0.077		0.065		0.013	
Skewness	2.693		2.533		−0.039	
Probability	(0.000)		(0.000)		(0.326)	
Kurtosis	68.123		69.046		−0.361	
Probability	(0.000)		(0.000)		(0.000)	
Jarque-Bera	647803.8		665675.4		20.838	
Probability	(0.000)		(0.000)		(0.000)	
LM-ARCH	0.095		0.050		3.751	
Probability	(0.983)		(0.995)		(0.005)	
Ljung–Box	50.384		53.728		41.007	
Probability	(0.001)		(0.001)		(0.017)	

model is its missing "jumps" factor. However, the component-GARCH is also far from perfect since the residuals suffer from large kurtosis.

The last column of Table 2 reports the estimated results of the GARCH-Jump model. T estimated $\alpha + \beta$ is again similar to that of the GARCH model. It is surprising to find that the kurtosis is substantially reduced from 68.123 in the GARCH model to −0.361 in the present GARCH-Jump model. Kurtosis aside, the skewness is also reduced from 2.693 to −0.039. Thus, it seems that adding the jump effect can largely reduce the phenomenon of fat tail and high peak. While the skewness and kurtosis are reduced, the LM test for the ARCH effect increases, becoming significantly different from zero. The likelihood ratio test is equal to 387, which also rejects the null of no jumps. Thus, the factor of adding jumps can reduce the effects of kurtosis and skewness but leave the ARCH effect unchanged.

As the null of no components and no jumps are rejected, it is worth considering the three features concurrently. Table 3 presents the estimated results of the component-GARCH-Jump model. Three interesting

Table 3
Parameter estimates from the component-GARCH-Jump model

Parameter	Estimate	$\|t\|$-stat.	Estimate	$\|t\|$-stat.
ω	0.038	4.074	0.001	3.515
α	0.278	10.246	0.340	16.622
β	0.402	8.359	0.564	19.611
δ	−0.001	0.546	0.000	0.346
λ	0.119	10.14	0.114	13.041
μ	0.042	1.314	0.021	0.518
ν	0.568	16.603	0.603	18.0963
ρ	0.994	676.973	1	–
ϕ	0.184	7.812	0.032	9.834
$\log L$	1360.150		1384.137	
H_0: component-GARCH	LR	2248.552		
H_0: GARCH-Jump	LR		40.782	
Diagnostic check of residuals				
Mean	−0.001		0.001	
Skewness	−0.057		0.008	
Probability	(0.159)		(0.832)	
Kurtosis	−0.303		−0.274	
Probability	(0.000)		(0.001)	
Jarque–Bera	15.966		11.457	
Probability	(0.000)		(0.003)	
LM-ARCH	1.541		2.387	
Probability	(0.187)		(0.049)	
Ljung–Box	40.609		37.478	
Probability	(0.018)		(0.039)	

results are worth highlighting. First, the estimated ρ is high reaching 0.994, which is very close to 1. This further strengthens our belief that the permanent component of volatility can be integrated. We examine this issue by providing the statistical test by using $\rho = 1$. Then, we re-estimate the model and calculate the restricted log-likelihood function, denoted as $\log L_{\mathrm{R}}$, while $\log L_{\mathrm{U}}$ is the unconstrained version. As shown in Table 3, the unrestricted and restricted log-likelihood value is 1360.15 and 1384.12, respectively. Then the log-likelihood ratio test $2 \times (\log L_{\mathrm{U}} - \log L_{\mathrm{R}}) = -47.97$, which cannot reject the restricted component-GARCH-Jump model. The permanent component of volatility is, therefore, a random walk.

Next, the jump parameter, $\lambda = 0.119$, is significant at the 5% significant level, which is consistent with past studies, e.g., Nieuwland et al. [16]. This estimate suggests that the average number of Poisson-distributed jumps is about 0.12. Hence, the flow of information that arrives in the market can be described most of the time by the heteroscedastic diffusion process, but is occasionally subject to jump risks.

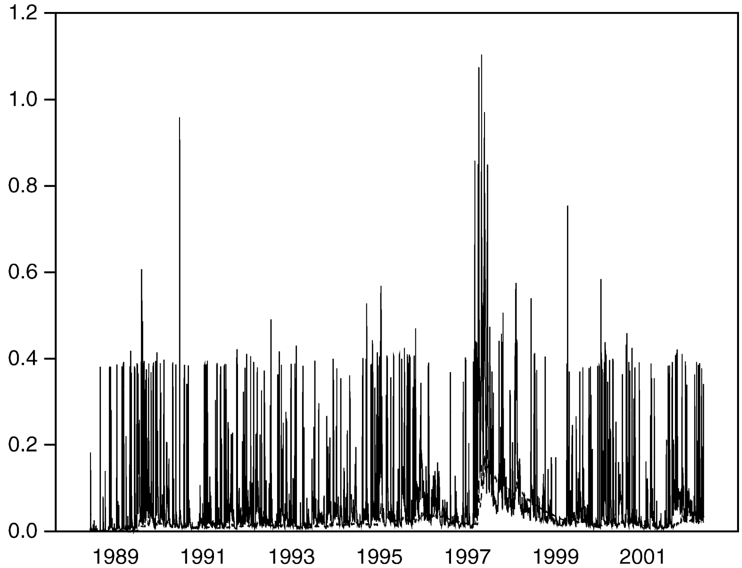

Fig. 4. Total volatility vs. permanent component.

Last, the high kurtosis and skewness found in the previous GARCH and component-GARCH models are again substantially reduced, which mirror the results from the GARCH-Jump model. While the testing of the statistics of the normality test is still significant at the conventional level, the size of the statistic is largely reduced, demonstrating that the diagnostic tests, when compared with those of the two models,

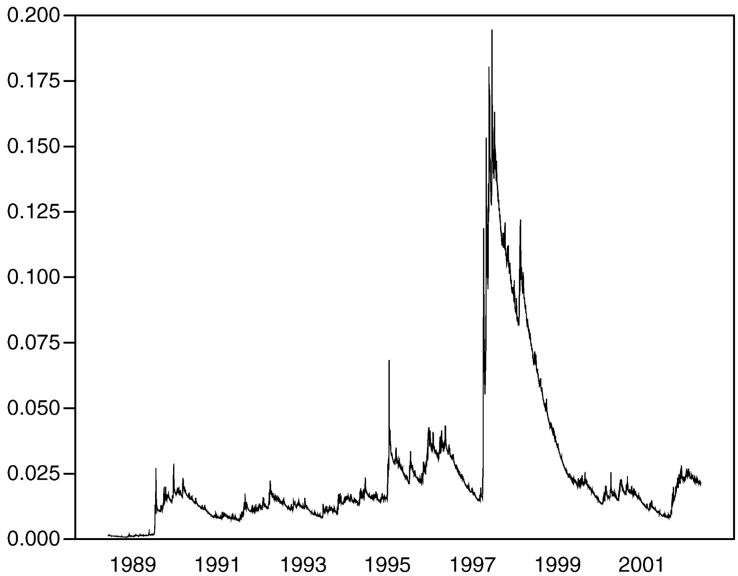

Fig. 5. Permanent component.

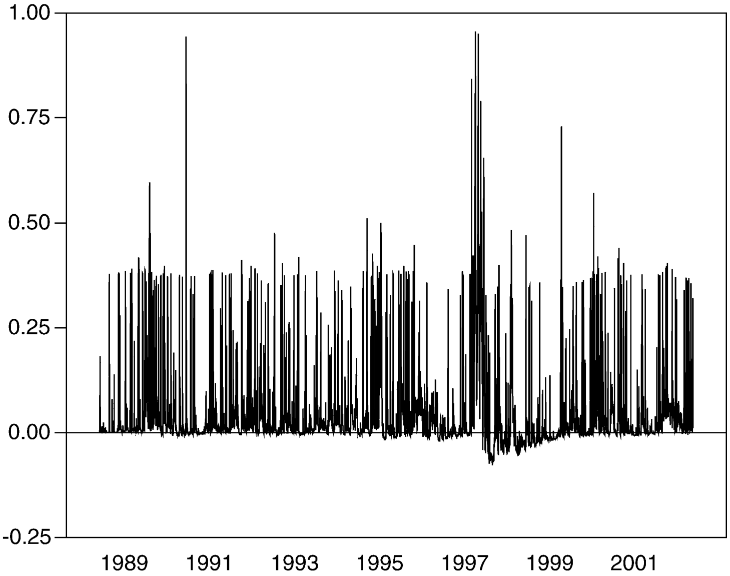

Fig. 6. Transitory component.

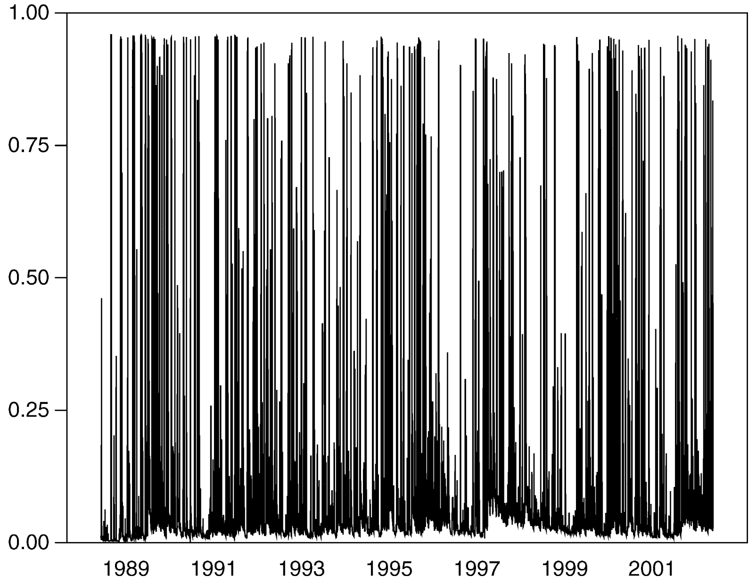

Fig. 7. Posterior probability for jump.

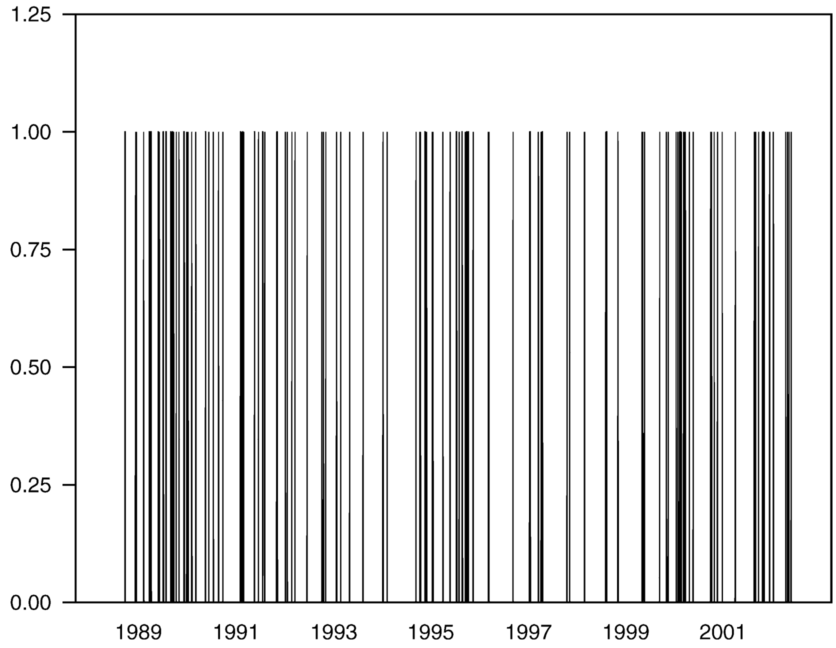

Fig. 8. Identified jump dates.

are indeed improved. Employing LR tests, we reject both the GARCH-Jump and component-GARCH model.

Figs. 4–6 plots the estimated (overall) conditional volatility and its two components, the permanent and transitory components. Figs. 4–6 shows total volatility is mostly flat with a slight peak around 1997. The permanent component is relatively smoothed before 1997 but displays a sharp rise after that. It drops down to a low level after 1999. The transitory component is simply the difference between the above two, resembling overall volatility. As the rising parts of the three volatilities are coincident with the occurrence of the Asian crisis, the effect of the crisis shock may have exerted not only a transitory jump effect, but also a permanent effect on Taiwan's exchange rate. It is worth noting that while the permanent component displays a sharp fluctuation around 1997, its absolute size is small (only 0.2). Hence, the influence of jumps is short-lived and has only a temporary effect on exchange rate volatility.

Fig. 7 explicitly identifies the dates of all jumps by using posterior probabilities. The top panel of the figure displays the posterior probability that jumps could have occurred with a magnitude of $J_t = 2$. The dates of the jumps are identified if the posterior probability is greater than 0.9.[7] The final identified dates are plotted in Fig. 8 and are also summarized in Table 4. The model identifies 172 jumps from 5 January 1988 to 21 March 2003. There are 26 jumps in 1989, and the frequency of occurring is more than in other years (Fig. 8).

[7] We simply select 0.9 as the cutoff for conservative reasons. Choosing a small cutoff, such as 0.7, yields more jumps. Nevertheless, our results showing that many jumps exist would therefore not be affected if different cutoffs being selected.

Table 4
Identified jump dates by the component-GARCH-Jump model

19880406	19900516	19950530	19990621
19880407	19900628	19950710	19990622
19880624	19900803	19950717	19991229
19880628	19910114	19950929	20000105
19880705	19910115	19951002	20000117
19880829	19910117	19951123	20000511
19881017	19910130	19951124	20000704
19881018	19910315	19960115	20000717
19881027	19910327	19960116	20000918
19881028	19910328	19960202	20000929
19881101	19910409	19960226	20001002
19881103	19910702	19960227	20001013
19881230	19910703	19960320	20001018
19890105	19910801	19960321	20001019
19890112	19910904	19960325	20001020
19890117	19910905	19960401	20001026
19890217	19910919	19960402	20001114
19890221	19920106	19960405	20001122
19890222	19920108	19960408	20001129
19890314	19920109	19960411	20010102
19890315	19920110	19960412	20010130
19890316	19920323	19960517	20010131
19890425	19920408	19960913	20010613
19890426	19920513	19960917	20010620
19890427	19920610	19970324	20010711
19890502	19920914	19970729	20010803
19890510	19930119	19970730	20010912
19890511	19930208	19970731	20011221
19890515	19930225	19970801	20020517
19890522	19930524	19970805	20020521
19890616	19930526	19971007	20020528
19890707	19930707	19971028	20020530
19890818	19930920	19971103	20020621
19890822	19940110	19971105	20020723
19890913	19940621	19971106	20020726
19890926	19940622	19971107	20020729
19891030	19940725	19980519	20020806
19891102	19950308	19980608	20020916
19891206	19950406	19980930	20021016
19900308	19950411	19981002	20030121
19900309	19950515	19990318	20030204
19900312	19950516	19990324	20030214
19900410	19950522	19990325	20030304

5. Conclusions

Three distinctive features in the financial asset prices—that is, time-varying conditional volatility, jump and the component factors in volatility—are separately found in the literature. Past studies have typically focused on the first feature by using the GARCH-type model, and others using the use GARCH-Jump and component-GARCH to describe the GARCH effect with the second or the third features, simultaneously. However, few, with the exception of Kim and Mei [12] and Chang and Kim [3], have taken the three features together. This paper adopts a component-GARCH-Jump, which can capture the three features at the same time.

Our results show that the three features exist in the Taiwan exchange rate. Besides time-varying conditional volatility, our model identifies 172 jump dates from 5 January 1988 to 21 March 2003, of which there are 26 jumps in 1989, a frequency of occurrence which is more than that in other years.

The permanent and transitory components are also found in the exchange rate. The permanent component of the conditional variance is relatively smoothed except for a sharp beginning in 1997, which coincides with the timing of the Asian crisis. This means that the effect of the Asian crisis shock could have exerted not only a transitory jump effect, but also a permanent effect on Taiwan's exchange rate. The size of the permanent effect, however, is small. Thus, the influence of the jumps was short-lived and only had a temporary effect on the exchange rate volatility.

Our results may provide useful insight into the filed of volatility forecasting, option pricing and futures hedging strategies, among other. We leave it as a future study.

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